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The physical environment and health: Implications for the planning and management of healthy cities

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The physical environment and health: Implications for the planning and management of healthy cities

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Editorial: The physical environment and health: implications for the planning and management of healthy cities

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Editorial on the Research Topic
The physical environment and health: implications for the planning and management of healthy cities

In recent years, there has been a significant upsurge in the demand for a high quality of life, as individuals strive to lead healthy and fulfilling lives. A multitude of health behaviors, outcomes, and issues (e.g., physical activity, obesity, diabetes mellitus, stress, depression, high blood pressure, and health inequalities and inequities) have emerged as major concerns, capturing the attention of governments, societies, academia, and other stakeholders (1–5). Recognizing the pivotal role of the physical environment—the geographic area and surrounding factors—in shaping human health behaviors and outcomes, extensive research has focused on understanding the complex connections between the two.

The physical environment encompasses various elements that directly or indirectly influence our health and overall wellbeing. Many aspects of the physical environment, such as air and water quality, noise pollution, exposure to hazardous substances, housing conditions, indoor environments, and access to open/green spaces and recreational areas, contribute to human health. Therefore, gaining a comprehensive understanding of how these aspects interact with health behaviors and outcomes is of utmost importance (6–10).

The concept of a "healthy city" was introduced by the World Health Organization in the last century and has since been widely discussed, explored, and advocated worldwide. The notion of a healthy city emphasizes the importance of improving the physical environment as a critical element in achieving optimal health and wellbeing for urban populations. The physical environment plays a crucial role in shaping health behaviors and outcomes within urban settings, making it essential to prioritize its enhancement as part of broader healthy city initiatives. Scientific advancements are constantly anticipated to foster collaboration between governments and society toward the establishment of healthy cities.

Furthermore, the recent outbreak of the coronavirus disease 2019 (COVID-19) has had an unprecedented impact on societies worldwide (11, 12). The rapid spread of the virus has underscored the need for cities to develop strategies that integrate the fight against COVID-19 with the framework of healthy cities (13–15). It is crucial to gather and summarize the experiences of cities in their response to the pandemic, encompassing not only strategic frameworks but also practical implementation. This includes a specific focus on enhancing the urban physical environment to mitigate the transmission of the virus, promote public health interventions, and ensure the resilience of cities in the face of future health crises.

To address these pressing concerns by gathering research and insights from diverse perspectives and to catalyze in-depth and thoughtful discussions on the intricate relationship between the physical environment and human health, this Research Topic was initiated in July 2022. (In *Frontiers* journals, a "Research Topic" corresponds to what is commonly referred to as a "special issue" or "virtual special issue" in many other journals.) It is supported by four *Frontiers* journals: *Frontiers in Public Health*, *Frontiers in Ecology and Evolution*, *Frontiers in Environmental Science*, and *Frontiers in Sociology*. It serves as a platform for disseminating the latest insights and discoveries in the realm of the physical environment and human health, particularly those with profound theoretical, methodological, and practical implications. The primary objectives are to promote scientific progress, offer research support for policy development and evaluation, and stimulate immediate attention from governments, businesses, researchers, and individuals.

After undergoing a rigorous review process, a total of 67 papers have been selected for inclusion in this Research Topic. Among these papers, 63 are classified as "Original Research," showcasing the innovative contributions made by the authors. One paper falls under the "Methods" category, emphasizing the importance of developing robust methodologies for studying the intricate relationship between the physical environment and human health. Additionally, three papers are designated as "Review" articles, synthesizing existing knowledge in the field and providing valuable insights. Moreover, the collected papers have been published across the four supporting journals, with 58 appearing in *Frontiers in Public Health*, 4 in *Frontiers in Ecology and Evolution*, 4 in *Frontiers in Environmental Science*, and 1 in *Frontiers in Sociology*. This diverse distribution of the 67 papers across these journals reflects the interdisciplinary nature of the topic, as scholars from diverse disciplines have brought forth their expertise and perspectives.

The selected papers are authored by over 300 scholars. The authors are from a wide range of countries, emphasizing the global scope of research in the field of the physical environment and health. Scholars from many countries such as China, the United States, the United Kingdom, Canada, Finland, Switzerland, Australia, Japan, India, and Nepal have contributed to this special issue. The inclusion of researchers from diverse cultural backgrounds enhances the richness and breadth of perspectives presented in the papers.

The collected papers cover a wide array of topics, addressing crucial issues related to the physical environment and multi-dimensional human health (e.g., physical and mental health). The topics include but are not limited to COVID-19 (Dubey et al.; Tang et al.), the physical environment and health behaviors (e.g., Yang et al.; Zeng et al.), the physical environment and health outcomes (e.g., Zhang et al.; Zhu et al.), urban public spaces (e.g., Chen et al.; Wei et al.), and evacuation risks (e.g., Li et al.; Lv et al.). To sum up, the diverse range of topics covered in this collection of papers reflects the interdisciplinary nature of research in the physical environment and human health. Scholars from fields such as public health, urban planning and design, architecture, landscape architecture, human geography, public administration, environmental science, and urban management have contributed to this special issue, highlighting the collaborative effort required to address the complex challenges at the intersection of the physical environment and human health.

Papers included in this Research Topic and a sea of previous studies highlight the critical importance of addressing physical environmental factors that can significantly impact human health and overall wellbeing. The findings underscore the urgent need to prioritize the protection of public health by creating a health-supportive environment. This necessitates the implementation of policies and regulations that enhance air and water quality, advocate for sustainable and healthy housing options, mitigate exposure to hazardous substances, manage noise pollution, and preserve and create green spaces. By taking proactive measures in these areas, we can positively influence the health outcomes of individuals and communities.

To further advance our understanding and approach in this field, numerous research directions can be envisioned for future exploration. These include (1) investigating the connections between the physical environment (e.g., the built environment, extreme heat/cold, urban flooding, water/air/soil pollution, the quality of transport/food/living/housing) and health behaviors/outcomes, (2) inequalities and inequities that exist within these connections (e.g., how different populations, particularly marginalized communities, are disproportionately affected by environmental factors and how these disparities can be addressed to promote health equity?), (3) health implications of new city concepts like healthy cities and 15-min cities, (4) health-oriented urban physical examination and design, (5) COVID-19 implications for the planning and management of healthy cities, (6) urban resilience in the face of pandemic disruptions and climate change, and (7) resilience management, governance, and policy formation for healthy cities. Finally, the translation of research findings into practical applications remains a persistent challenge. Bridging the gap between research and practice is essential to ensure that evidence-based interventions and policies are effectively implemented. Further research should focus on identifying strategies to enhance the dissemination and application of research findings, fostering collaborations between researchers, policymakers, and practitioners, and fostering knowledge exchange platforms. We can hope that after gaining valuable insights into designing health-supportive urban environments, evidence-based interventions can be effectively implemented for the benefit of individuals and communities.

Author contributions

LY: conceptualization, funding acquisition, writing-original draft, and writing-review and editing. BH, LC, RW, and YA: writing-review and editing. All authors listed have made a substantial, direct, and intellectual contribution to the work.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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Contribution of local climate zones to the thermal environment and energy demand

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Urban heat islands (UHIs) and their energy consumption are topics of widespread concern. This study used remote sensing images and building and meteorological data as parameters, with reference to Oke's local climate zone (LCZ), to divide urban areas according to the height and density of buildings and land cover types. While analyzing the heat island intensity, the neural network training method was used to obtain temperature data with good temporal as well as spatial resolution. Combining degree-days with the division of LCZs, a more accurate distribution of energy demand can be obtained by different regions. Here, the spatial distribution of buildings in Shenyang, China, and the law of land surface temperature (LST) and energy consumption of different LCZ types, which are related to building height and density, were obtained. The LST and energy consumption were found to be correlated. The highest heat island intensity, i.e., UHILCZ 4, was 8.17°C. The correlation coefficients of LST with building height and density were −0.16 and 0.24, respectively. The correlation between urban cooling energy demand and building height was −0.17, and the correlation between urban cooling energy demand and building density was 0.17. The results indicate that low- and medium-rise buildings consume more cooling energy.

KEYWORDS

urban heat island, energy consumption, degree-days, neural network, air temperature inversion

Introduction

Climate change has become a formidable challenge faced by all countries in the world because of its possible consequences (1). It impacts sea level rise, biodiversity, agricultural production, frequency of extreme weather, human health, and energy demand (2). There is a direct relationship between climate change and energy demand. Climate warming mainly results from the excessive absorption of long-wave radiation from the underlying surface by greenhouse gases (3). Large quantities of fossil fuels are utilized to meet the needs of human production and life processes, resulting in the emission of greenhouse gases (4). Among them, global building energy consumption accounts for ∼20 to 40% of total energy consumption and ∼33% of greenhouse gas emission (5).

To cope with rising temperatures and manage living standards, residents increase the use of air-conditioning and other refrigeration facilities to reduce indoor temperatures, but these measures in turn intensify the heat island effect. The environmental changes in cities are more complex, owing to many impervious surfaces and human activities (6). High-density buildings change the path and quantity of regional energy absorption and storage, flow and reflection, release, and consumption (7). The response of energy consumption and demand to temperature rise is more complicated. There are differences in the temperature of cities in different regions and scales, at different times and seasons, and even in the distribution characteristics of temperature within cities (8, 9). In general, the growth in expenditure caused by the increase in cooling demand exceeds the savings brought about by the reduction in heating demand, especially at low latitudes. For every 2°C increase in the average land surface temperature (LST), the global net building energy expenditure will increase by 0.1% of the total global economic expenditure (10).

The estimation of energy consumption concentrates on the city scale, and the estimation methods can be divided into two categories: top-down and bottom-up (11). The top-down approach is based on statistics and uses regional urban data to estimate the spatial distribution of energy consumption across cities, based on macroeconomic indicators such as population density, income, energy prices and types, and urban morphology (12). The bottom-up approach is based on each individual building and can be a statistical or physical-based hybrid model (13). Previous research has shown that the net energy impact of the urban environment depends on climate type (14), the urban context density, and functional and structural characteristics of buildings (15).

To improve the accuracy of bottom-up methods, some studies have incorporated local climate into the energy performance simulation of urban buildings. The urban heat island (UHI) effect, which refers to the phenomenon wherein the temperature in cities is higher than that in suburban rural areas (16), is also considered in the estimation of building energy consumption. Palme et al. (17) put forward the method of incorporating the UHI effect into building performance simulation and found that when UHI is incorporated, the energy demand increased by 15–200%. However, simulation methods are often calculation-heavy, and the relationship between urban features and energy consumption is indirect and unclear.

The intensity of heat islands is generally measured by the temperature difference between urban and rural areas. However, there has been no unified statement on how to define urban and rural areas. Over the past century, many scholars have made the division based on population density, building density, and landscape differences, or used gradients to illustrate problems. The duality of urban and rural areas has weakened with the development of cities (18, 19). Stewart and Oke (20) proposed the local climate zone (LCZ) concept to study UHIs, in which the city is divided into different areas according to the height density of buildings and other ground cover. Wong et al. (21) found that the influence of floor area ratio on temperature in Singapore is as high as 2°C, and buildings can save 4.5% on energy consumption by improving urban form. This deconstruction of urban internal structure divides it into organizational units, which can account for the internal form of buildings while segmenting urban areas, and is suitable for studying the influence of urban form on the thermal environment and energy demand.

The scope of energy consumption is highly complex, and all climate changes determined by the urban environment should be considered when performing simulations. For this reason, some coupling techniques between the building energy model and microclimate CFD model have been proposed (22, 23). However, this considers too many measured data (such as climate, wind speed, temperature, building texture, and thermal radiation), which require longer calculation times and higher costs. This is unfavorable for discussing the continuous changes of heating and cooling energy demand in the future. Invidiata and Ghisi (24) also emphasized that meteorological data were not updated in time in the process of estimating indoor air temperature. Obtaining reliable time-sensitive data to evaluate energy consumption is a major challenge in this research.

The scope of energy consumption is highly complex. Cooling energy consumption for the thermal environment under the UHI effect can be calculated from electricity consumption and remote sensing inversion data (25), such as the effective *U*-value method, degree-days, bin method, load frequency table method, equivalent full load hours, weighting factor method, and heat balance method (26). For cities, the degree-days method is simple and suitable for larger areas (27); however, traditional degree-days can only describe a single region at once and cannot analyze the distribution of energy consumption within the entire city. Combined with local climatic zone, the influence of different building forms and land use types on the urban thermal environment and refrigeration energy consumption can be examined in more detail. This macroscopic and easy-to-measure method is more universal and operable.

This new attempt requires more spatial distribution density of meteorological data, and traditional station data cannot meet the requirements. Traditional interpolation analysis using meteorological station data is less accurate. Remote sensing data is appropriate as continuous data. LST data is used frequently for calculations of the surface heat island, whereas for the cooling energy demands of urban dwellers indoors, air temperature is clearly more appropriate. Mesoscale weather Research and Forecasting Model and neighborhood-scale microclimate simulations, for example, are not suitable for urban studies (28).

Of the methods that can be applied, regression statistics is the simplest and easiest to build; however, establishing a relevant model depends on the time and place of data acquisition, which may cause large errors. The temperature-vegetation index method is highly dependent on plants; therefore, it is not suitable for cities with a large impermeable surface coverage. The surface energy balance method has good portability and universality, but many physical parameters needed by the model cannot be obtained directly by remote sensing, and the data cannot be updated in real time. Such models yield sufficiently accurate estimates, provided that all the required parameters are involved in the calculation. The parameters is not always possible, and thus, the data-driven model was selected. Neural network machine learning relies on large amounts of sample data, which can experience difficult modeling problems starting as a black box and express the nonlinear relationship between LST and air temperature (29, 30).

This study used remote sensing images, building data, and meteorological data as parameters and referred to Oke's LCZ method to divide urban areas according to the height and density of buildings and land cover types. The research attempted to apply neural networks for retrieving air temperature to calculate cooling energy demand, combining the number of degree days with the division of local climatic zones. The aims of the study were to improve energy demand structure of space and provide a relevant reference for urban planning under the prerequisite of ensuring the comfort of urban residents.

Materials and methods

Study area

Shenyang City (Figure 1) is located in Northeast China, central Liaoning (122°24′59″-123°48′30 E; 43°2′25″-41°11′53″N). The terrain gradually changes from hills in the northeast to plains in the southwest. The region has a temperate, semi-humid continental climate. Rainfall is concentrated in the summer months, but the area is sunnier than South China, making it conducive to the acquisition of remote sensing images. It is the political, economic, and cultural center of the Northeast region, as well as an important transportation hub. The building types are diverse and comprised of varying building height densities. Human activities have affected this area, leading to local climate change. In recent years, the annual maximum temperature in Shenyang exceeded 38°C in the summer.

Data sources and processing

The data used mainly included MODIS remote sensing, temperature, building outline, land cover, and administrative division. Table 1 contains detailed information on the remote sensing platforms and related data processing. In terms of time selection, according to the "Uniform Standard for Civil Building Design" GB 50352-2019, building climate zoning uses the average temperature in July as the main reference for summer. In traditional Chinese solar terms, dog days, the days of highest temperature generally start in mid-July. Considering the availability of data, the study period ranged from mid-July to early August. The technical flowchart is shown in Supplementary Figure 1.

Local climate zone

The urban form and nature of the surface are one of the main reasons for the difference between the urban LST and air temperature. In this study, we referred the definitions of Stewart and Oke (20) to divide the city into LCZ A–G according to the types of natural cover (Detailed classification diagrams are in the Supplementary material). Vertically, the height of the building class was divided from low-rise to super high-rise buildings at consistent intervals of three floors. Horizontally, the building densities were divided into dense and open building groups with a boundary of 40%. Accordingly, LCZ 1–10 were obtained (31). Finally, 17 categories were obtained, as shown in Supplementary Table 1. The height (BH) and density (BD) of the buildings were calculated on a 30 × 30 m grid using Eqs. (1) and (2).

$$BH = \frac{\sum_{i=1}^{n} H_i}{n} \tag{1}$$

$$BD = \frac{\sum_{i=1}^{n} S_{building}}{S_{grid}} \tag{2}$$

Where n represents the number of single buildings in a grid, H_i represents the number of floors of the i-th building in a grid, S_{grid} represents the area of a grid, and $S_{building}$ represents the base area of all buildings in the grid.

Heat island effect intensity

The LST was retrieved using Tan Zhihao's single-window algorithm, and Landsat was selected for heat island intensity analysis (32) (see the calculation section of the Supplementary materials). The intensity of the heat island effect is usually measured by the temperature difference between urban and rural areas. Stewart and Oke combined this temperature difference with the local climate zoning of the city and defined the formula of UHI intensity as the difference between a certain type of LCZ (X) and LCZ D (low vegetation,

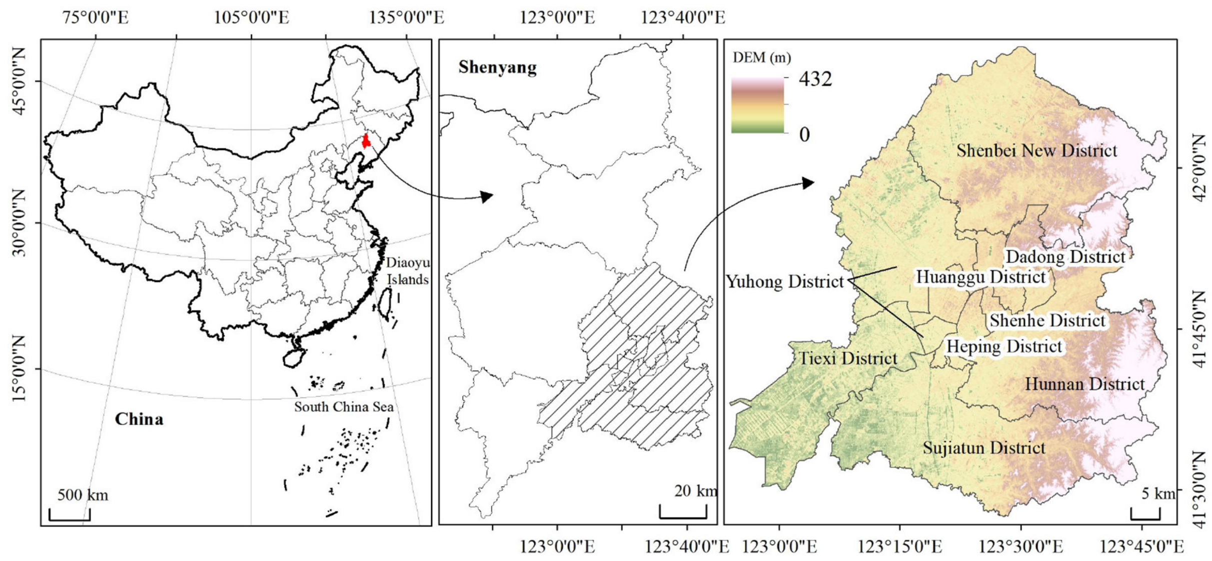

FIGURE 1
The location of the study area.

such as grass) (33). The intensity of the heat island effect is shown by Eq. (3).

$$UHI_{LCZX} = T_{LCZX} - T_{LCZD} \quad (3)$$

Where UHI_{LCZX} and T_{LCZX}represent the heat island effect intensity and LST of a certain type of LCZ X, respectively, and T_{LCZD} represents the LST of the LCZ D type.

Cooling energy demand

Using the method of combining cooling degree-days (CDD) (34) with LCZ, we calculated the change in building energy demand for different types of LCZ at different summer temperatures. The basic formula is shown in Eq. (5). According to previous experience, 23–24°C is the most comfortable ambient temperature for human life (35), and the difference between the interior design temperature of a building and the heat balance temperature of the building is usually 3–7°C (36). Finally, the base temperature of the cooling day was determined to be 26°C.

$$CDD26 = \sum_{days} \left(t - t_{ref}\right)^{+} \quad (4)$$

Where *CDD26* represents the number of cooling degree-days with 26°C as the base temperature, t is the average temperature of approximately a month, and t_{ref} is the base temperature.

Weather station data are generally used when calculating the number of degree-days. However, the meteorological station data were discrete point data, and were not detailed enough for research on urban interior building patterns. Therefore, we used remote sensing images in this study to retrieve air temperature as the basic temperature data calculated by CCD to evaluate the energy demand of buildings in a typical month.

Considering the accuracy and difficulty of calculation, the four factors, namely remote sensing albedo, normalized difference vegetation index (NDVI), elevation, and LST, were selected (37–39). The meteorological station data in the study area were used as the verification data, and the neural network regression model (40, 41) was used to train a model for inversion of air temperature. After several attempts, the training algorithm was finally settled on Levenberg-Marquardt, a toolbox already written in Matlab. For MODIS MCD43C3 products, the daily surface albedo α of the short-wave band can be calculated using Eqs. (5) and (6) (42–44). Finally, the formula for calculating the building energy demand under a certain type of LCZ is shown in Eq. (7).

$$\alpha = r\alpha_W + (1 - r)\,\alpha_B \quad (5)$$

$$r = 0.122 + 0.5\exp\left(-4.8\cos\theta\right) \quad (6)$$

$$CDD26 = \left(t_{LCZX} - 26\right)^{+} \quad (7)$$

In the formulas, α_W represents the albedo of the white sky, $\alpha_B$represents the albedo of the black sky, r represents the ratio of the sky scattered radiation to the downward solar radiation, and θ represents the solar zenith angle of the study area at noon. The values required in Eqs. (5) and (6) are given in MODIS

TABLE 1 Data sources and descriptions.

Type	Description	Time	Resolution	Data sources	Process
Remote sensing data	MODIS MOD11A2 (land surface temperature products)	2018.07.12–20180.8.04	1 km	https://search.earthdata.nasa.gov	Calculate the average daily maximum land surface temperature within the study time range.
	MOIDS MOD13A3 (vegetation Index Products)		1 km		
	MODIS MCD43C3 (surface albedo products)		0.05 deg		Obtain the black and white sky albedo in the shortwave band (0.3~5.0μm), also noon solar altitude angle.
	Landsat 8		OLI 30 m TIRS 100 m	USGS https://glovis.usgs.gov	
Meteorologicaldata	Daily maximum temperature			http://www.resdc.cn/	The average daily maximum temperature corresponding to the study tie.
Elevation	ASTER GDEM V2	2018	30 m	China Academy of Sciences http://www.gscloud.cn	Data splicing and clipping
Building outline	Building outline and floor number	2018	–	Baidu Map	Calculate the height of buildings, and find the height and density of the building within a 30 m grid.
Land cover	Land use cover type	2018	30 m	http://www.resdc.cn/	–
Administrative boundary	–	2020	–	–	–

MCD43C3. t_{LCZX} is the average air temperature within the study time range of X under the LCZ system.

Results

Spatial pattern distribution of local climate zones

The main urban area of Shenyang is dominated by low-rise buildings, which are widely and evenly distributed, followed by the middle-rise and mid-high-rise buildings, which are concentrated in the center of the main urban area. The number of buildings below 40% density is evenly distributed, rising steeply up to 40%, reaching a peak, and then slowly falling. In terms of spatial distribution, urban buildings were high-density and low-density, with low-density buildings dominating, but with no specific area of concentration. The LCZ distributions are shown in Figure 2.

LCZ 10 accounted for 11.69% and featured the largest proportion of building coverage due to the large number of villages outside the built-up area; LCZ 9 ranked second, accounting for 1.66%, and contained mostly residential land. LCZ 2 accounted for the smallest proportion (0.94%) and was concentrated in the city center, around the factory, near the high-speed railway station, and on the south bank of the Hunhe River. The proportion of LCZ 7 was slightly higher than that of LCZ 2. Natural cover was dominated by cultivated land in the northwest and lush forest land in the southeast, accounting for 39.21 and 25.99%, respectively; sparse forest land accounted for the lowest coverage (0.30%). The city center of Shenyang is surrounded by arable land and woodland, but the center itself has less green space and is crowded by buildings. The surrounding development requires strengthening.

Urban thermal environment space

The LST (Figure 3) of the building coverage was generally higher than that of the natural coverage. The average temperature of various LCZ overall displayed the following distribution law: LCZ 4 > LCZ 9 > LCZ 5 > LCZ 8 > LCZ 3 > LCZ 10 > LCZ 7 > LCZ 2 > LCZ 6 > LCZ 1 > LCZ E > LCZ F > LCZ A > LCZ B > LCZ D > LCZ G > LCZ C (Figure 4).

Among them, the temperature of LCZ D is 33.77°C. The highest heat island strength, $UHI_{LCZ\ 4}$, was 8.17°C, and the

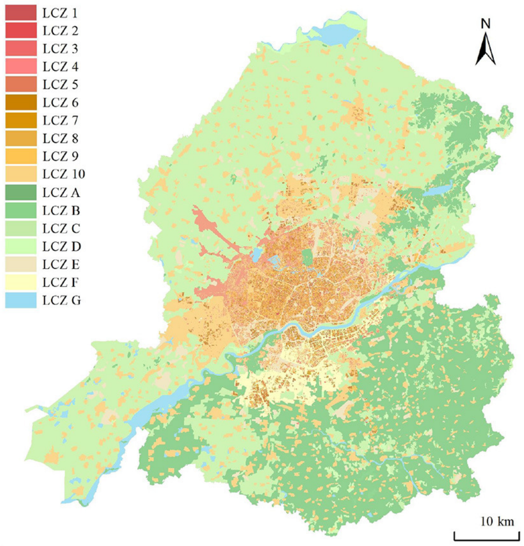

FIGURE 2
LCZ distribution in study area. LCZ, Local climate zone.

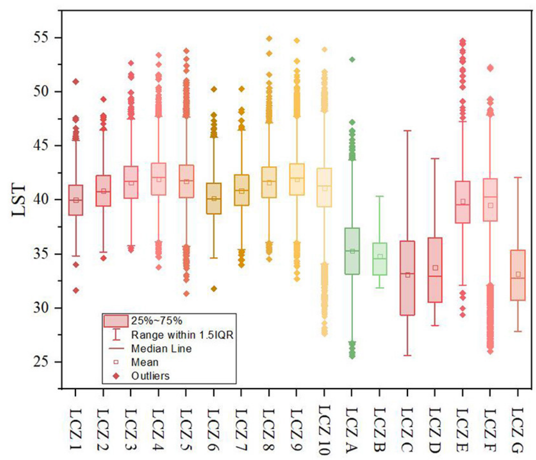

FIGURE 4
Distribution of LST in LCZ (LST unit:°C). LST, land surface temperature. LCZ, local climate zone. The results are sampled and counted according to the calculation results associated with the LCZ grids.

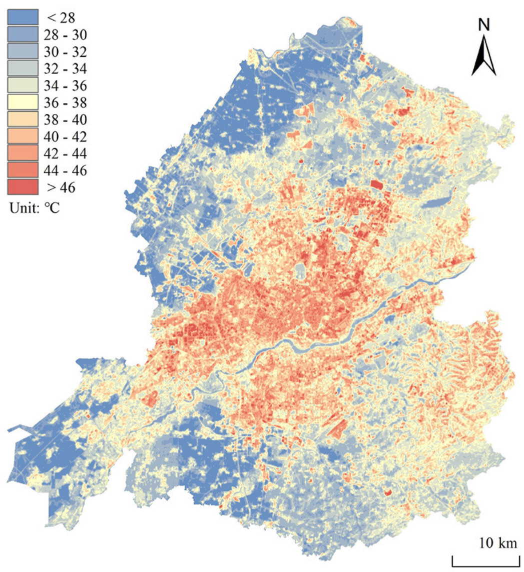

FIGURE 3
Land surface temperature distribution.

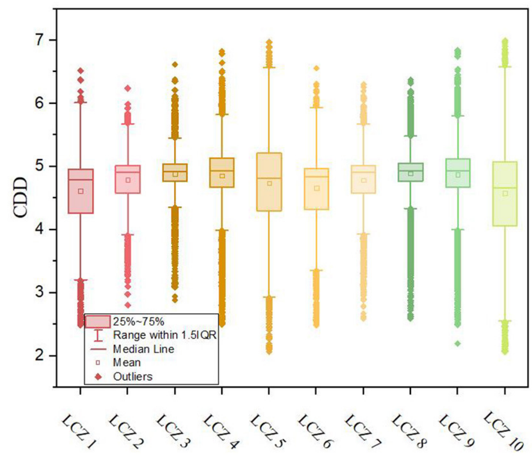

FIGURE 5
Distribution of CDD in LCZ (CDD unit:°C d). CDD, cooling degree-days. The results are sampled and counted according to the calculation results associated with the grid of the different LCZ plots.

lowest, UHI_{LCZC}, was −0.68. The lowest heat island strength of the building coverage UHI_{LCZ1} was 6.23°C. The LST changes of LCZ 1 were the most stable, with a standard deviation of 1.96, while LCZ G showed the most dramatic changes, with a standard deviation of 4.11, and the standard deviations of the other types were concentrated in the range of 2.8 ± 0.96. LST was negatively correlated with building height, with a Pearson correlation coefficient of −0.16, reaching significance at the 0.01 level, and positively correlated with building density, with a correlation coefficient of 0.24, reaching significance at the 0.01 level. These results can be explained by the fact that although higher buildings accumulate artificial materials and create more light reflections in three dimensions, they also cast larger shadows on the ground, which reduce the LST.

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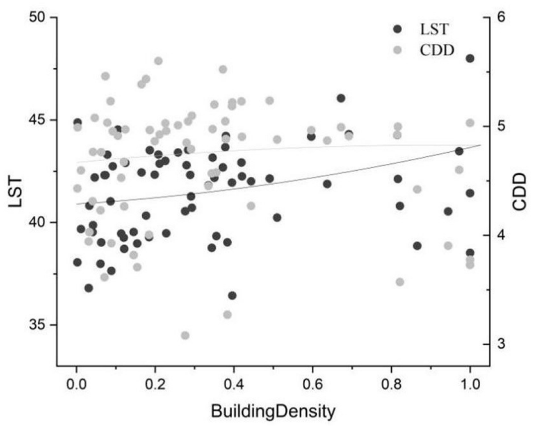

FIGURE 6
Correlation between LST (CDD) and building density (LST unit:°C).

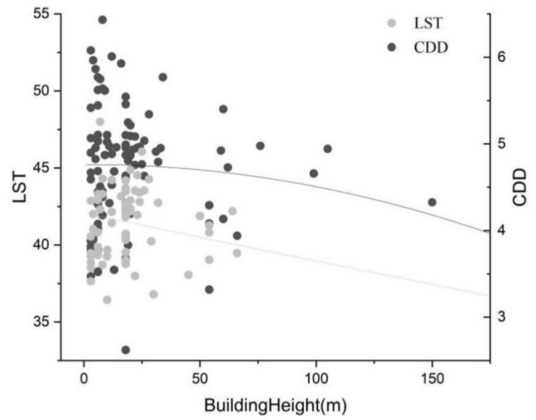

FIGURE 7
Correlation between LST (CDD) and building height (CDD unit:°C d).

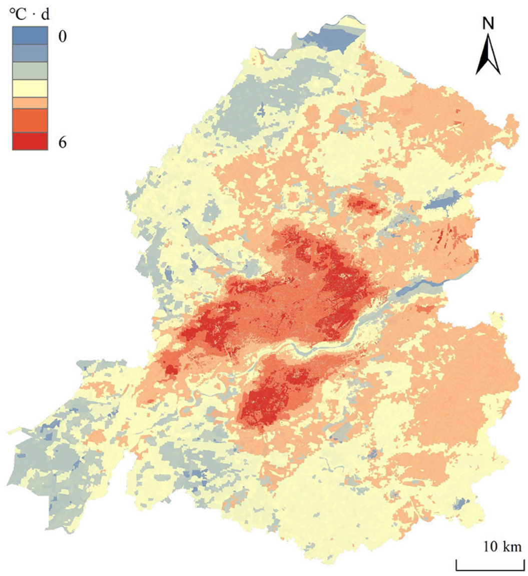

FIGURE 8
CDD of study area. CDD, cooling degree-days.

Urban cooling energy demand

In neural network estimation of air temperature, 70% of the data were randomly selected as the training sample, 15% as the verification sample, and 15% as the test sample to invert the air temperature. The model mean square error was RMSE = 0.32, R = 0.92, and R^2 = 0.84 (Supplementary Figure 4). According to these data, the overall range of air temperature was included in the distribution interval of the LST, and the value was between 28 and 33°C. The various types of air temperature change ranges were relatively stable and exhibited low volatility.

The average energy consumption of the building covering generally presented the distribution law of LCZ 8 > LCZ 3 > LCZ 9 > LCZ 4 > LCZ 2 > LCZ 7 > LCZ 5 > LCZ 6 > LCZ 1 > LCZ 10 (Figure 5). Among them, the maximum value of CDD was 7.00°C · d, the lowest value was 2.06°C · d, and the standard deviation of the different building coverage types varied between 0.232 and 0.76°C · d. The Pearson correlation between urban cooling energy demand and building height reached −0.17, and the correlation with building density was 0.17, both of which passed the 0.01 level two-tailed significance test. Compared with the distribution of cooling energy demand, LST is more affected by building height and density.

Discussion

Impact of local climatic zones on cities

The distribution of air temperature is more concentrated than that of LST, and the temperature is lower; however, the distribution difference between different local climatic zones is not so obvious. LST and cooling energy demand are positively correlated with building density. Compared with cooling energy demand, LST is more affected by building density (Figure 6); however, there is a weak negative correlation between LST and building height (Figure 7). The negative correlation may be explained by the addition of super high-rise buildings (43–45). Although the taller buildings accumulate man-made materials and produce more light reflection in three dimensions, they also cast larger shadows on the ground, thus lowering the LST. The correlation with building height is not as high as that with building density because of these complex relationships.

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Figure 8 shows that the CDD value gradually increases from the outskirts of the city to the center, but the range greater than 5.0°C · d surrounds the range of 4.5–5.0°C · d, showing a concave distribution. This phenomenon was attributed to the effects of the Hun River, which flows east-to west and appears in the south-central part of the study area, and Youth Street that runs north to south and is located in the middle of the city. The summer winds blow north through the Hunhe River and pass through Qingnian Street, forming a ventilation corridor that somewhat controls the regional temperature and reduces the potential cooling energy demand (46). Based on the dark red area in Figure 8, for general planning we recommend that coverage by green spaces (47, 48) or water bodies is increased to reduce energy consumption, and LCZ8, LCZ3, and LCZ9 should be focused on and reduced.

The difference of air temperature is not as large as that of land surface temperature, which also shows the importance of the material selection of the underlying surface from the side. It is recommended to increase vegetation and water area, sprinkle water on the road, and appropriately reduce the density of urban buildings to reduce the temperature.

Limitations

The Landsat image for heat island intensity analysis has relatively high resolution. Although Landsat's temporal resolution cannot meet the needs of daily data in the study time range, the spatial distribution of LST in sunny weather is still representative.

As a calculation method of cooling energy demand, the degree-days are simple and effective in characterizing urban energy; however, this method does not fully consider the effect of individual building differences (49, 50). For the study of overall characteristics, these parameters are simplified in the modeling process, but for urban planning, these factors are closely integrated with energy conservation.

The accuracy of the model used in this study was mainly limited by the remote sensing data and the number of meteorological stations in the study area. Because the calculation of energy consumption requires a high temporal resolution of remotely sensed images, MODIS products were finally selected from the available data (51, 52). The air temperature retrieved by combining various factors can show the characteristics of distribution in space, but the improvement of the initial data quality can greatly improve the accuracy of the results. Due to the limited availability of data, this study selected provincial capital cities with richer building data for analysis; however, there are still missing data in some areas. Future studies should focus on other thermal environment characteristic indicators, simultaneously consider the energy consumption requirements of cooling and heating, and use long time series and high-resolution data.

Conclusions

This study used remote sensing images, building data, meteorological data, and other basic data, referring to Oke's LCZ, to divide urban areas according to the height and density of buildings and land cover types, and explored the distribution characteristics of energy consumption that may be generated by urban residents' refrigeration demand in different regional thermal environments. The following conclusions were obtained.

The main urban area of Shenyang is dominated by low-rise buildings, which are widely and evenly distributed, and mid-high-rise buildings, which are crowded in the center.

The distribution of air temperature is more concentrated than that of LST, and the temperature is lower; thus, the difference in the distribution among the various local climatic zones is not evident.

The LST of the building covering is generally higher than that of the natural covering. The average temperature overall displays the distribution law as LCZ 4 > LCZ 9 > LCZ 5 > LCZ 8 > LCZ 3 > LCZ 10 > LCZ 7 > LCZ 2 > LCZ 6 > LCZ 1> LCZ E > LCZ F > LCZ A > LCZ B > LCZ D > LCZ G > LCZ C. Among them, the temperature of LCZ D is 33.77°C. The highest heat island intensity of UHI_{LCZ4} was 8.17°C. The LST is negatively correlated with building height, with a correlation coefficient of −0.16, reaching significance at a level of 0.01; and a positive correlation with building density, with a correlation coefficient of 0.24, reaching significance at the 0.01 level.

The average energy consumption of the building covering generally presents the distribution law of LCZ 8 > LCZ 3 > LCZ 9 > LCZ 4 > LCZ 2 > LCZ 7 > LCZ 5 > LCZ 6 > LCZ 1 > LCZ 10. Among them, the maximum value of CDD was 6.997°C · d, and the lowest value was 2.06°C · d. The correlation between urban cooling energy demand and building height reached −0.17, and the correlation between urban cooling energy demand and building density was 0.17, with both correlation coefficients shown to be statistically significant through a two-tailed significance test ($p < 0.01$).

Data availability statement

The original contributions presented in the study are included in the article/Supplementary material, further inquiries can be directed to the corresponding author/s.

Author contributions

RY wrote the main manuscript text. JY directed and revised the manuscript and contributed to all aspects of this work. LW, XX, and JX conducted the experiment and analyzed the data. All authors reviewed the manuscript.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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Supplementary material

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/fpubh.2022.992050/full#supplementary-material

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Spatially varying associations between the built environment and older adults' propensity to walk

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Population aging has become a severe issue facing most nations and areas worldwide—with Hong Kong being no exception. For older adults, walking is among the most well-liked travel modes, boosting their overall health and wellbeing. Some studies have confirmed that the built environment has a significant (spatially fixed) influence on older adults' walking behavior. However, little consideration has been given to the potential spatial heterogeneity in such influences. Hence, this study extracted data on older adults' (outdoor) walking behavior from the 2011 Hong Kong Travel Characteristics Survey and measured a series of built environment attributes based on geo-data (e.g., Google Street View imagery). Logistic regression and geographically weighted logistic regression models were developed to unveil the complicated (including spatially fixed and heterogeneous) association between the built environment and older adults' propensity to walk. We show that population density, land-use mix, street greenery, and access to bus stops are positively connected with the propensity to walk of older adults. Intersection density seems to impact walking propensity insignificantly. All built environment attributes have spatially heterogeneous effects on older adults' walking behavior. The percentage of deviance explained is heterogeneously distributed across space.

KEYWORDS

population aging, physical environment, street greenery, walking behavior, travel behavior, geographically weighted regression, spatial heterogeneity, spatial non-stationarity

Introduction

Population aging has become a pressing global concern (1). According to the United Nations, by 2030, 2050, and 2100, the number of the world's older populations (aged 65 years or above) will reach 1, 1.30, and 2.46 billion, respectively. Along with the sharp increase in absolute numbers, the ratio of older adults to the total population is constantly booming. This figure reached 9.1% in 2019 and is projected to increase to 11.7, 15.9, and 22.6% in 2030, 2050, and 2100, respectively (2). Hong Kong, a global city with ∼7.5 million inhabitants, shares this issue with other metropolises worldwide. In 2020, the proportion of the older population aged 65 years or above was 18.2%, second in Asia and only behind Japan (28.4%, the highest in the world). Additionally, it is anticipated that the proportion of the older population in Hong Kong will progressively increase and is predicted to rise to 34% in 2049.

It is commonly acknowledged that older adults' quality of life is highly correlated with their mobility, a lack of which leads to lower overall health and wellbeing. Daily mobility is a prerequisite for improving personal life, promoting social engagement, and enhancing emotional health (3). Particularly, older adults become less socially engaged because of life cycle stage changes (e.g., retirement) or aging-related events (e.g., death of the spouse) (4). Conceivably, people need to travel (mobility) to access urban services and engage in social activities, ultimately affecting their quality of life.

Walking has been widely recommended due to its economic, environmental, social, safety, and health benefits (5, 6). Walking helps reduce the prevalence of cardiac disease, psychosis, Alzheimer's disease, and hypertension (7–10). Furthermore, walking encourages social engagement, activity involvement, and interpersonal communication, contributing to active aging (11). Therefore, encouraging walking activities among older adults is essential for enhancing their quality of life. Furthermore, in many Chinese cities, limited car access makes walking a critical and indispensable travel mode for older adults (11, 12). This is especially true for Hong Kong, a city famous for its diverse land uses, pedestrian-friendly urban planning, and high walkability (13).

The built environment is a significant component of the geographic environment and has received enormous scholarly attention from many disciplines, including urban planning, geography, transportation, public health, psychology, and GIS (14–20). The most popular of these assessment methods is the "3Ds"/"5Ds"/"7Ds" model, which categorizes the built environment attributes into either three, five, or seven dimensions (21, 22). Numerous studies have revealed that the built environment profoundly affects individuals' travel behavior (23), especially for older adults who prefer to travel short distances due to their functional and cognitive limitations (24). They have demonstrated that a walkable and mixed urban form, green spaces, and parks are fundamental to their walking behavior (25–27).

Identifying the complex relationships between the built environment and older adults' walking behavior is the primary step toward spatial intervention. However, existing studies have emphasized the spatially fixed correlation between built environment attributes (e.g., street greenery and land-use mix) and older adults' walking behavior while largely ignoring the potential presence of spatial heterogeneity. Exploring whether there is a spatially heterogeneous connection between the built environment and older adults' propensity to walk is a crucial point of discussion. A fuller understanding of this connection serves as an indispensable and crucial reference for targeted treatments implemented to encourage walking activity among older adults. Following previous studies on the spatial heterogeneity in the connection between travel behavior and the built environment (28, 29), this study hypothesizes that there are spatially heterogeneous associations between older adults' propensity to walk and built environmental variables. It extracted the socio-demographic and walking behavior data from the 2011 Hong Kong Travel Characteristics Survey (HKTCS) and measured five built environment attributes based on multi-source geo-data. Notably, Google Street View (GSV) imagery was assessed through fully convolutional neural networks to quantify street greenery. Besides, we developed a logistic regression model to analyze the global relationship and establish a geographically weighted logistic regression (GWLR) model [a member of the geographically weighted regression (GWR) family] to scrutinize the local relationship and the presence of spatial heterogeneity in the relationship.

This study contributes to the literature by (1) exploring the global association between built environment characteristics and older adults' propensity to walk, (2) spurring further understanding of the spatial heterogeneity in this connection, and (3) serving as a reference for studies exploring whether there is spatial heterogeneity between the built environment and people's travel patterns.

The remainder of this paper proceeds as follows. Section "Literature review" reviews related studies on the built environment and older adults' mobility/travel behavior. Section "Data" presents the HKTCS 2011 data and built environment data. Section "Methodology" introduces the logistic regression model, the GWLR model, and the variables used in this study. Section "Results" reveals the global and local modeling results. Section "Conclusions and discussion" concludes the paper and discusses the implications.

Literature review

Existing studies mainly use the travel survey data collected by the government or researchers and apply econometric models (e.g., linear regression models, discrete choice models, and structural equation models) to identify the factors influencing people's travel outcomes and to unveil and assess the marginal effects or elasticities of attributes which play a decisive role. Travel outcomes consist of travel frequency, travel propensity (whether to travel or not), travel time or distance, walking duration, walking frequency, the propensity to walk (whether to walk or not), transit travel frequency, etc.

The factors that either promote or hinder people's travel behavior can be roughly categorized into individual or household socio-demographic characteristics and the built environment. Other factors such as the social environment, transit service attributes (e.g., priority seats and free bus passes), attitudes, and preferences received little scholarly attention.

Individual or household socio-demographic characteristics

Previous studies often adopt several variables to comprehensively capture, characterize, and control the socio-economic attributes of individuals or households, in which both age and gender are the factors receiving the most attention. Some studies have suggested the consistent effect of age on older adults' mobility and travel behavior. That is, with advancing age, the mobility of older adults generally decreases because of the degradation of physical function. For example, the older the population in Hong Kong is, the more reluctant they are to go out (30) and the lower trip frequency (31), which coincides with the evidence gathered from studies in Washington (32), Hamilton (33), and London (34).

The effect of gender on the mobility of older adults remains controversial. Yang et al. (30) concluded that male seniors in Hong Kong are more likely to go out than their female counterparts. By contrast, Kim and Ulfarsson (35) concluded that the travel frequency by motor, bus, and para-transit of female seniors in Washington is higher than that of their male counterparts.

Conflicting evidence on the correlation between older adults' educational attainment and mobility exists. Evans (36) and Kim (32) deemed that older adults who have a higher education level are more inclined to travel. However, Feng's (37) research elaborated that in Nanjing, there is no significant discrepancy between the activity frequency of older adults with elementary school education and those with college education or higher.

The effect of car availability on the mobility of older adults has also received substantial scholarly attention. Yang and Cui (31) hold that motor ownership displayed no association with older adults' mobility in Hong Kong, coinciding with the Nanjing-based findings of Feng et al. (38, 39) and Feng (37). However, this outcome differs from the findings presented in many studies, especially those from North America, Oceania, and Europe, where scholars such as Schwanen et al. (40), Paez et al. (33), and Roorda et al. (41) emphasized that having a car facilitates older adults' mobility. The reason for such discrepancy is understandable. In car-dominant or car-centric cities, most people regard cars as a decisive means of mobility, which is largely different from transit-dependent cities in East Asia such as Beijing, Hong Kong, and Singapore, where the high transit market share resulted in a low significance of car ownership on older adults' mobility.

Other socio-demographic factors such as household size (39), monthly household income (42), employment status (30), job type (39), mobile phone ownership (43), living alone or not (31), housing property rights (36), and race (36) have also received some scholarly attention.

Built environment attributes

Recently, the impact of the built environment on older adults' travel behavior and mobility has increasingly attracted much attention. Population density, leisure facility density, transit accessibility, and green space are oft-discussed built environment attributes. Analysis methods consist of linear regression, discrete choice models, order logit/probit regression, Poisson or negative binomial regression, structural equation models, and the models incorporating spatial autocorrelation, spatial heterogeneity, and variable hierarchy (e.g., spatial regression models and the GWR model). Moreover, these built environment attributes are mainly measured through GIS analysis and field survey, with a small portion of the studies using street view imagery.

Most of these studies looked at North America (the USA and Canada). Evans (36) utilized stepwise discriminant analysis to identify characteristics impacting the travel propensity of older adults without a vehicle and older adults aged 75 years or above using data extracted from the 1995 National Personal Transportation Survey. Neighborhood housing density and community environment significantly affected the travel propensity of older adults, while no evidence of associations with travel propensity of older adults was found for variables such as population density and transit accessibility. Kim (32) used structural equation modeling to examine the variables influencing older adults' mobility and concluded that population density and employment density did not have significant effects on mobility (after controlling for individual or household socio-demographic characteristics). Paez et al. (33) found that the location of residence was significantly related to the frequency of non-work trips among older adults in Hamilton, Canada, and that mobility was higher among those living in the eastern and northern regions of the city. Mercado and Páez's modeling results show that population density has insignificant effects on travel distance for older adults in Hamilton, Canada (44). Roorda et al. analyzed the mobility of those who were transportation disadvantaged in three Canadian cities using the ordered probit model. They found that population density improves the mobility of the transportation disadvantaged (including older adults) in Montreal but gets otherwise inhibited (41).

Scholars have also conducted similar research in both the European and Australian contexts. Based on the outcomes of the order probit model, Schmöcker et al. concluded that older adults living in central London travel less frequently than those living in the suburbs. However, when conducting personal business, few differences are seen in the travel frequency between the two groups (34). Su and Bell used a nested logit model to scrutinize the variables affecting the travel mode choice of older adults in London and found that bus stop density and service frequency play a decisive role (45). In the Australian city of Adelaide, Truong and Somenahalli examined the variables determining the frequency of transit usage by older adults and concluded that access to the city center and station density had a negligible impact (43). Additionally, Pettersson and Schmöcker discovered that in Manila, Philippines, older adults made more journeys as population density rose (46).

Some studies have recently used Chinese cities as study areas as well. According to Feng et al., population density had no discernible effect on the travel frequency among older adults in Nanjing, but subway accessibility did (39). Yang's analysis of HKTCS data revealed that older adults' trip frequency is significantly impacted by transit accessibility (31). Unlike intersection density (which had a negative impact) and land use entropy (which had an insignificant impact), population density and retail store density had a positive influence on older adults' propensity to walk in Hong Kong; population density significantly enhances older adults' walking duration, while street greenery positively affected both the propensity to walk and walking duration (47). Using the Poisson and negative binomial models, Yang and Cui discovered that transit accessibility positively affects the travel frequency of older adults in Hong Kong, whereas road network density plays a negative role. Furthermore, they identified that transit accessibility has a considerable impact on the travel frequency of younger seniors (60–75 years) but not on that of older ones (75 years or above) (31). Yang et al. clarified a significant effect of street greenery on older adults' propensity to travel in Hong Kong using data from GSV imagery (30). However, Cheng et al. indicated that residential location in Nanjing had a greater effect on older adults' travel behavior than it did on younger adults (48).

Some studies concentrated on the built environment with Chinese characteristics and reached conclusions distinct from Western studies, thereby enhancing the West-dominated senior mobility research. Feng et al. assessed the travel distance and frequency of older adults in Nanjing. They discovered that the residents of unitary welfare housing traveled frequently but were still far less than those of mixed communities and regular commercial housing estates (38). Similarly, Feng adopted ordered logit and linear regression models to scrutinize the correlation of the built environment with older adults' travel based on the 2012 Nanjing Resident Travel Survey data and concluded that chess rooms and parks/plazas are more attractive to older adults than facilities such as gymnasiums and museums (37). However, Cheng et al. identified what factors are related to walking/cycling frequency and duration of older adults in Nanjing and determined that park/plaza and chess room accessibility have a significant effect, unlike market and gym accessibility which did not show any correlation (11).

Thrust of this study

To our knowledge, senior travel behavior and mobility research first appeared in developed countries (e.g., the US and Canada). A compelling explanation is that population aging happens very early in such countries, facilitating social concerns about related issues. However, the social characteristics of Western countries starkly differ from those of China. For instance, many Western countries (e.g., the US, Canada, and Australia) feature low-density urban development, single land use, the predominance of car-based transport, and a meager transit share. Chinese cities are generally featured by high density, mixed land use, well-developed transit systems, and high transit share. Therefore, the Western experience cannot be directly transposed in China because of vastly different social and urban traits.

Related research has been recently conducted in China. Much scholarly attention has been given to variables that affect older adults' travel behavior. Generally, their results are relatively dispersed, and there remains a lack of locally focused research to seek out more insightful solutions. Besides, the spatial heterogeneity in the connection between the built environment and older adults' travel behavior has received insufficient scholarly attention, which is the primary focus and a key task of this study.

Data

Travel data

The Transport Department of Hong Kong conducts the HKTCS, a thorough and detailed periodical travel survey. The latest was carried out from September 2011 to January 2012. It consisted of three main dimensions: the Household Interview Survey to gather 24-h travel data from Hong Kong residents, the Stated Preference Survey to determine the variables influencing people's choice of transportation mode, and the Hotel/Guesthouse Tourists Survey to collect travel data from guests staying in hotels/guesthouses.

The Household Interview Survey, similar to many comprehensive government travel surveys, had three dimensions: (1) household data (e.g., residence location, household size, and residence type); (2) household member data (e.g., gender); and (3) 24-h travel data. Additionally, HKTCS 2011 included the respondents' residence location information, allowing the geocoding of the data in the ArcGIS Pro (version 2.8) platform for residence-centered built environment assessments.

Following international standards, this study extracted walking behavior data and divided the older adults (65 years or above) into two groups based on their propensity to walk: those who made at least one walking trip within 24 h (propensity to walk = 1) and those who did not (propensity to walk = 0; Figure 1). Figure 2 reveals the spatial distribution of the sampled older adults ($N = 10{,}700$).

Street greenery data and other built environment data

Given its perspective that is highly comparable to human vision, street-view imagery precisely captures a 360° high-resolution panoramic view of the physical urban environment.

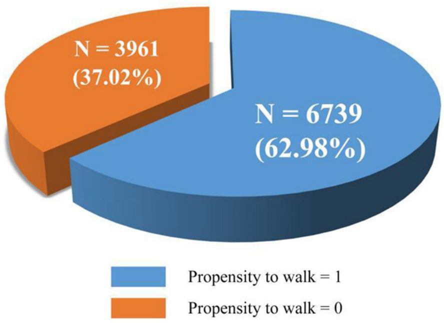

FIGURE 1
Propensity to walking details of the sampled older adults.

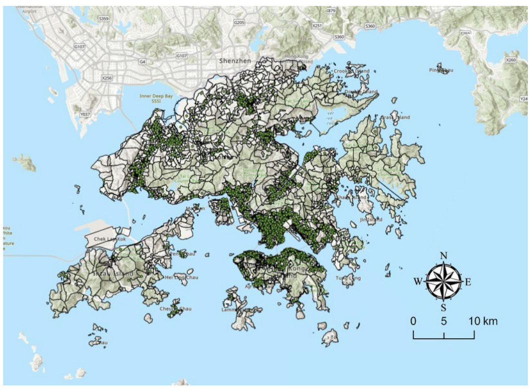

FIGURE 2
The spatial distribution of the sampled older adults.

Compared to conventional data sources, it has the unique strengths of high geographic coverage, low data bias, cost-effectiveness, and human-centeredness (49). Introduced in 2007, GSV was one of the first online street-view services and has since covered cities in roughly 90 countries (50). GSV data are mainly collected by GPS-equipped sensing vehicles.

Eye-level street greenery, which reflects actual pedestrian perceptions of street greenery, has been proven more relevant to people's active travel than other green space measures (30). Hence, this study assessed the eye-level green view index using GSV imagery to stimulate people's perception of street greenness as follows: first, the residence locations were geocoded into the ArcGIS platform. Second, all street segments in the vicinity of the geocoded locations were automatically identified. Third, the generated locations of GSVs were automatically created with a fixed spacing of 50 m and then recorded in the coordinates. Fourth, the matching GSV imagery was downloaded. For each point, four images together represented a 360° panorama (51). Last, fully convolutional neural networks (FCN-8s) were applied to investigate greenfield pixels (Figure 3) (52). The formula for the green view index at a GSV generation location is,

$$Green\ view\ index = \frac{\sum_{i=1}^{4} Greenery\ pixels_i}{\sum_{i=1}^{4} Total\ pixels_i} \tag{1}$$

The built environment was assessed in the ArcGIS Pro platform based on the "3Ds" built environment evaluation framework and available data. POIs (points of interest) and region boundaries were crawled from *OpenStreetMaps*, while land use, TPU (tertiary planning unit)-level data were obtained from the government website.

Methodology

A logistic regression model was first employed because the propensity to walk of older adults is a binary (dummy, dichotomous, or indicator) variable. Moreover, the availability of location attributes is a prerequisite for adopting the GWLR model to analyze spatial heterogeneity. As an advanced version of the logistic regression model, the GWLR model, using the geographic coordinates of all observations embedded in the data, estimated the spatially varying correlation between the predicted and predictor variables (predictors). Hence, logistic regression models and GWLR models were developed in this study.

Global model: logistic regression model

Logistic regression analysis is developed to investigate how predictors affect the predicted variable. The logistic regression model is widely developed to examine situations where the predicted variable has exclusively two outcomes. In this study, it was used to link the propensity to walk with the predictors. The model is presented in the form below:

$$P_i = \frac{e^{U_i}}{1 + e^{U_i}} \tag{2}$$

Or likewise,

$$U_i = logit(P_i) = \ln\left(\frac{P_i}{1 - P_i}\right) \tag{3}$$

where P_i is the likelihood that person i takes at least one walking trip, $\frac{P_i}{1-P_i}$ is often referred to as the odds ratio, and U_i represents the utility of older person i, which reflects the determinants affecting person i's trip. The following statement describes the connection between U_i and the predictors:

$$U_i = \beta_0 + \sum_k \beta_k X_{ik} + \varepsilon_i \tag{4}$$

FIGURE 3
The estimation of the green view index.

where X_{ik} is the k-th predictor, β_k is the coefficient of X_{ik}, β_0 is a constant, and ε_i is the error, which follows the logistic distribution.

Local model: GWLR model

In stark contrast to traditional regression models that employ a single equation to describe the association between the predicted variable and predictors, the GWR model creates a battery of equations to account for the possible spatial heterogeneity in the relationship, making it possible to visualize broad patterns in the coefficient estimates. Furthermore, every point has a unique equation that is assessed using this point and its neighbors. Simply put, by relaxing the assumption of spatially invariant associations, the GWR model expands the classical regression framework and permits the estimate of point-varying parameters. It has been utilized in numerous empirical studies (53–57).

The GWLR model belongs to the GWR family and is represented as follows:

$$U_i = \beta_0(u_i,\ v_i) + \sum\nolimits_k \beta_k(u_i,\ v_i)X_{ik} +\ \varepsilon_i, \quad (5)$$

where $(u_i,\ v_i)$ stands for the coordinates of point i, $\beta_k(u_i,\ v_i)$ denotes the coefficient of X_{ik}, $\beta_0(u_i,\ v_i)$ is the constant of point i. $\beta_k(u_i,\ v_i)$ and $\beta_0(u_i,\ v_i)$ are parameters to be collaboratively calculated.

A kernel function is required to calculate the weights of nearby points for any given point. Four frequently employed functions are fixed Gaussian, adaptive Gaussian, fixed bi-square, and adaptive bi-square kernel functions. For the fixed Gaussian and fixed bi-square kernel functions, weights are allocated as a continuous function of distance. The adaptive Gaussian and adaptive bi-square kernel functions, in contrast, permit the geographical extent (bandwidth) to fluctuate over space rather than maintaining a constant bandwidth. The formulas of the four kernel functions are as follows.

$$\text{Fixed Gaussian kernel: } w_{ij} = \exp(-{d_{ij}}^2/\theta^2) \quad (6)$$

$$\text{Adaptive Gaussian kernel: } w_{ij} = \exp(-{d_{ij}}^2/{\theta_{i(k)}}^2) \quad (7)$$

$$\text{Fixed bi-square kernel: } w_{ij} = \begin{cases} (1 - {d_{ij}}^2/\theta^2)^2 & \text{if } d_{ij} < \theta \\ 0 & \text{otherwise} \end{cases} \quad (8)$$

Adaptive bi-square kernel:

$$w_{ij} = \begin{cases} (1 - {d_{ij}}^2/{\theta_{i(k)}}^2)^2 & \text{if } d_{ij} < \theta_{i(k)} \\ 0 & \text{otherwise} \end{cases} \quad (9)$$

where w_{ij} is point j's weight for the local equation of point i, d_{ij} is the Euclidean distance between points i and j, θ is a fixed bandwidth, and $\theta_{i(k)}$ is an adaptive bandwidth depending on the kth nearest neighbor distance.

Variables

Eight predictors, which were comprised of three socio-demographic variables and five built environment variables, were selected in this study. The choice of built environment

TABLE 1 Summary of the predicted variable and predictors.

Variable	Description	Mean/proportion	Std. Dev.
Predicted variable			
Propensity to walk	= 1 for having walked out in the reference 24 h, = 0 otherwise	0.63	
Predictors: socio-demographics			
Male	= 1 for male, = 0 for female	0.49	
Age	(unit: year)	73.82	6.93
Car	= 1 for a person with household car availability, = 0 otherwise	0.07	
Predictors: built environment			
Population density	Neighborhood-level population density (unit: 10^3 people/km^2)	47.98	32.95
Land-use mix	Entropy for neighborhood land uses.	0.44	0.23
Intersection density	Neighborhood-level street intersection density (unit: 1/km^2)	72.14	49.75
Street greenery	Green view index	0.15	0.03
Access to bus stops	Number of bus stops in the neighborhood	20.10	11.34
Number of observations	10,700		

variables follows the "3Ds" built environment assessment framework (21). Table 1 shows the summary of the predictor and predicted variables. Figure 4 shows the spatial distribution of the five built environment attributes.

Results

A pair-wise correlation analysis was conducted to analyze whether collinearity exists among the predictors. Figure 5 shows the outcome. It reveals that Pearson's correlation coefficients are far smaller than 0.7, indicating the absence of collinearity.

Global and local modeling results are shown below.

Global modeling results

A logistic regression model was developed herein to demonstrate the correlation between the built environment and the propensity to walk of older adults in Hong Kong. Table 2 displays the outcomes. Almost all predictors (control variables and explanatory variables) have a significant effect on this propensity. Specifically, population density is shown to increase the propensity to walk of older adults significantly. This outcome meets our expectations and reinforces earlier research conducted in the same city (42). A convincing explanation may be that high population density areas mean that pedestrians are allocated more road space and amenities, which makes walking easier, safer, and more enjoyable (58). Moreover, areas with high population density have various facilities (e.g., retail stores, chess rooms, and stores), which can better meet the travel needs (shopping, leisure, fitness, etc.) of older adults, thus promoting walking trips.

Land-use mix positively affects older adults' propensity to walk, reinforcing earlier research showing that older adults living in communities with a high land-use mix are more inclined to walk. This observation is because a high land-use mix typically indicates that destinations have abundant types of amenities that meet the walking requirements of older adults, hence encouraging walking trips.

Street greenery has a positive and statistically significant connection with older adults' walking trips at the 99% confidence interval. This outcome concurs with most of the evidence obtained from the existing literature (47, 59, 60), indicating that older residents living in neighborhoods with more greenery prefer to walk more.

A significant and positive correlation between bus stop accessibility and the propensity to walk of older adults is also identified. Older adults will typically walk to and from the bus stop if they need to travel by bus, thus increasing their walking trips (57). Furthermore, regions with high bus accessibility direct travelers to walk to transit stations, which create a walkable atmosphere and, from the perspective of perceived safety, potentially encourage people's walking trips (58).

However, intersection density has zero or unexpected correlation with aspects related to older adults' propensity to walk. This finding is significantly different from previous studies, particularly those conducted in East Asia (58). We should know that the above outcome merely presents an insignificant average effect of intersection density and thus may be, at least partially, attributable to spatial heterogeneity.

Local modeling results

The abovementioned findings provide an answer on whether the built environment does affect older adults' propensity to walk. However, they cannot clarify whether there is spatial heterogeneity in this effect. Simply put, the global model can examine the average effect, but it cannot discern the

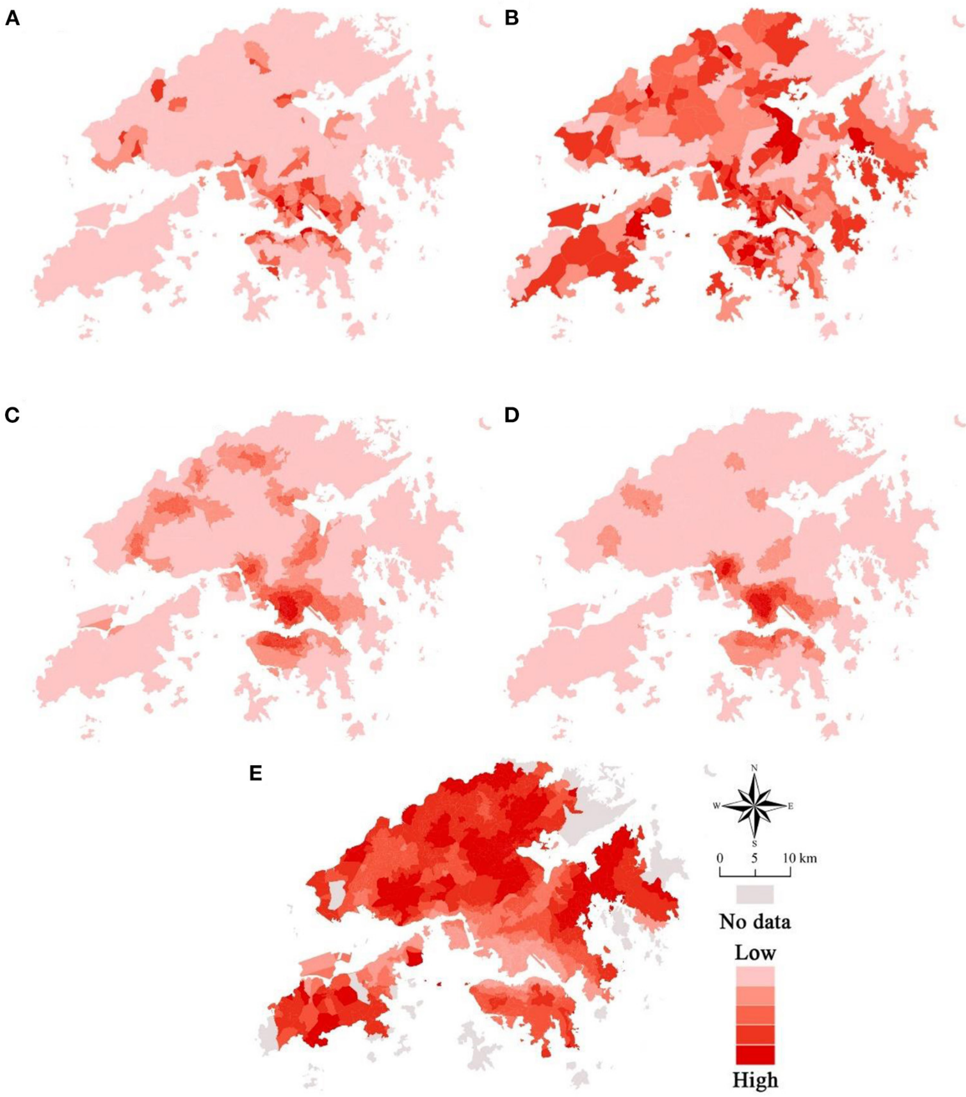

FIGURE 4
The spatial distribution of the five built environment attributes. **(A)** Population density. **(B)** Land-use mix. **(C)** Intersection density. **(D)** Access to bus stops. **(E)** Street greenery.

potential spatial variation effect. Therefore, the GWLR model was employed in this study to uncover this effect. The software MGWR (version 2.2.1) (61) was applied to estimate the model.

Table 3 presents the outcomes of the regression model. The GWLR model has lower AIC and AICc than the logistic regression model. This observation indicates that the GWLR model outperforms the logistic regression model in fitting the data and justifies our shift from global models to local ones. Moreover, great variations in the coefficients of the built environment variables are also determined. Furthermore, the variation range for each predictor seems to be large. Positive and negative coefficients can be observed for each predictor, indicating that the variables exert positive effects in some regions and negative effects in others. This observation also means that the global regression estimation is inadequate and echoes the argument made by Mulley (62) that "inferring policy from a single, average, global value might well be misleading" (p. 1,722).

As noted above, GWR-family models, including the GWLR model, have the advantage of ease of visualization. Inverse distance weighted (IDW) interpolation is used to assign values to unknown points in the ArcGIS Pro platform. Figure 6 shows the spatial distribution of the percentage of deviance explained, namely the proportion of the predicted variable variance accounted for by the predictors. We observed that the deviance explained is not homogeneously distributed across space. For example, the deviance explained is highest in the east

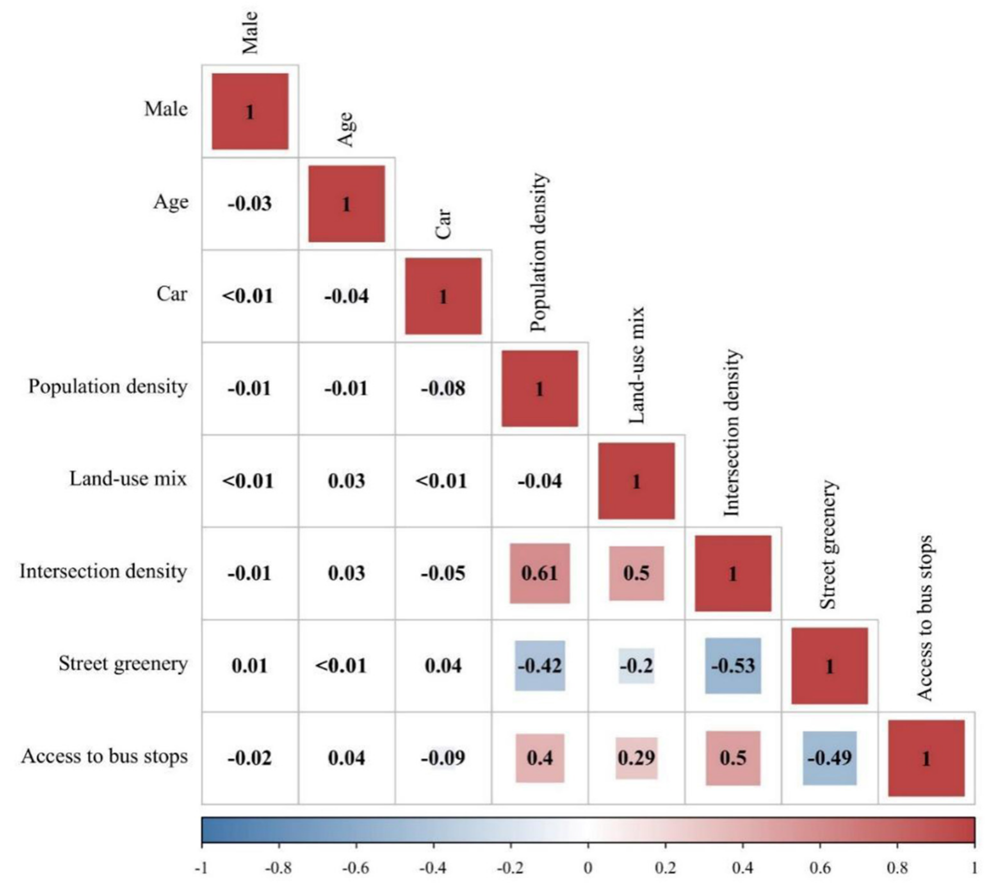

FIGURE 5
Correlation coefficients among the predictors.

of Lantau Island, indicating that the relationships between the propensity to walk and the eight selected predictors can be better predicted in the east of Lantau Island, and that the propensity of older adults in other regions is more likely to be affected by other unobserved factors.

The spatial distribution of the coefficients of the five built environment variables is of predominant interest herein. It is revealed in Figure 7, where IDW interpolation was once again adopted. We observed that the distribution patterns are highly irregular, but patterns for a variable remain inapplicable to other variables.

Figure 7 exhibits the effect of a predictor in affecting the predicted variable in each location. Population density has the largest effect in Shatin, followed by Tuen Mun. Access to bus stops has the greatest effect in Mong Kok and the areas adjacent to Lo Wu Port. Furthermore, intersection density has positive effects in places like the east of Lantau Island and Cheung Sha Wan but has negative effects in places such as Sha Tin and Tai Wai. This observation provides suggestive evidence for the insignificance of the average effect of intersection density.

Conclusion and discussion

A rapidly aging global population will create varying degrees of socio-economic effects worldwide. Hong Kong, the region with the second-highest aging rate in Asia, undoubtedly faces this issue as well. The unstoppable rise in the number and share of the older population has drawn increasing concern from the government, society, and academia. Meanwhile, walking is among the most crucial travel modes for older adults, and insufficient walking activities have a clearly detrimental impact on their overall wellbeing. Therefore, it is important to consider the preferences and needs of older adults and turn the development of walkable built environments for older adults into viable areas of focus for future studies. This study looks at the spatially varying association between older adults' walking behavior (specifically, propensity to walk) and the built environment and aims to develop the latter to be able to satisfy older adults' walking demands and promote their walking trips. Based on HKTCS data and geo-data (e.g., GSV imagery), this study develops a logistic regression model and a GWLR model

TABLE 2 Global modeling results.

Variable	Coefficient	Std. Dev.	*t*-statistic	*p*-value
Male	−0.285**	0.041	−6.938	0.000
Age	0.045**	0.003	14.347	0.000
Automobile	−0.400**	0.084	−4.781	0.000
household income	−0.020**	0.005	−4.215	0.000
Population density	0.056**	0.010	5.908	0.000
Land-use mix	0.314*	0.124	2.531	0.011
Intersection density	0.009	0.008	1.232	0.218
Street greenery	3.157**	0.748	4.223	0.000
Access to bus stops	0.009**	0.002	3.864	0.000
Constant	−3.595**	0.284	−12.648	0.000
Performance statistic				
AIC	13,593.37			
AICc	13,593.39			

*Significant at the 5% level.
**Significant at the 1% level.

TABLE 3 Local modeling results.

Variable	Coefficient				
	Mean	Std. Dev.	Min	Median	Max
Male	−0.312	0.245	−1.218	−0.291	0.320
Age	0.050	0.025	−0.020	0.049	0.125
Automobile	−0.237	0.714	−3.337	−0.232	1.737
household income	−0.009	0.040	−0.104	−0.011	0.112
Population density	0.157	0.330	−2.650	0.077	1.259
Land-use mix	1.265	8.571	−28.259	1.186	119.403
Intersection density	−0.096	0.480	−4.079	−0.012	1.228
Street greenery	−8.866	49.562	−410.161	−7.134	109.353
Access to bus stops	0.014	0.032	−0.112	0.010	0.123
Constant	−2.702	7.141	−18.229	−3.375	43.185
Performance statistic					
AIC	13,113.53				
AICc	13,137.73				

to determine how the built environment affects the propensity to walk of older adults and the effect's spatial heterogeneity. This study has found that older adults' propensity to walk was positively and significantly related to population density, land-use mix, street greenery, and access to bus stops, but it was insignificantly related to intersection density. Built environment attributes were also found to have spatially heterogeneous effects on walking propensity. Methodologically, this study assesses street greenery by applying big geographical data, demonstrating the great necessity of integrating big data into urban studies. Employing new/big data can greatly improve our understanding of the relationship between activity behavior and the built environment and is a valuable addition to traditionally built environment measurements, which should become an important perspective for future studies.

This study presents several theoretical, methodological, and practical implications for decision-makers, practitioners, and planners. First, the results can offer crucial theoretical backing for the development of senior-friendly built environments that promote their walking trips. Older adults' propensity to walk can be enhanced by increasing population density, land-use mix, and accessibility to bus stops. Moreover, the GSV-based measure of street greenery strongly influenced older adults' propensity to walk, indicating its direct ties to their daily walking trips. These four factors ought to be crucial in the planning of a senior-friendly built environment in the future

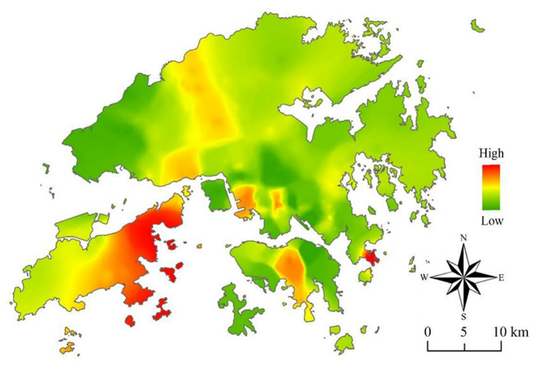

FIGURE 6
The spatial distribution of the proportion of the predicted variable variance that is accounted for by the predictors.

to improve the living standards and wellbeing of older adults. Furthermore, the people-oriented urban design must consider older adults' preferences and behavior (63). As an age group with considerable leisure time, older adults (unlike younger people) rarely make mandatory trips (e.g., commuting) but often make optional ones. In China, chess rooms, parks, and grocery markets are essential destinations for older adults, and making them accessible by walking is recommended (37). Therefore, in the development of senior-friendly communities, policymakers should focus on attributes that are significantly relevant to promoting older adults' walking behavior. Finally, since most studies recently conducted concentrated primarily on the global (spatially fixed) associations between the built environment and older adults' travel behavior and ignored spatial heterogeneity, this study focusing on the local associations deepens our understanding of the spatially heterogeneous effect between the built environment and older adults' walking behavior.

Traditionally, due to the prevalence of regression-based correlation studies, policymakers and urban planners tend to assume unidirectional effects between built environment attributes and people's travel behavior (42). They prefer to singularly raise/lower a certain indicator and overlook the potential non-linear effects. For example, population density was once thought to affect walking behavior positively and monotonically. This is because high-density areas always imply well-equipped neighborhoods and facilities which encourage walking (42). However, many recent studies based on machine learning techniques have described the non-linear and threshold effects of the built environment, thus triggering a change in conventional wisdom. Cheng et al. (58) countered that population density above a particular threshold could have a detrimental impact on walking behavior because ultra-dense areas induce crowding and a higher risk of injury, thereby discouraging walking. Therefore, confining built environment variables to a reasonable (perhaps moderate) interval may be the most effective approach. Furthermore, nearly all machine learning techniques cannot model spatially varying relationships, although some exceptions exist (64). We believe the incorporation of spatial heterogeneity into the machine learning framework is an interesting future research direction.

A voluminous body of literature (including this study) has been devoted to teasing out the relationships between the "physical" dimension of the living/neighborhood environment (i.e., the natural and built environments) and activity behavior. Nevertheless, very limited scholarly attention has been paid to the "social" dimension of the environment (i.e., the social environment), which may also be a determinant of activity behavior. Currently, due to urban development patterns, changes in technology, and hectic lifestyles, people are always separated from their neighborhoods and communities and detached from their surroundings. Promoting social interaction, building a sense of community, and creating an inclusive and cohesive social environment have thus been extensively advocated. We suspect that many social environment variables, such as social cohesion and trust, social support, social interaction, and sense and inclusiveness of community, influence people's activity behavior. More studies are recommended to devote themselves to this issue, where profound policy and practical implications can be obtained. Summarily, we continue to urge that the definition of the neighborhood environment should be considerably broadened, arguing that the addition of the social dimension advances our knowledge of the relationships between the living environment and activity behavior.

Despite some highly insightful conclusions, this study inevitably has the following shortcomings. First, the models used in this study presupposed the global and local correlations between variables. However, employing machine learning models can accurately identify the complicated non-linear associations between older adults' walking behavior and the built environment without the need to pre-determine variable relationships (65). Second, this study identified correlations between variables but could not examine causality given the cross-sectional nature of HKTCS data. Therefore, conducting longitudinal surveys is needed to gather multi-wave first-hand data, obtain causality evidence, and develop more insightful conclusions. Third, this study exclusively concentrates on the role of the outdoor environment while ignoring the indoor environment. The indoor environment is important because people spend 80% of their time indoors (66, 67). It is likely to influence people's outdoor activity behavior. For example, if living in a cramped and congested home, a person may prefer to go outdoor. Fourth, older adults are arguably not a homogeneous group. For example, the oldest people may need rest facilities on the walking path, but younger seniors may not need them so urgently. Looking into senior subgroups (e.g., male vs. female) can determine diverse demands and preferences and obtain richer findings (68). Last, Hong Kong is well-known

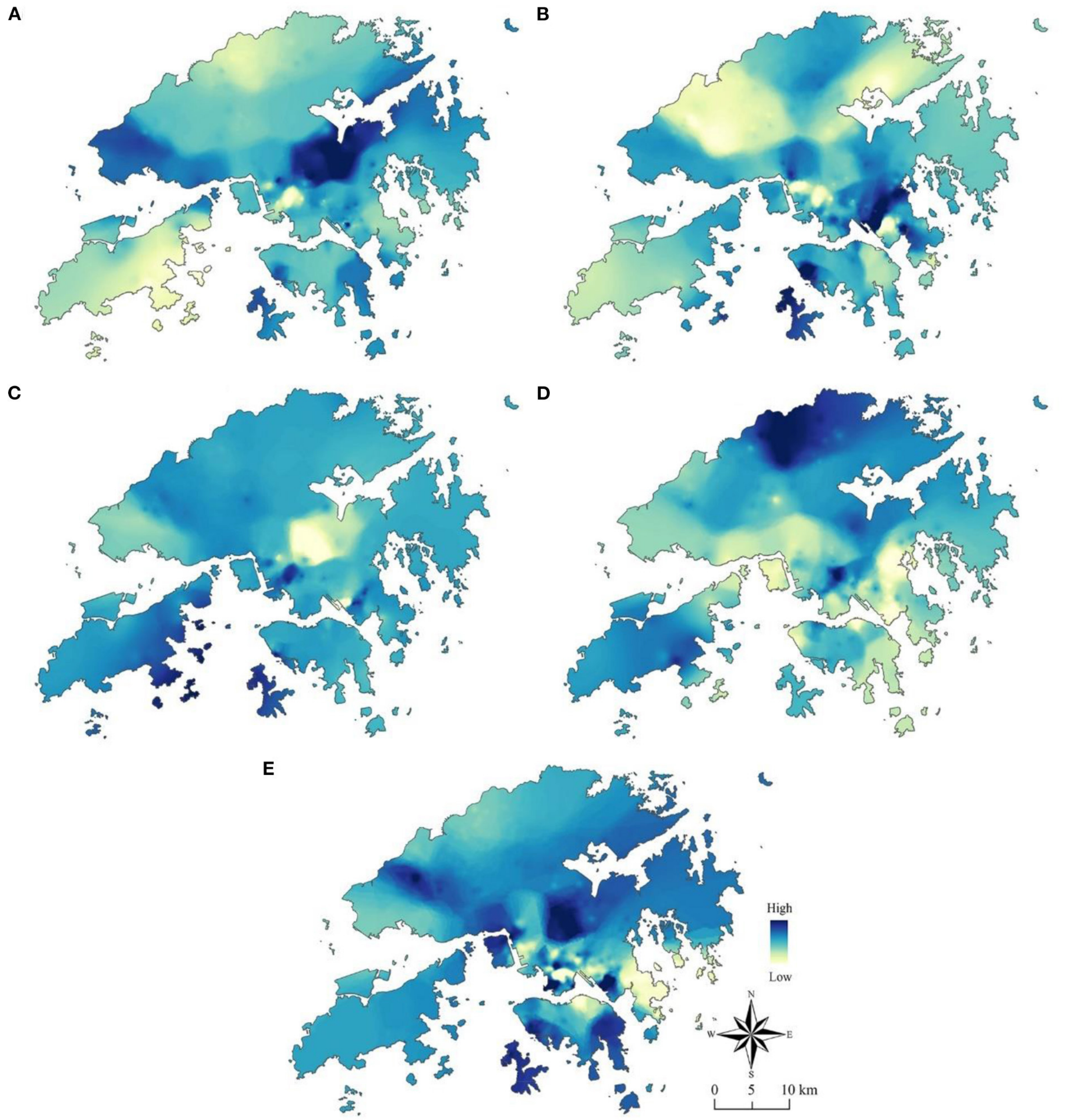

FIGURE 7
The spatial distribution of the coefficients of the built environment variables. **(A)** Coefficient of population density. **(B)** Coefficient of land-use mix. **(C)** Coefficient of intersection density. **(D)** Coefficient of access to bus stops. **(E)** Coefficient of street greenery.

as an extremely compact, highly mixed-use metropolis. The extent to which the findings of this study are externally valid in mainland Chinese cities and beyond remains to be tested. Further empirical studies in various contexts are required to draw more thorough conclusions.

Data availability statement

The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding author.

Author contributions

CY: conceptualization, funding acquisition, supervision, and writing—original draft. XT: validation and writing—review and editing. LY: formal analysis, methodology, formal analysis, and writing—review and editing. All authors contributed to the article and approved the submitted version.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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Fire system safety risk cognition model and evaluation of major public safety risks

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Along with the expansion of city scale, and the increase in the density of population and buildings, the occurrence of a major public fire safety incident in cities will lead to a serious threat to the overall public safety and the sustainable economic and social development of the relevant region. A simple and practical safety risk assessment method of fire prevention in gas stations is of great value for disaster prevention and application in key industries. The constituent elements of a gas station fire prevention safety system are complex, and include equipment, materials, environment, operation, and other factors. This element of information has randomness and temporal dynamics. To promote the transformation of the safety supervision mechanism of gas stations, realize the dual objectives of risk classification and risk dynamic management, and control the gas stations' safety systems the gas stations safety systems are the objectives of our paper. By taking the "fire" risk point of fire prevention in gas stations' system as the research object, this paper puts forward the cognitive path of fire prevention in gas stations' safety system for risk disasters, and explains the coordination between characteristics of inherent, initial, and real risks and the structure of the risk system's attributes. A realistic risk assessment model of fire risk with inherent and dynamic risks is established. An example was introduced to apply the real risk model, and the results were consistent with the actual prediction results, thereby showing the effectiveness and practicability of this method. This risk assessment method can provide a scientific basis for the prevention of fires and control of the fire prevention safety system, showing the changes in risk levels in different stages, and providing risk warning for project managers in taking prompt corresponding risk control countermeasures and improving the efficiency of risk management.

KEYWORDS

system security risk, risk characteristics, real risk cognition, evaluation model, fire

Introduction

Fire is the most frequent and destructive disaster in urban gas stations. Most of these accidents are caused by the corrosion of pipeline equipment (1), inflammable materials, and dense personnel at the gas stations, causing large casualties and property losses. With the increase in supply and demand of gas stations, the causes of accidents are diversified, and there are widespread posts, links, and operations pertaining to out-of-control pipe leakage. Therefore, prevention of these major risks requires advanced control, and must highlight risk prevention and control of key equipment, technology, materials, places, and other system attributes to employ effective means of ensuring urban fire safety. As such, it is key to evaluate whether prevention of major risks is efficient to strengthen the control of labor-intensive sites and high-risk processes, and reasonably define the key parts to be controlled such as hazardous substances, processes, equipment, sites, and operations. Therefore, it is of great practical significance to conduct an in-depth study on the assessment of fire risk at gas stations and discover assessment indicators that are more consistent with the actual situation of the city, establishing a more reasonable assessment system.

Risk has many different definitions (2–4), and often referred to as the combination of probability and consequences of a specific hazardous event. Most of the early risk matrix methods used the description method or scoring method to determine two grades to measure the degree of risk: the qualitative scale of possibility and risk severity (5, 6). This discrete scale limits its application in evaluation (7). Garvey et al. (8) and Qazi et al. (9) focus on traditional risk identification technology that emphasizes the necessity of system interaction between capturing risks. Qazi et al. (10) believed that decision-makers encountered risks at all stages of risk management, and proposed that the risk matrix method could effectively deal with risk dependence and risk bias. Although traditional risk analysis methods have been widely used, such as formal safety assessment, event tree, fault tree, and analytic hierarchy process that have been used for risk analysis and prevention, there remain some defects, such as insufficient quantification of risk estimation (11). To resolve the above shortcomings, some advanced evaluation methods were proposed, such as Bayesian networks (12, 13), evidential reasoning, and the fuzzy logic reasoning model (14–18). Although it is beneficial to improve the integrity of data, it fails to analyze the causal relationship between risk data. These models are only applicable to risk assessment at a site or risk point, but not that of security systems.

Through the investigation of major accidents, it is found that the causes of accidents are often accompanied by new unknown risks, meaning there is a scenario gap; risks are accompanied by dynamic uncertainty (19), the unexpected nature of natural disasters (20), new technologies (21), and other scenarios that constantly emerge, and their risk consequences are dynamic. In other words, due to the uncertainty of risk, its state is dynamic and accompanied by diversified industrial accident incentives, and the widespread existence of out-of-control management positions, links, and regions, also makes decision-making based on risk assessment results uncertain (22–24). In actual management, there is a gap between known risks and unknown risks, which leads to inconsistency in the expected accident scenario. Only by compensating for this defect and investigating the causal relationship between risk changes and the occurrence of major accidents can we effectively prevent them.

Since the operation process is a dynamic continuous process, to reflect the changing trend of risk accumulation, most scholars consider system security risk as the main line and propose new research methods. Hou et al. (25) discussed and analyzed the framework of hazardous chemical leakage accidents from two aspects of the safety management system and emergency rescue. Merch et al. (26) pointed out that most of the available risk assessments and occupational health and safety were originally designed to meet the needs of large enterprises, and it seems to be widely accepted that the overall accident rate would be significantly higher when applied to small enterprises, resulting in a gap. Lindhout et al. (27) proposed that there is a significant gap between the major accident scenarios predicted by the company's safety management department and the actual situation. This finding points out that there is a gap in the results of the risk assessment method, and led to proposing a major risk assessment method for systematically dealing with "unknown risks," concluding that making comprehensive preparations for hazard identification and risk assessment in safety management was impossible. Lindhout and Reniers (28–30) analyzed potential hazard scenarios and proposed effective measures to mitigate these potential hazards through the set scenarios and a series of management modes related to industrial processes. Zhang et al. (31) rebuilt the framework of accident prevention in the construction industry, identified the main causes of construction accidents as a whole system, and then decomposed them into 6 sub-systems, 16 hierarchical factors, and 39 sub-factors. This paper defines the construction accident causation system model by using accident causation theory and a system thinking method. Gjerdrum and Peter (32) pointed out that due to the uncertainty of "risk preference," the risk list may be incomplete, meaning that there are many factors of "unknown risk," proving once again that risk factors cannot be fully identified. Existing system assessment methods do not fully consider online monitoring of risk assessment and new risks arising from changes in technology, products, operations, and organizational structure in industrial development (33). The system risk assessment method has strong applicability. Although the above research has achieved significant results in major risk identification, risk structure mode, and assessment method of specific scenarios of system risk, it is also proposed to study the prevention of major risks in key industries considering many risk factors. However, in practice, there may be risks in operation due to unexpected changes in equipment or substances, deterioration of process equipment, and failure of online monitoring (34, 35). Given the problem that risk identification in complex systems is not hierarchical and focused enough, and the dynamic correlation of causality is ignored, there will be a large deviation between the risk identification results and the actual situation. To highlight the key prevention and control parts of safety system risk identification, and improve the completeness and accuracy of the identification process, it is necessary to reconstruct the system safety risk assessment model and apply it to key industries under control.

According to the new requirements of standards and regulations related to risk assessment methods of the global industrial development, risk management pays increasing attention to simple and widely applicable methods, and tends to focus on researching for comprehensive risk assessment methods with high-risk positions and online dynamic monitoring. For example, Xu and Chen (34) proposed a theoretical framework for systematic risk assessment based on equipment and facilities, materials or energy, environment, and operation in dangerous industries, and formed a major risk index system of key industry safety systems, including inherent risk index, risk control index and dynamic risk index. Based on this theoretical system framework, Li et al. (35) established a quantitative method for assessment of an inherent risk of system attributes, considering the disturbance caused by the management state to inherent risk, proposing a correction method of inherent risk, and forming the realization risk assessment model. These studies provide a good theoretical framework, but the systematic quantitative evaluation needs further research.

To sum up, an increasing number of scholars have adopted different analysis methods based on different assessment perspectives for related research on risk identification, index analysis, and assessment model. Although they provide certain theoretical and technical support for risk management, prevention and control, most scholars' risk assessment is based on research on humans, property, and management. Lack of hierarchical and feedback analysis on the inherent risk of the system, the effectiveness of the management level, and the influence of external environmental disturbance index factors. In addition, most of the previous studies focused on risk identification analysis in the internal or local system operation stage of enterprises, and lacked systematic analysis and research on attributes and management status indicators of fire safety management systems, as well as a structural description of the construction of these indicator systems. Consequently, the risk of the fire safety system based on the analysis of the cognitive and system security attribute index makes it necessary to explore a suitable set for fire local static, a dynamic and complex system as a whole system for the dynamic control theory of risk identification and evaluation methods, pay attention to the transfer between elements, a dynamic feedback effect, make the safety risk identification and the evaluation of dynamic research appear more valuable for application. This provides a reference for realizing the online risk dynamic control platform of the public fire prevention and safety system.

System security risk reconstruction and assessment process

A new approach to system risk regards system security risk as a whole assessment system. Starting from the risk source, a study on the inherent attribute risks of equipment, facilities, materials or energy places, processes, and high-risk parts of the operation is performed, and is then combined with the initial risks formed after the protection of existing safety protection measures, and finally the dynamic risk impact after the emergence of new information is considered. Consequently, a series of risks are finally manifested as real risks. Therefore, the system risk assessment model would be reconstructed before studying the real risk. To prevent major risks from being pre-controlled in advance, highlighting and strengthening the key control of labor-intensive places and high-risk processes, and reasonably defining the key control parts such as equipment and facilities, materials or energy, places, processes, and operations are key to evaluate whether the prevention of major risks is efficient.

Analysis of system security risk characteristics

Most studies ignore the inherent properties of system risk, that is, the uncertainty and dynamic change information in specific scenes (36). Chen et al. (37) established a risk grading assessment method for enterprises in chemical industrial parks based on the source of inherent risks, effective prevention mechanism, and vulnerability of receptors according to the risk system theory and characteristics of chemicals, but the influence factors of dynamic change are weakened. Considering the inherent risk perspective as the main line, the inherent risk of system attribute and the dynamic risk related to the complex system security risk were analyzed again. To understand system security risks, it is necessary to clarify the main relationship between system elements, to facilitate the analysis of the transformation of system risk events in different dimensions. The concepts of system security risk are defined as follows:

Inherent risk refers to the energy (e.g., electric energy, potential energy, mechanical energy) inherent in equipment and facilities, materials or energy, etc. The hazard source exists objectively, and its attribute determines that the accident will cause serious consequences, once it happens. Thus, inherent risks are considered risks that do not take into account existing control measures. Therefore, the inherent risk is objective, and the fire prevention system risk refers to the risk of harmful equipment and facilities, materials or energy, operation, and others.

The formation of initial risk can be regarded as the inherent risk of system attributes and the uncertainty of local system management state triggered together. It is the risk present after considering the existing safety protection measures based on the inherent risk. In other words, the degree of risk depends not only on the degree of inherent risk, but also on the level of prevention and control, and the environmental sensitivity of the recipient (37). Therefore, based on the inherent risks of system attributes, the frequency index generated in the process of management and control is introduced to modify the inherent risks, and thus the initial risks can be obtained. The relationship is expressed in Equation 1:

$$R_0 = H \times G \tag{1}$$

where R_0 is the initial risk, H is an inherent risk, and G is the risk of key controlled objects.

The uncertainty of risk involves whether the risk and the subsequent consequences after the risk will occur. Risk is an objective existence independent of people's consciousness and not subject to people's will. In other words, we can only measure the risk generated by a certain event and take relevant measures to avoid or reduce the risk, but we cannot prevent the occurrence of the risk. However, risk has certain controllability. Under certain conditions, the risk can be judged by a series of measures and certain means can be used to avoid or reduce the risk. In addition to randomness, there is a certain inevitability between risk and probability. The inevitability of risk in its frequency is that risky events must have consequences. Therefore, the operation process is a dynamic continuous process, which creates real risks.

Actual risk refers to a system under actual control by external disturbances, and not subjected to subjective control of a dynamic state that may lead to the occurrence of accidents. That is, the aggregation of initial risk and dynamic risk constitutes a real risk. Paying attention to the actual risk assessment of the system and the transmission and dynamic feedback between risk elements has more practical value for the research of safety risk identification and dynamic assessment of complex systems.

The actual risk is represented by R, and its value is calculated by integrating the initial risk R_0 with the dynamic risk correction coefficient K_m. The actual risk can be expressed as a function in Equation 2:

$$R = R_0 \times K_m \tag{2}$$

In the face of a complex safety system, the risk management model of coordinating major risk system attributes and dynamic regulation is explored from the inherent risk, initial risk, and real risk of the system, and the internal, external, and internal logical relationship between different factors in the occurrence process of risk events is revealed. General risks can be further discussed when a mature risk management system integrates a big data and other technologies to facilitate data acquisition in the future. Given this situation, focusing on the background of major risk events in the system, combined with the actual production situation of the enterprise in the safety management work, tracking and tracking, explores the coordination mode between system attribute risk and dynamic risk structure elements, which is helpful for clarifying the coordination mode between system risk elements, risk structure, and evaluation objects.

Different from the traditional simple system risk assessment method, the system has complex constituent elements and many evaluation elements. Hence, it is necessary to adopt the key prevention and control method, that is, a "dimension reduction" idea. Based on the importance of the system attribute prevention and control object, the research focus is to adapt its risk prevention and control ability. To reflect the changing trend of risk accumulation, build a logic line of risk change as shown in Figure 1, and explore the changing trend of major risk system attributes coordinated with dynamic regulation from the inherent risk, initial risk, and real risk of the system.

System security risk assessment process

System security risk includes static risk and the dynamic risk of the whole system. The former represents the objective static characteristics of the system and the control changes of local risk management status. The latter reflects the dynamic situation of the system as a whole caused by external influences, such as online monitoring, early warning feedback results, continuous rainstorm, earthquakes, special periods, and other factors affecting the overall risk status of the system with timely changes. Although the emphasis of the two analyses is different, there is a certain correlation. From the perspective of management, the dynamic risk assessment of the system as a whole is convenient for managers to clarify the dynamic risk of the whole system, while the dynamic risk analysis of static risk and local management is convenient for managers to arrange targeted risk control measures in daily life. Only by cooperating with them can the risk assessment achieve the best practical effect. However, most scholars focus on risk analysis of some common accidents or local system problems, ignoring the coordination between dynamic risk assessment of the system as a whole, static risk, and local dynamic risk analysis. Next, the system attributes are quantitatively analyzed to form a risk point initial risk and unit initial risk classification model, which can reflect the causal logic relationship of accident risk points. Then, according to the input dynamic hidden danger data, special period data, natural disaster data, and other evidence of the online monitoring system, the timely and dynamic risk assessment of the fire prevention system attribute is carried out to provide a theoretical basis for managers. Therefore, the key dynamic indicators are used to modify the system attribute indicators, and the dynamic risk indicators are used to adjust the risks in each unit of the fire prevention system. In other words, the initial risks of the unit are modified timely to form the real risks in line with the actual state of the system. Combined

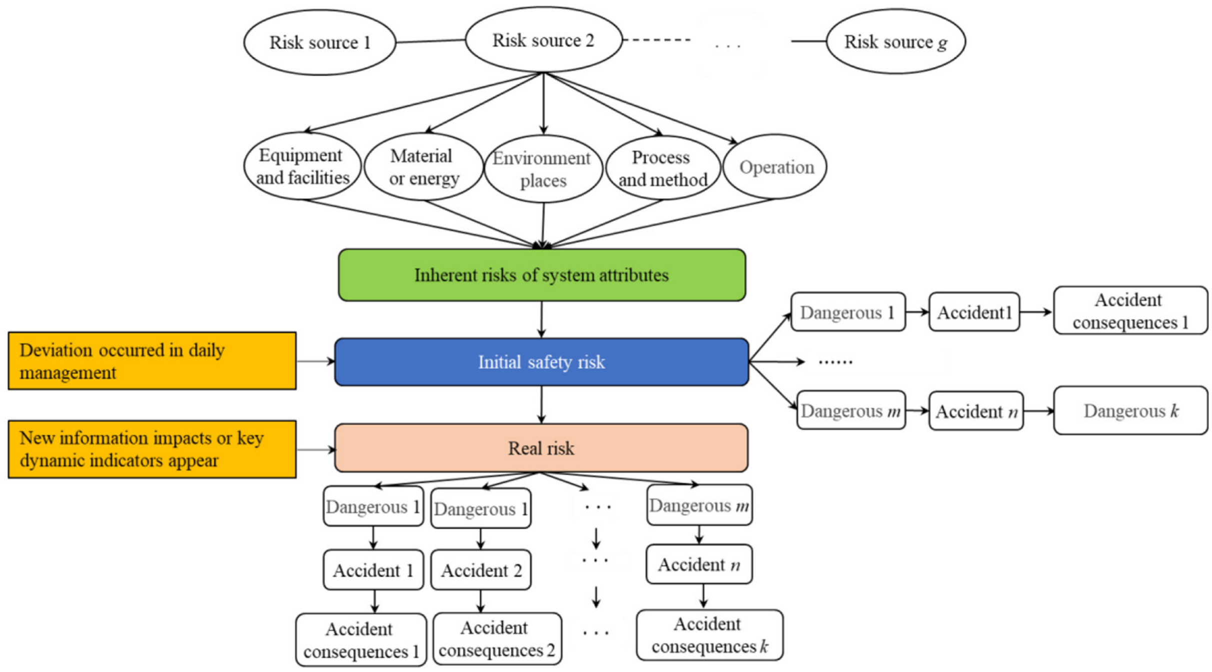

FIGURE 1
Main logic line of risk structure.

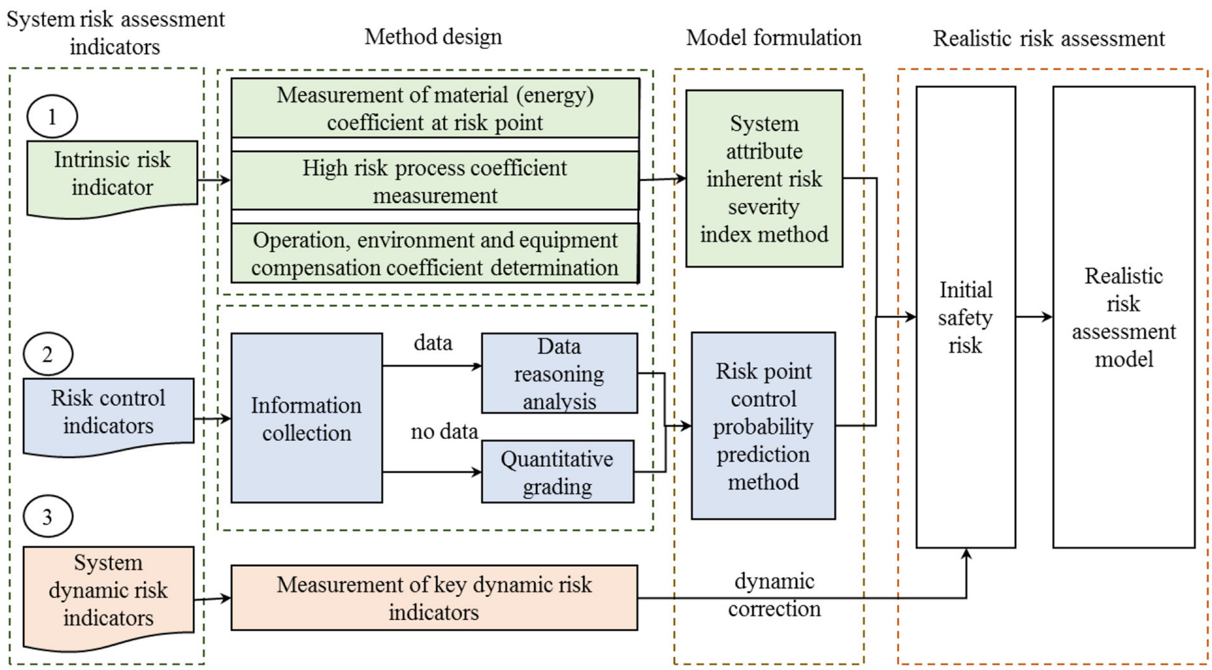

FIGURE 2
System risk assessment process.

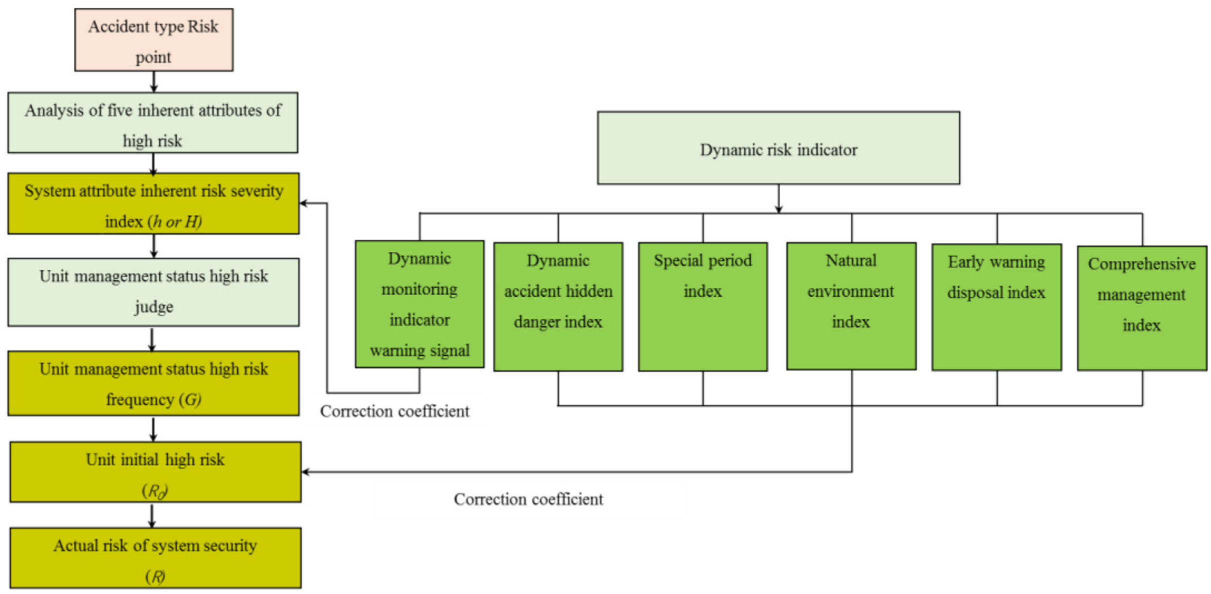

FIGURE 3
Realistic risk assessment model.

with system attribute indicators and key dynamic risk indicators, a realistic risk assessment model is constructed, as shown in Figure 2.

Firstly, as shown in the system risk assessment process in Figure 2, a quantitative method of "five key parameters" is proposed for the equipment and facilities, material or energy, place, process, and operation compensation coefficient of the inherent attributes of the risk point to quantify the severity of the inherent risk index of the fire prevention system. Secondly, to solve the difficult and static problems of obtaining the risk analysis data of disturbance factors, the initial evaluation parameters are obtained by taking the risk control indicators as the center. Then, the inherent risk severity index and risk control frequency index are aggregated into the initial risk of the risk point. Finally, according to the characteristic values of monitoring items, the key dynamic risk index correction method is proposed, and the initial risk is dynamically corrected. After the dynamic timely correction, the real risk assessment model is integrated to form the timely risk assessment coupled with system attributes and management status.

Methodology

Our study aims to prevent and defuse major risks and fire risk point system attributes and management status of timely risk assessment as the background. Thus, a realistic risk assessment model is constructed, as shown in Figure 3, that is different from traditional risk assessment methods, based on the systematic risk cognitive structure model, analysis system property risk point of equipment, materials, place, process, operation inherent risk indexes and quantitative methods, to manage state and local controls risk frequency calculation method, considering the key dynamic risk indicators of overall risk.

Determination of inherent risk index of fire risk point

The places or regions that may induce serious accidents within the unit are considered risk points, and the fire risk points are often highlighted in the gas station fire prevention system. The inherent risk of system safety is classified according to the five major disaster-causing factors of major accidents in order to solve the inherent risk, and the steps are as follows:

Step 1: Hazardous equipment and facilities are measured by the intrinsic safety level of storage tanks at risk points.

Step 2: Hazardous substances are determined through the energy characteristics of the substances in the storage tank at this risk point.

Step 3: A dangerous place refers to the exposure risk index of personnel within the risk point.

Step 4: A dangerous process refers to the failure rate of static eliminators, alarm devices, monitoring videos, and other monitoring facilities.

Step 5: Dangerous operations refer to high-risk operations that are involved, such as special operations, dangerous operations, special equipment operations, etc.

The inherent risk index h calculation method of risk points is shown in Equation 3:

$$h = h_s \cdot M \cdot E \cdot K_1 K_2 \quad (3)$$

where, h_s is an index of dangerous equipment and facilities, ranging from 1 to 1.7; M is the dangerous material or energy risk coefficient, ranging from 1 to 9; E is the exposure index of personnel in dangerous places, ranging from 1 to 9; K_1 is the correction coefficient of monitoring failure rate, with $K_1 = 1{+}p$, p being the average value of monitoring facility failure rate; K_2 is the risk correction coefficient of dangerous operation, with $K_2 = 1{+}0.05q$, q being the number of high-risk operation types involved in risk points.

Unit high-risk frequency index calculation

An inherent risk mainly emphasizes the inherent risk of the objective existence of substances, and the quality of management only represents the high and low probabilities of risk events. The greater the accident probability, the greater the risk control intensity, indicating that the gas station safety system risk events are more likely to occur. However, the risk of an inherent risk will not disappear, but the change of the management state in the process of risk management will make the inherent risk fluctuate, so the complement of the occurrence probability of uncontrolled management is used as the risk control to measure the fluctuation of inherent risk. Unit high-risk management frequency index is expressed as Equation 4:

$$G = 1 + P \quad (4)$$

where P is the accident risk point event probability.

Dynamic risk correction

The dynamic risk indicator regulation aims to correct the initial risk by taking the real risk status as the parameter. It mainly refers to the real-time correction of early warning results of online monitoring characteristic indexes. Other indicators contain five key dynamic risk factors including dynamic accident hidden danger data, the impact of holidays and other special periods, the impact of natural disasters, and the impact of governance measures to timely modify the initial risk of the unit.

(1) The inherent risk severity index (h) of risk points was modified by using the warning signal coefficient Km, a characteristic index of online risk monitoring. The real-time alarm of online monitoring items is divided into a level I (low alarm), a level II (medium alarm), and a level III (high alarm) alarms. When the online monitoring items reach three level I alarms, it is recorded as one level II alarm; when the monitoring items reach two level II alarms, it is recorded as one level III alarm. Given this, after several rounds of tests, the base number of the corresponding dynamic monitoring characteristic index coefficient Km is set to 1.20, and the dynamic risk correction expression of the online monitoring characteristic index's early warning signal is established (Equation 5):

$$K_m = 1.20(a{+}2b{+}3c) \quad (5)$$

where a is the number of yellow warnings, $a = 0$, 1, 2, and 3; b is the number of orange warnings, $b = 0$,1, and 2; c is the number of red alerts, $c = 0$ or 1.

(2) Other dynamic indicators to modify the initial high-risk security risks of the unit

i) Dynamic accident hidden danger index correction According to the accident hidden danger data reported by the enterprise, if there are only general accident hidden dangers, but no major hidden dangers, the initial risk (R_0) of the unit shall be modified according to the number of hidden dangers based on the accident investigation standard 100: If the number of hidden dangers is between 1 and 5, k_i =1.20; if the number of hidden dangers is between 6 and 20, k_i =1.40; if the number of hidden dangers exceeds 20 times, the correction rules of major accident hidden dangers shall be implemented. As long as there is a major potential accident, the dynamic indicator correction coefficient k_i is directly used to correct the initial unit realistic risk ($R0$). The value of the dynamic indicator regulation coefficient k_i is shown in Table 1.

ii) Special period index correction Special periods refer to statutory holidays and important national or local activities. In the quantification of indicators during special periods, the initial unit realistic risk (R_0) is corrected by the dynamic index correction coefficient k_i. The value of k_i is shown in Table 1.

iii) Correction of natural environment index For the quantification of natural environment indicators, such as earthquakes, and debris flow, the dynamic index correction coefficient k_i is used to correct the initial unit actual risk (R_0). The value of k_i is shown in Table 1.

iv) Correction of early warning disposal index If a yellow warning information appears, then the enterprise failed to

TABLE 1 Values of dynamic risk index correction coefficient.

Initial risk (R_0)	Correction coefficient k_i			Correction coefficient
	$i = 1$	$i = 2$	$i = 3$	kc
I level	1.20	1.44	1.73	0.84
II level	1.30	1.69	2.20	0.67
III level	1.40	1.96	2.74	0.50
IV level	1.50	2.25	3.38	/

Here, i represents the adjustment times of other dynamic indicators, and direct adjustment of more than 3 times is considered a major risk.

TABLE 2 Classification of realistic risk levels.

Unit realistic risk(R_0 or R)	Unit realistic risk level	Risk level symbol
$R<48$	Low risk	IV level
$48\leq R<105$	General risk	III level
$105\leq R<150$	Larger risk	II level
$R\geq 150$	Major risk	I level

dispose within 24*h*. In the case of an orange warning information, then the enterprise did not dispose within 12*h*. The dynamic index correction coefficient k_i is used to correct the initial unit actual risk (R_0). The value of k_i is shown in Table 1.

v) Comprehensive management index revision If the enterprise adopts the comprehensive management of the closed and sold gas stations, the system risk will be significantly reduced. Therefore, the correction coefficient k_c is adopted to reduce the initial unit realistic risk (R_0), as shown in Table 1.

Actual risk of unit

(1) Dynamic correction of unit inherent hazard index As the gas station is a safety system, it is found that there is only one major fire risk point in the whole unit. In addition, since the correction coefficient (K_m) of the alarm signal, a characteristic index of dynamic monitoring of high risk, is dynamically modified for the inherent risk (h) of risk points, as shown in Equation 6, the dynamic correction of the inherent risk index of the construction unit is as follows:

$$H = hK_m \tag{6}$$

where H is the modified value of the dynamic monitoring index of inherent risk point.

(2) Unit initial high risk As shown in Equation 7, the high-risk risk control frequency (G) of the unit is aggregated with the inherent risk index (H) of the unit to determine the initial safety risk value of the unit. The risk level is determined in Table 2.

$$R_0 = GH \tag{7}$$

where R_0 is the initial safety risk value of the unit.

(3) Actual risk of system security System actual risk R is the result of revising the initial high risk (R_0) of the modified unit by other dynamic risk indicators. Other dynamic risks do not always exist. If this index does not exist, its modified value is 1. If it does exist, modifying R_0 should be done by referring to Table 1. Finally, the actual safety risk of the fire prevention system is calculated (Equation 8):

$$R = R_0{}^*k_c{}^*k_i \tag{8}$$

where k_i is to increase the risk correction coefficient. Among the dynamic indicators, the special period index, early warning disposal index, and natural environment index appear, which should and will increase the risk. i is the adjustment times of these three indicators, i = 1,2,3; while kc is to reduce the risk correction coefficient. Note, that due to the existence of a comprehensive management index, when the risk is managed in time, the dynamic risk is significantly reduced, and should be corrected.

The values of k_i and k_c are shown in Table 1. If k_i and k_c do not exist, that is, there is no dynamic index, both k_i and k_c take the value of 1.

(4) Actual risk level of the unit The risk regulated by the risk control index and dynamic risk index is regarded as the actual risk of the final fire event, as shown in Table 2. The realistic safety risk level of a gas station system is divided into I, II, III, and IV (38).

Case study

The construction area of a city gas station is about 1,000 square meters, generally used to add fuel oil, lubricating oil, and so on. There are 5 gasoline tanks with a total of 260t, and the critical value of gasoline is 200t. The correction coefficient is 2.1, and convenience stores with other convenience measures are supported. The gas station area is equipped with 7 types of monitoring facilities, such as an electrostatic eliminator, fire alarm devices, and video surveillances, with a normal daily online monitoring system. The risk control frequency index of fire occurrence is 0.13. The gas station staff of 5 people, and the fire accident, may affect the number of surrounding residents reaching 80 people, the daily inspection found 15 hidden dangers, and an emergency plan. Based on the above examples, the risk point of a gas station fire accident is taken as the evaluation object, the system risk assessment model is applied to these examples, and the feasibility assessment analysis is carried out.

(1) Inherent risk index of fire risk points Gas stations contain tanks of diesel, gasoline and their attached facilities, which are high risk. Therefore, the corresponding relationship between the essential safety level of tanks and the risk index is shown in Table 3.

According to the "oil tank" and "auxiliary facilities" indices to classify quantification, each index selects a characteristic value that is multiplied, with the solution result being a risk index of high-risk equipment and facilities characteristic value of 1.70.

Regarding the hazard factor of fire incident risk point, the material coefficient M is determined by the fire, explosion, toxicity, and other characteristics of dangerous goods at the event risk point, mainly characterized by the combustibility and chemical activity of the substance, and it describes the internal characteristics of the energy released by the fire, explosion

TABLE 3 The corresponding relationship between intrinsic safety level of tanks and hazard index.

Indicator	Indicator description	Characteristic value
Oil tank	Advanced equipment	1.10
	The tank is in good condition	1.30
	Poor quality of tank body	1.70
Affiliated facilities	Fully equipped and in good condition	1
	The warning system is in good condition	0.90
Risk index of dangerous equipment and facilities (h_s)		1.70

TABLE 4 Assignment table of risk point exposure personnel index.

Number of people exposed	Characterization value *E*
More than 100 people	9
30–99	7
10–29	5
3–9	3
0–2	1
Index of Persons exposed to dangerous places(E)	5

and other chemical reactions of the substance. The larger the quantity of storage, the greater the possible consequences of instability. Therefore, according to the hazard classification standard stipulated by the identification of major hazard sources of hazardous chemicals, the ratio between the actual quantity of hazardous substances and the critical quantity at the fire event risk point was determined, and the M was measured by the sum of the ratio corrected by the correction coefficient β of the corresponding hazardous chemicals. The dangerous substance at the fire event risk point is calculated as follows:

$$M = \beta_1 \frac{q_1}{Q_1} + \beta_2 \frac{q_2}{Q_2} + \cdots + \beta_n \frac{q_n}{Q_N} \quad (9)$$

where M is the coefficient of chemical combustibility or active characteristic substance;$q_1, q_2, \cdots q_n$ are the actual quantity of each dangerous substance; $Q_1, Q_2, \cdots Q_n$ are the critical quantity corresponding to each dangerous substance;$\beta_1, \beta_2, \cdots \beta_n$ are the correction coefficients corresponding to each dangerous substance.

In our case, the high-risk item is gasoline, and M is equal to 2.73 as determined by Equation 9.

High-risk sites are refueling areas where residents can be affected by the fire. A total of 85 people work in the refueling area due to the number of residents nearby. The corresponding relationship between the number of people that can be affected by the fire and the risk index is shown in Table 4.

A high-risk process is composed of monitoring and monitoring systems. Considering the high impact and high-risk characteristics of fire and explosion, effective monitoring is an important part of ensuring the safety of gas stations, and the effectiveness of monitoring and monitoring system technology has an important impact on the refueling area. The case involved 7 types of monitoring facilities, and the monitoring status was intact, so $K1 = 1$ was obtained. A high-risk operation is determined by the type of operation in the refueling area, and so $K2$ is equal to 1.5.

Therefore, the inherent risk index of fire accident risk points can be obtained from Equation 3, calculated as h and equal to 48.73.

(2) Probability of risk point control As for the calculation of risk changes in daily management, the probability index of fire accident risk point control can be obtained from Equation 4, calculated as G and equal to 1.13.

(3) Systematic realistic risk assessment Risk dynamic simulation and risk evolution should be considered for a gas station. Since the online monitoring system is normal, it can be seen from Equation 5 that the correction coefficient of the alarm signal of the characteristic index of dynamic monitoring of high risk is 1. According to Equations 6 and 7, the result of dynamic correction of the inherent risk index of the calculation unit is 48.73, and the initial risk result of the unit is 55.07, belonging to general risk. According to Equation 8, the actual risk result of system safety is 71.59, belonging to a large risk and the risk level II. Compared with the actual situation, the realistic risk assessment results are more consistent with the reality.

Discussion

Inherent risk change law analysis

To verify the effectiveness and feasibility of the method, an inherent risk assessment was conducted for the fire accident risk points of 10 gas stations. The assessment results are shown in Table 5. Because the article takes the inherent risk of fire accident risk points as the main line, the real risk is calculated after the two corrections of the control state and dynamic risk. Because it is difficult to obtain the corrected data, that changes based on the inherent risk, most of the updated results increase the real risk data, so the risk change law can be analyzed according to the main data results of the inherent risk.

(1) The established system security risk assessment model highlights the focus on prevention and control. Mainly from "dangerous equipment and facilities, dangerous materials or energy, dangerous place, dangerous process, dangerous operation" to highlight the prevention and control role of key people, equipment, processes, sites, and other risks, that can fully

TABLE 5 Inherent risk assessment results of fire risk points in 10 gas stations.

Serial number of 10 gas stations	Accident risk point	h_s	M	E	K_1	K_2	h
1# gas station	Fire	1.30	3	7	1.10	1.20	36.04
2# gas station	Fire	1.70	4	7	1.30	1.30	80.44
3# gas station	Fire	1.50	5	5	1.30	1.40	68.25
4# gas station	Fire	1.70	6	9	1.50	1.50	206.55
5# gas station	Fire	1.70	3	9	1.20	1.20	66.10
6# gas station	Fire	1.50	6	7	1	1.30	81.90
7# gas station	Fire	1.10	8	3	1	1.40	36.96
8# gas station	Fire	1.30	9	7	1.10	1.50	135.14
9# gas station	Fire	1.50	2	5	1.60	1.60	38.40
10# gas station	Fire	1.70	5	3	1.50	1.70	65.03

TABLE 6 Matching supervision principle of risk classification and risk level.

Supervision level / Risk level	Risk status, regulatory countermeasures and measures	Level and status of supervision			
		Major risk	Higher risk	General risk	Low risk
I Level (major risk)	Unacceptable risk: significant regulatory measures; First-level warning: strong supervision; Comprehensive investigation, rectification.	Reasonable Acceptable	Unreasonable Unacceptable	Unreasonable Unacceptable	Unreasonable Unacceptable
II Level (higher risk)	Expected risk: large risk regulatory measures; Second-level warning: strong supervision; High-frequency inspection.	Unreasonable Acceptable	Reasonable Acceptable	Unreasonable Unacceptable	Unreasonable Unacceptable
III Level (general risk)	Limited risk acceptance: general risk regulatory measures; Third level warning: medium supervision; Local restrictions: limited checks, warning policies, etc.	Unreasonable Acceptable	Unreasonable Acceptable	Reasonable Acceptable	Unreasonable Unacceptable
IV Level (low risk)	Acceptable risk: negligible; Fourth-level warning: weakening supervision; Attention strategy: random check, etc.	Unreasonable Acceptable	Unreasonable Acceptable	Unreasonable Acceptable	Reasonable Acceptable

Red indicates that the risk result is extremely serious and may cause catastrophic consequences. The risk result is unacceptable and prevention and control measures must be taken immediately.
Orange is second, indicating that the risk result is serious, the risk result is unacceptable, and the prevention and control measures should be taken immediately.
Yellow indicates that although the risk result is not controllable, it is acceptable, and daily control needs to be strengthened.
Blue indicates that the risk result is within the control range, acceptable, and strengthen control.

control the actual situation, further explaining the rationality of the model evaluation results.

(2) Material hazard index (M) and site personnel exposure index (E) accounted for most of the assessment, that is, the higher the mass of the fuel, the higher the M; The greater the number of people affected by the fire explosion, the greater the E.

(3) The normal operation of online monitoring and monitoring facilities can effectively control the safe operation process parameters of the gas station system and reduce the inherent risk, which would otherwise increase. In addition, the more types of special operations used, the higher the potential inherent risks; Reducing the number of high-risk workers is by implementing automation is one of the effective ways to reduce the inherent risk at the gas station.

Risk classification prevention and control

(1) Risk classification supervision According to the risk assessment results, the technical and supervisory countermeasures and suggestions for eliminating or weakening risks and hazards should be put forward, and prevention and control measures should be taken to reduce risks until the risk reduction is within the acceptable range. The risk of fire is divided into four grades from high to low: red, orange, yellow, and blue, and the “red, orange, yellow, and blue” safety supervision and management warning mechanism must be constructed and implemented. According to the risk value calculated by the risk classification model and based on as low as reasonably practicable, the risk assessment level of the

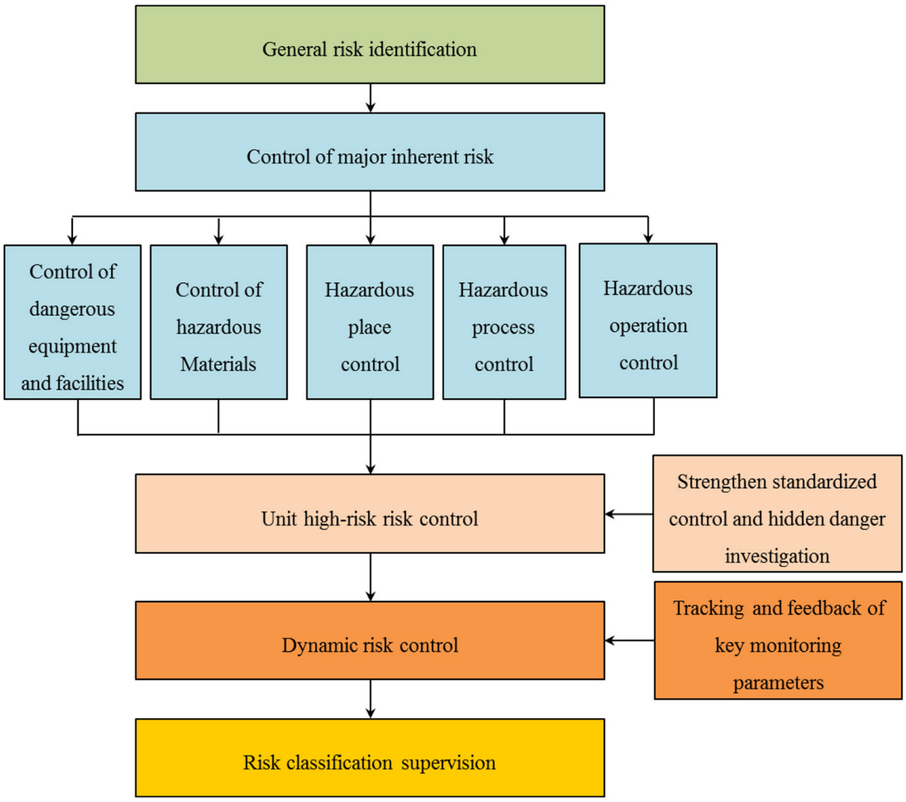

FIGURE 4
Classified management and control of security risks based on realistic risk assessment technology.

supervised object is graded into four levels, namely, major risk, higher risk, general risk, and low risk. According to the scientific and reasonable "matching regulation principle," the corresponding level of regulatory measures should be applied to the corresponding level of risk objects. For example, the supervision objects of major risk levels should be subjected to high-level regulatory measures, as shown in Table 6. Safety supervision departments at all levels should combine their regulatory power according to different risk levels, formulate scientific and reasonable law enforcement inspection plans. Concerning the law enforcement inspection frequency, the respect such as law enforcement inspection should focus on differentiation and encourage enterprises to strengthen the self-management, enhance the level of safety management, and adopt effective risk control measures and efforts to reduce risk.

(2) Implement inherent risk classification control According to the evaluation results, we should focus on high-risk processes, equipment, articles, sites, and operations, and strengthen dynamic risk control, which is conducive to prevention and control. Enterprises should implement "three simultaneous" for dangerous equipment and facilities, strictly follow the design and safety regulations, and improve the essential safety level of equipment and facilities. For inflammable materials that may lead to accidents, strict control of the parameters of high-risk materials according to relevant safety standards and design requirements is required, accompanied by daily detection and maintenance management. Enterprises should reduce personnel exposure in dangerous areas, adopt measures of "automatic personnel reduction and mechanical personnel replacement," promote remote inspection technology, and monitor mobile personnel. Strengthening the control of the dangerous processes and improving the reliability of key monitoring dynamic data would also be essential. The employees would receive education and training on topics pertaining to production safety, production safety, and safety risk control measures.

(3) Improve the standard management level of enterprise safety Establishing hidden dangers and illegal intelligent identification system, while also strengthening hidden danger investigation and report would also be important.

(4) Strengthen dynamic risk control According to the dynamic early warning information, natural disaster, special periods, and other relevant information must be used to take timely response measures and reduce dynamic risks. Improving the real-time effectiveness of risk dynamic index data is important to avoid data distortion.

Moreover, risk classification control is implemented over five levels: general risk list identification control, major risk control, unit high-risk risk control, dynamic risk control, and risk classification supervision, as shown in Figure 4. Through targeted and advanced measures for prevention and control, improving safety prevention and control ability is possible. This further indicates that risk assessment technology is beneficial for enterprises in implementing timely and synchronous dynamic monitoring and decision-making.

Advantages of realistic risk assessment method

Realistic risk assessment technology is developed based on the inherent attributes of the system, and the risk assessment object is divided over three stages. The first stage comprises the inherent risk, which mainly evaluates the risk of equipment, facilities, processes, materials, places, and operations, and highlights the key prevention and control parts; The second stage encompasses the unit management and control risk, which mainly assesses the risk in the management processes; The third stage is concerned with dynamic risk regulation, which mainly evaluates the impact of dynamic changes such as high-risk online monitoring, monitoring-characteristic indicators, special period indicators, and natural environment on the initial risk. The realistic risk assessment tool based on the system accident risk point is helpful to clarify the coordination between the system risk elements and the assessment objects.

The results of the realistic risk assessment methods are usually expressed by the index data obtained from statistical data or given certain data rules, and are processed and sorted in a mathematical way to obtain the risk value. This method can not only reflect the local dynamic variability of risk management and control indicators, but also facilitate the proposal of targeted risk management and control measures, further improving the accuracy of risk management prevention and control objects. This may also solve the difficult and static problem of obtaining risk analysis data in the process of complex and uncertain system management. This evaluation method may quantitatively analyze the relationship." This may summarize the sentence in a more concise manner. Kindly check may quantitatively analyze the relationship of a given enterprise's safety status; The results of risk assessment are convenient for researchers or risk decision makers to make effective judgments and interpretations through the comparative analysis of these data.

Conclusions

Compared to the previous simple risk assessment model, the fire accident risk point system discussed in this study is taken as the main line of risk assessment, and the transformation process of the risk points from inherent risk, to initial risk, and then to a real risk is explored, redefining the major risk assessment model and risk perception path. The static risk characterization method of the inherent attributes of dangerous equipment, facilities, materials, places, processes, and operations, in a fire safety system, is studied. Combined with the possible degree of occurrence of fire risk points during daily operations and management, the initial risk of fire risk points under local dynamic conditions is determined. With the update of a fire complex system information and abnormal information, the dynamic risk correction method is proposed again to correct the initial risk. Finally, a static risk assessment model, a local dynamic risk assessment model, and a realistic risk assessment model that can modify the initial risk are established. The system's timely risk assessment, combined with system attributes and management status, is realized, making the enterprise risk management status timely adjusted, and transparent. The shortcoming of the study is that there are other types of disasters besides fires that can occur in gas stations. The previous study was oriented to curb major accidents and focused on preventing major risks.

Data availability statement

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

Author contributions

WL: conceptualization, formal analysis, funding acquisition, investigation, methodology, software, validation, visualization, roles, writing—original draft, and writing—review and editing. XL: data curation, formal analysis, funding acquisition, methodology, project administration, resources, visualization, and writing—review and editing. XD: resources, and writing—review and editing. All authors contributed to the article and approved the submitted version.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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Exploring seasonal diurnal surface temperature variation in cities based on ECOSTRESS data: A local climate zone perspective

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High urban temperatures affect city livability and may be harmful for inhabitants. Analyzing spatial and temporal differences in surface temperature and the thermal impact of urban morphological heterogeneity can promote strategies to improve the insulation of the urban thermal environment. Therefore, we analyzed the diurnal variation of land surface temperature (LST) and seasonal differences in the Fifth Ring Road area of Beijing from the perspective of the Local Climate Zone (LCZ) using latest ECOSTRESS data. We used ECOSTRESS LST data with a resolution of 70 m to accurately interpret the effects of urban morphology on the local climate. The study area was dominated by the LCZ9 type (sparse low-rise buildings) and natural LCZ types, such as LCZA/B (woodland), LCZD (grassland), and LCZG (water body), mainly including park landscapes. There were significant differences in LST observed in different seasons as well as day and night. During daytime, LST was ranked as follows: summer > spring > autumn > winter. During night-time, it was ranked as follows: summer > autumn > spring > winter. All data indicated that the highest and lowest LST was observed in summer and winter, respectively. LST was consistent with LCZ in terms of spatial distribution. Overall, the LST of each LCZ during daytime was higher than that of night-time during different seasons (except winter), and the average LST of each LCZ during the diurnal period in summer was higher than that of other seasons. The LST of each LCZ during daytime in winter was lower than that of the corresponding night-time, which indicates that it is colder in the daytime during winter. The results presented herein can facilitate improved analysis of spatial and temporal differences in surface temperature in urban areas, leading to the development of strategies aimed at improving livability and public health in cities.

KEYWORDS

Local Climate Zone, diurnal variation, land surface temperature, ECOSTRESS data, urban morphology, Beijing

Introduction

With the rapid development of urbanization, the proportion of impervious surface in cities is increasing, and these materials usually have higher heat storage capacity and lower reflectance. In addition, the increase in population of cities will also bring about an increase in energy consumption and greenhouse gas emissions. As a result, the temperature of the inner city is higher than that of the surrounding areas, which is called the urban heat island (UHI) effect (1, 2). The UHI affects air quality (3), vegetation phenology (4), and energy and water demand (5–7), while also increasing heat-related human casualties (8). By 2050, 68% of the global population is expected to live in urban areas, according to UN statistics (9). Previous studies have shown that the change of thermal environment will not only affect people's physiological condition, but also have serious psychological effects (10). Meanwhile, global heat wave events are increasing in frequency (11–13), and climate warming have also changed the urban thermal environment to some extent. Therefore, the spatial and temporal patterns and variability of the urban thermal environment must be explored to improve livability and public health in cities for global urban development (14–16).

Based on the location of the heat island, UHI effect can be divided into Subsurface UHI, Surface UHI, Canopy layer UHI and Boundary layer UHI (17, 18). The UHI effect is usually quantified through urban heat island intensity (UHII) (19). It is defined as the difference between urban surface temperature and suburban surface temperature (20). The temperature data are mainly obtained through the temperature data measured by weather stations or the inversion based on satellite remote sensing data. Meteorological station data have high temporal resolution and continuity; however, due to the limitations of observation instruments as well as the number and spatial location of meteorological stations, the data cannot reflect the overall spatial variation of urban temperature comprehensively. For example, Zhang et al. (19) obtained long-time series temperature data from 50 stations for 3 years (2014, 2015, and 2017) to analyze the UHI characteristics of Xi'an during summer daytime; however, on-site measurement methods are often labor-intensive. In contrast, remote sensing inversion can be used to obtain large-scale surface temperature data in a short period of time and analyze the characteristics of the urban thermal environment on different scales (21–23). Depending on the satellite orbit, remote sensing data can be divided into near-polar orbit satellite remote sensing data and geostationary satellite remote sensing data (24, 25). The commonly used MODIS, ASTER, and Landsat data are all near-polar orbit satellite data, which are acquired in essentially the same amount of time for a given location. Therefore, near-polar orbit satellite data can perform long-term comparisons of UHI effects.

The difference of surface temperature between cities and adjacent non-urban areas is called surface urban heat island (SUHI), which is usually calculated by land surface temperature (LST) measured by satellite (26). Different scholars have studied the changes of surface temperature from many perspectives, including seasonal and diurnal surface temperature variation in cities. From the perspective of spatial scale, these studies are mainly divided into global scale, regional scale and individual city surface temperature variation (27–29), and from the time perspective, mainly into diurnal, seasonal and inter-annual variation (30–32). Most scholars use MODIS data for research to ensure good consistency in space and time series (33, 34). Some scholars combine Landsat data with MODIS data, for instance, Md. Omar Sarif and Rajan Dev Gupta used multi-time Landsat and MODIS Terra to study the ecological status of Prayagraj city and its surrounding environment during summer and winter (35). However, MODIS data have certain deficiencies when used in the research of some small-scale areas. First, in terms of spatial resolution, MODIS data are suitable for large-scale studies of surface temperature variability (36, 37), while ASTER and Landsat satellite inversions are more suitable for urban-level studies of thermal environments (38). In terms of diurnal surface temperature data acquisition, MODIS and ASTER data have low spatial resolution and cannot accurately reflect intra-urban variability, despite the availability of night-time data (39–41) and good applications for observing UHI effects in large cities or metropolitan areas (42). In addition to polar orbiting satellites, geostationary satellites can also acquire diurnal surface temperature data and have shown good accuracy (43). For satellites such as the Geostationary Operational Environmental Satellite (GOES) (44), Meteosat (45), and Meteosat Second Generation (MSG) (46), it is often difficult to obtain an accurate picture of the thermal environment inside cities due to spatial resolution limitations. For example, Chang et al. (20) explored the diurnal UHII cycle in Boston based on GOES-R surface temperature data, but its spatial resolution was only 2 km.

In 2018, NASA developed the ECOsystem Spaceborne Thermal Radiometer Experiment on Space Station (ECOSTRESS), which is mainly used to study the response patterns of plant temperature to water. With a short revisit period of 3–5 days, a resolution of 70 m, and the ability to acquire LST images at different times during the day and night, ECOSTRESS data have a high spatial and temporal resolution, and ECOSTRESS LST and emissivity (LST&E) data have been widely applied to research urban thermal vulnerability (47), agricultural monitoring (48), and surface temperatures in volcanic regions (49) with good accuracy. Thus, retrieving ECOSTRESS data for surface temperature can provide a more comprehensive understanding of the spatial and temporal impacts of urban morphology on LST. Understanding the influence of urban landscape patterns on LST heterogeneity is essential for improving the urban thermal environment (50, 51); however, the urban/rural division traditionally only distinguishes between urban and suburban areas, limiting research at the local urban scale. To overcome these limitations, Stewart and Oke (52) proposed the Local Climate Zone (LCZ) scheme, which divides the landscape into 10 "built types" and 7 "natural types," each of which characterizes land cover, surface properties, and human activity. Li et al. (53) based on the classification of LCZ, analyzed the variation rules of surface temperature (LST) and frontal area index (FAI), and put forward the suggestion of urban cooling by wind. In addition, Xie et al. (54) produced the LCZ map of the Guangdong–Hong Kong–Macao Greater Bay Area for a long time series to analyze the spatial and temporal changes of urbanization gradient and urban form from a three-dimensional perspective. Therefore, the LCZ scheme represents the thermal environment of homogeneous surfaces within cities in detail and has been widely applied to the study of urban thermal environments (36, 55–57) and urban wind environments (58, 59).

In summary, due to the high heterogeneity within cities and availability of satellite data, the current research on LCZ–LST is mostly based on near-polar orbit satellite data, and the use of geostationary satellite remote sensing data is relatively rare. However, the ECOSTRESS experiment can capture temperature data at high resolution during the day and night; thus, it can better observe the heat phenomenon inside the city better. Therefore, this study mainly includes three objectives: (1) use 70 m resolution ECOSTRESS data to obtain night and day surface temperatures for all seasons and explore the spatial variability between surface temperatures; (2) classify different LCZ types using Geographic Information System (GIS) identification based on remote sensing and building data; and (3) spatially overlay LCZ and LST to analyze the spatial variability of different LCZs between various seasons and between day and night.

Data and methods

Study area

Beijing is located at 115.7–117.4°E, 39.4–41.6°N. The total area is ~16,410.54 km^2, This study takes the Fifth Ring Road as the research area. The main reason for this selection is that according to the 7th National Population Census (2021), the permanent population of Beijing is about 21.89 million. The permanent population in the central urban area, which accounts for only 4% of the total area, is about 10.99 million and accounts for 50.2% of the total population. The limited land area and the increasing population exert great pressure on the urban thermal environment, especially during summer season. In addition, the area has little relief and shows minor changes in the form and function of internal buildings over time (Figure 1).

Data sources

We have combined building vector data with land cover data to classify LCZ types in Beijing and combined them with OpenStreetMap data to obtain the Fifth Ring Road area. In addition, we downloaded diurnal ECOSTRESS LST data for different seasons and used ECOSTRESS CLOUD data for data filtering. At the same time, we selected images with better quality based on time requirements (In this article, we describe December, January, and February as winter; March, April, and May as spring; June, July, and August as summer; and September, October, and November as autumn). The data sources and times are shown in Table 1. To quantify the diurnal and seasonal thermal response of the LCZ, we superimposed the obtained LST data on the LCZ and produced corresponding graphs to highlight the differences between and within classes. We performed *t*-tests for the four seasons and diurnal LST, and a one-way ANOVA for the differences between LCZs.

ECOSTRESS LST&E data

The ECOSTRESS experimental mission, which focuses on measuring plant temperature to better understand plant water requirements and how they relieve stress, consists of four levels of data, from which the level 2 product LST&E data and cloud mask product have been widely used for agricultural crop monitoring, volcanic surface temperature estimation, and studies of urban thermal environments with good accuracy (60, 61). In a systematic and comprehensive evaluation study of different satellite LST products, Li et al. (48) found that ECOSTRESS data had the highest consistency with ground-based observations during the day, with absolute deviations of <1.89°C at night. In this study, LST and cloud mask data for the study area were downloaded from the AppEEARS website (https://appeears.earthdatacloud.nasa.gov/explore), which allows the extraction of an individual dataset, as well as data reprojection (60, 62, 63). We selected diurnal LST images for each of the four seasons. After screening, eight high-quality images were selected for each day and night.

LCZ division

To maintain spatial resolution consistency with the LST data, the entire study area was divided into a 70 m × 70 m grid, and then divided into LCZs 1–9 based on building height and density. Based on the 2004–2020 urban master plan, most heavy industries were removed from the study area by 2016; therefore, LCZ10 is not divided (64). In addition, natural-type LCZ was classified based on land cover data. Due to the resolution difference, we reclassified the 10 m resolution land use data to 70 m in ArcGIS 10.5, and the type with the largest area of the pixel was taken as the attribute of the pixel. In addition, due to the lack of detailed geometric data on trees, LCZA (dense trees) and LCZB (sparse trees) were used as a mixed type, while scrubs, cultivated and grassland, and bare land in the land cover data were classified as LCZC, LCZD, and LCZF, respectively; streets and other impermeable surfaces were classified as LCZE, and water bodies were classified as LCZG (Table 2).

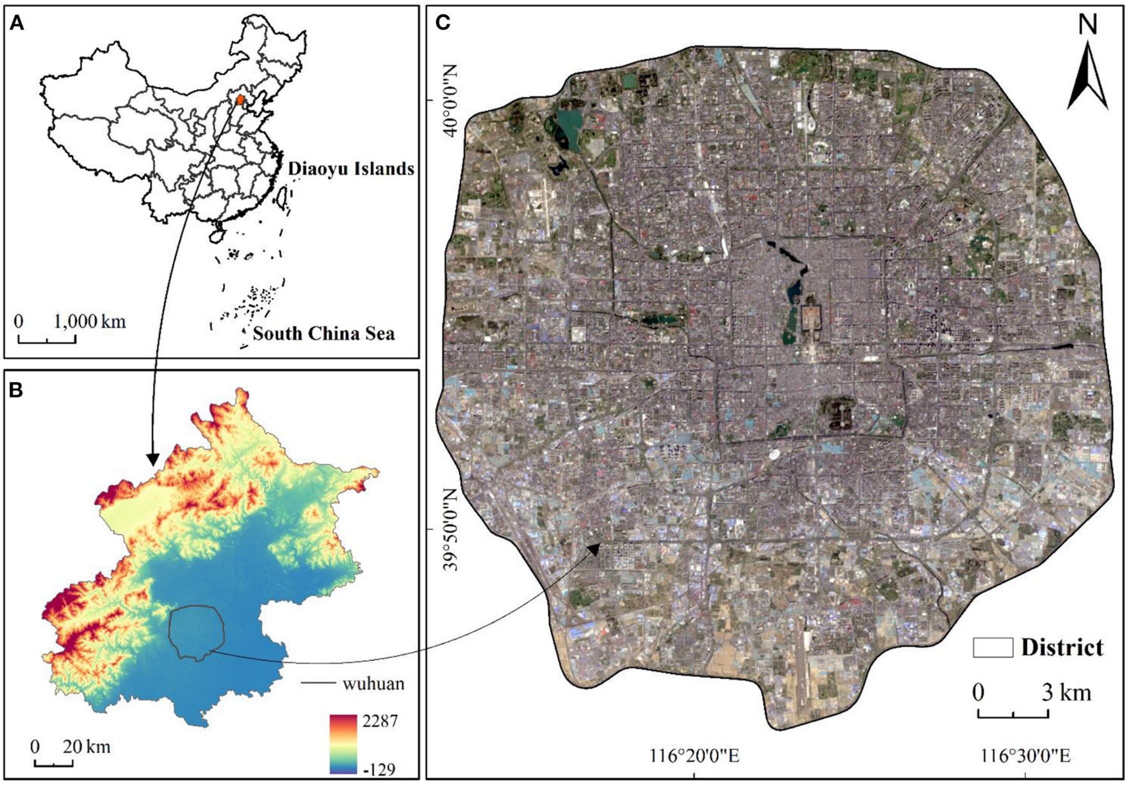


FIGURE 1
The location of the study area. **(A)** The red shaded area represents the location of the study area in China, **(B)** Beijing decorated with elevation data, and **(C)** satellite images of the study area.

TABLE 1 Data sources and descriptions.

Data type	Descriptions	Time	Sources
Building data	Buildings outlines, height and floor	2018	Baidu map
ECOSTRESS LSTE	Land surface temperature and emissivity data (70 × 70 m)	2019–2020	https://lpdaacsvc.cr.usgs.gov/appeears/
ECOSTRESS CLOUD	cloud mask product (70 × 70 m)	2019–2020	https://lpdaacsvc.cr.usgs.gov/appeears/
OpenStreetMap	Road location information	2021	https://www.openstreetmap.org/
Land cover data		2017	http://data.ess.tsinghua.edu.cn/

Results

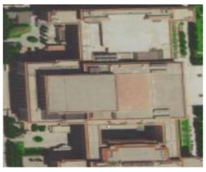
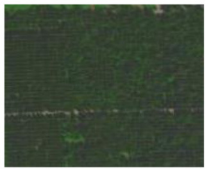
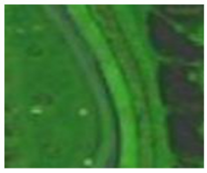
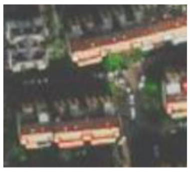
LCZ classification results

Figure 2 shows the LCZ classification results of the study area, which is divided into 13 LCZ types. Overall, the area within the Fifth Ring Road of Beijing was mostly covered by building-type LCZs, while natural-type LCZs were smaller in size. It also shows a decreasing trend from the center to the periphery, which is attributed to the height limit policy of Beijing. Meanwhile, combining with Figure 3, it can be found that LCZ9(sparse low-rise building) and LCZ1(compact high-rise building) are the dominant and the lowest among building types, with 28,814 and 1,415 pixels, respectively, while only four natural types are obtained, which are LCZA/B, LCZD, LCZE and LCZG. LCZC and LCZF did not appear in the entire study area. In addition, the combination of Google Earth satellite images shows that LCZA/B and LCZG are spatially distributed in line with the location of the park while LCZE mainly consists of a network of ring roads.

Diurnal and seasonal LST variation

Figure 4 shows the spatial distribution of day and night LST in the study area during four seasons. Figures 4A–D show

TABLE 2 LCZ types and description.

LCZ type	Description	Examples	LCZ type	Description	Examples
LCZ1	Compact high-rise (more than 9 floors)		LCZA\B (Dense trees)	Dense\ Sparse coniferous forest and evergreen forest.	
LCZ2	Compact mid-rise(4–8 floors)		LCZC (Shrub)	Open arrangement of bushes, shrubs, and short, woody trees.	
LCZ3	Compact low-rise(1–3 floors)		LCZD (Low plants)	Grassland or herbaceous plants crops. Few or no trees.	
LCZ4	Open high-rise (more than 9 floors)		LCZE (Bare soil or paved)	Rock or impervious road surface virtually vegetation free	
LCZ5	Open mid-rise (4–8 floors)		LCZF (Bare soil or sand)	Featureless landscape of soil or sand cover.	
LCZ6	Open low-rise (1–3 floors)		LCZG (Water)	Large, open water bodies or small bodies.	
LCZ7	Sparse high-rise (more than 9 floors)		LCZ8	Sparse mid-rise (4– 8 floors)	
LCZ9	Sparse low-rise (1–3 floors)		LCZ1–3: building density >0.4. LCZ4–6: building density is between 0.2 and 0.4. LCZ7–9: building density <0.2.		

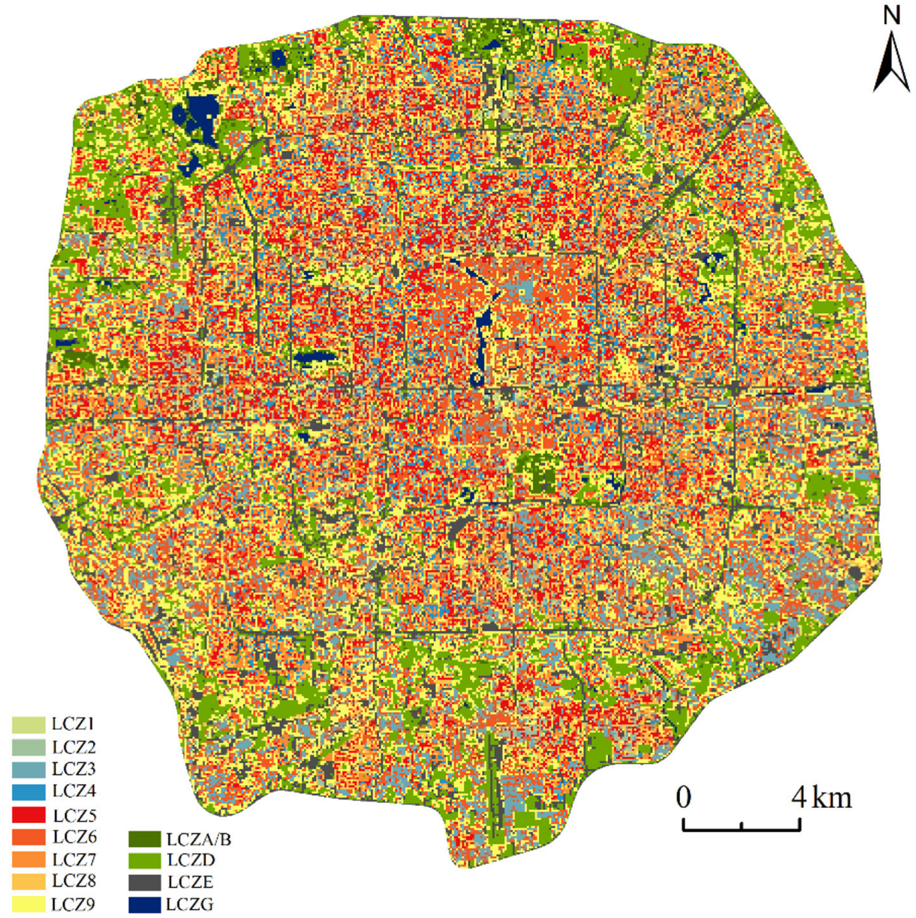


FIGURE 2
Urban local climate zone (LCZ) map of the study area.

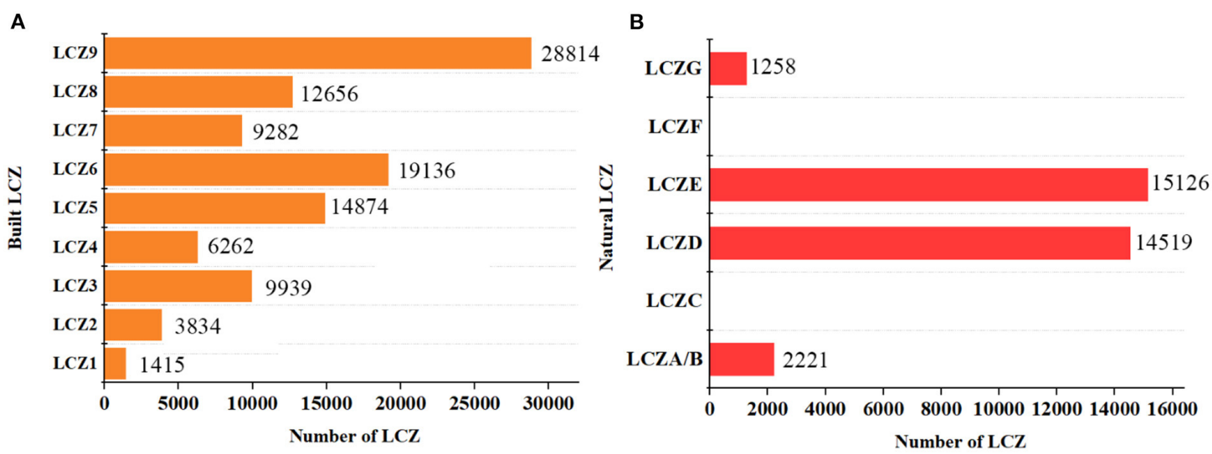


FIGURE 3
Number of built and natural type LCZs in the study area, **(A)** is the number of buildings type LCZs; **(B)** is the number of nature type LCZs.

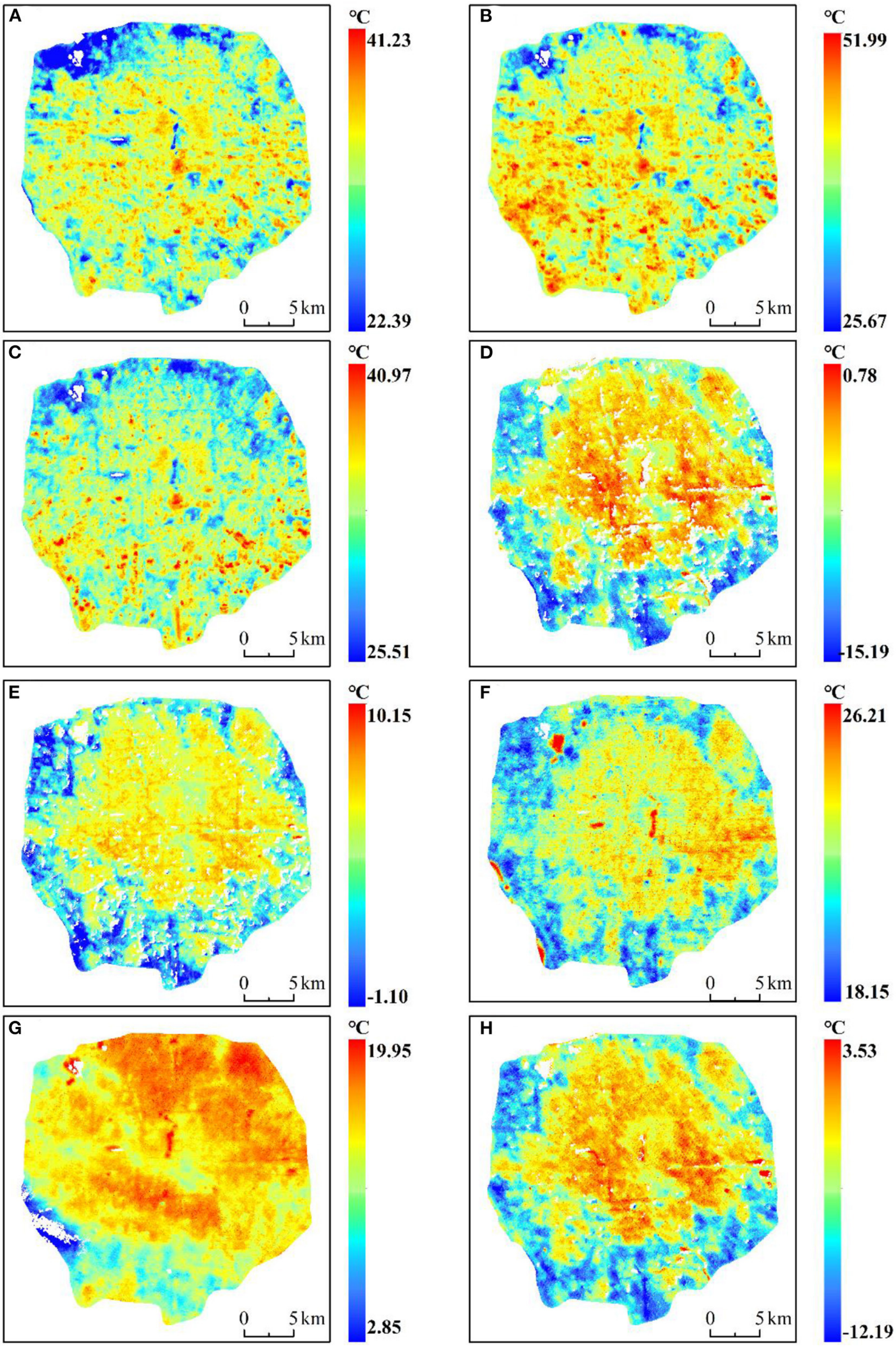


FIGURE 4
Diurnal and seasonal land surface temperature (LST) variation in the 5th Ring Area, Beijing, China. **(A–D)** Daytime LSTs during spring, summer, autumn, and winter, respectively. **(E–H)** Night-time LSTs during spring, summer, autumn, and winter. All times are in Beijing time (UTC+8). The white areas in the map indicate missing data **(G)** and areas with clouds removed.

TABLE 3 Statistical results of diurnal surface temperature in different seasons.

Time	Max (°C)	Min (°C)	Avg (°C)
Spring daytime	38.89	30.95	34.72
Summer daytime	46.58	34.55	40.44
Autumn daytime	35.73	27.98	31.83
Winter daytime	−4.47	−14.51	−9.45
Spring nighttime	9.51	1.42	5.37
Summer nighttime	24.35	19.07	21.69
Autumn nighttime	18.83	11.20	14.87
Winter nighttime	−1.85	−11.09	−6.49

daytime LST, and Figures 4E–G show nighttime LST during four seasons. The spatial distribution of land surface temperature is different between seasons and day and night. Therefore, we explored the diurnal variation of urban thermal environment. The daily LSTs of four seasons were measured and *t*-test was performed, and the results showed that LSTs was significant ($P < 0.05$). The results of LST in daytime were in the order of summer (40.44°C) > spring (34.72°C) > autumn (31.83°C) > winter (−9.45°C), and the highest LST at night was in summer (21.69°C). followed by autumn (14.87°C), spring (5.37°C) and winter (−6.49°C) (Table 3). In addition, combined with Figure 2, it can be discerned that the high temperature areas during the daytime are mainly concentrated in the building area, because the building materials have high heat absorption, leading to higher surface temperature. However, the areas with low temperature are concentrated in natural landscapes with trees and water bodies. Combining Figure 1C and Google Earth satellite images, it can be discerned that these areas are mainly composed of parks, such as Beihai Park and Shichahai Park in the center, the Old Summer Palace and the Summer Palace in the northwest, and the Olympic Park in the north. The results show that urban park areas usually have lower LST, which can mitigate the UHI effect to some extent, which is consistent with previous studies (41). In addition, different landscapes in urban parks also have different effects on human comfort (65). The nighttime temperature in the study area was lower than the daytime temperature during all the seasons (Table 3). In addition, the water body absorbs a large amount of heat during the day, while at night, due to its high specific heat capacity, it is lost more slowly, resulting in higher temperatures than surrounding buildings, especially during summer (Figure 4F).

Diurnal and seasonal LST distribution in LCZs

The statistical analysis results show that the LST and LCZ spatial distributions were highly consistent. We found

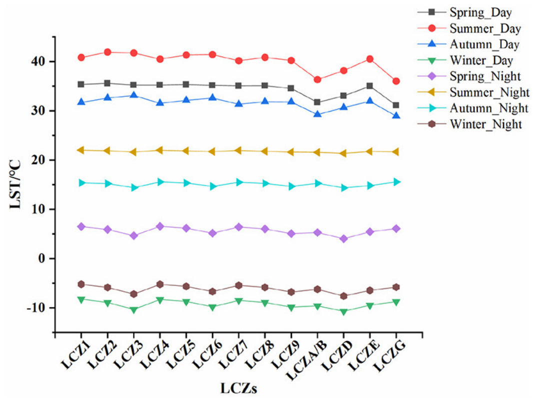


FIGURE 5
Temperature variation of each day and night LCZ during the different seasons.

that daytime LST was higher than night-time LST for each LCZ during the different seasons (Figure 5), and the average summer LST for each LCZ was higher than that of the other seasons, except for winter. Furthermore, daytime LST for each LCZ was lower than night-time LST during winter season, indicating that it was colder during winter. In addition, we further analyzed the diurnal LSTs of each LCZ during the different seasons and visualized their distribution through box line plots. Figures 6A–D show the box line plots for daytime LCZs during spring, summer, autumn, and winter, respectively, while Figures 6E–H show the box line plots for their respective night-time LCZs. The results were confirmed using one-way ANOVA (daytime values: $F = 3259.696$, $P < 0.01$; night-time values: $F = 3514.9$, $P < 0.01$). However, since LSTs obtained were for different seasons, we ranked each LCZ according to its average temperature. In daytime (Figures 6A–D), the highest LSTs during spring, summer, autumn, and winter were 35.54°C (LCZ2), 41.90°C (LCZ2), 33.09°C (LCZ3), and −8.24°C (LCZ1), respectively. Thus, the LSTs of building-type LCZs were generally higher than those of natural-type LCZs. The LST of the natural LCZG (water body) was the lowest in all seasons (except winter). At night, the LSTs of building-type LCZs did not show an obvious consistent pattern of change, while the LSTs of the natural LCZD (grassland) were the lowest during spring, summer, autumn, and winter (4.02°C, 21.33°C, 14.34°C, and −7.64°C) respectively.

Meanwhile, we studied the distribution of day and night surface temperature of the same LCZ in different seasons. The results are shown in the Figure 7. It can be seen from the figure that the daytime average surface temperature of all LCZ was the highest in summer, with LCZ3 reaching 41.73°C, and the lowest LCZG reaching 36.01°C, which indicates that it is necessary to formulate corresponding heat mitigation measures in summer. For all LCZ, the surface temperature in daytime was higher

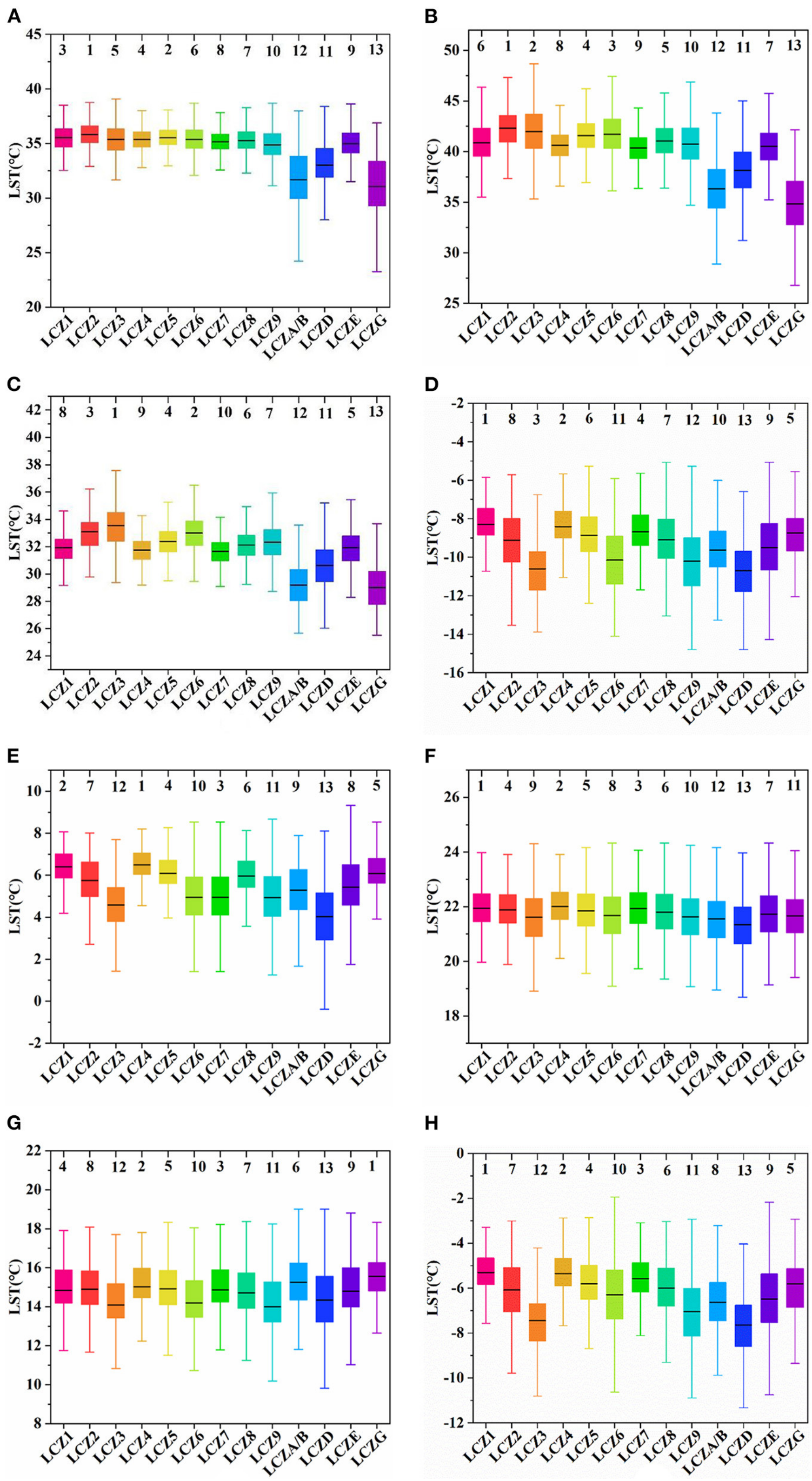


FIGURE 6
(A–D) Box line plots for each daytime LCZ during spring, summer, autumn, and winter, respectively; **(E–H)** Box line plots for each night-time LCZ during spring, summer, autumn, and winter, respectively. The lines in the box represent the average, and the numbers above represent LCZs ranked according to average LST (the warmest to the coldest zones from 1 to 13).

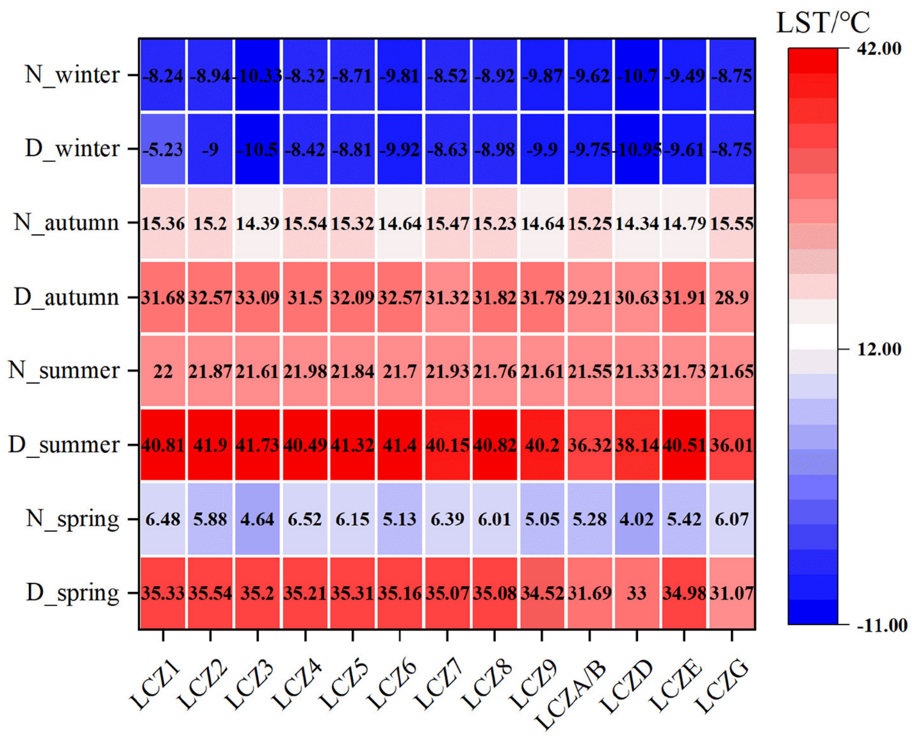


FIGURE 7
Diurnal variation of the same LCZ in different seasons.

than that at night in the same season, which was mainly due to the large amount of heat absorbed by all LCZ during daytime and heat loss at night. In addition, in the same season, the LCZ surface temperature had significant difference between day and night.

Discussion

Changes in LST as a function of LCZ

We inventoried the seasonal variations in the urban thermal environment as well as diurnal variations due to intra-city heterogeneity using the LCZ framework in the Fifth Ring Road area of Beijing. Overall, our results showed significant differences in the LSTs of the LCZs between the daytime and night-time as well as in different seasons. The temperature differences between LCZs (LCZ2 and LCZG) with large differences in surface material and cover type reached 5.89°C during the daytime in summer, while the differences were generally <2.50°C at night (except in winter). Compared with the building type LCZ, the natural type LCZ had a lower surface temperature (except in winter). Taking summer as an example, the daytime surface temperature was LCZG(13) < LCZA/B(12) < LCZD(11) < LCZE(7), the nighttime surface temperature presented LCZD(13) < LCZA/B(12) < LCZG(11) < LCZE(7), which indicates that in the hot summer, the vegetation and water bodies have lower surface temperatures in both daytime and night-time, related studies have shown that vegetation and water bodies are important components of urban heat island mitigation in cities (66). Zhou et al. (34) quantified diurnal and seasonal UHII of 32 major Chinese cities to analyze their spatial variability and influencing factors, and suggested that a variety of strategies are needed to effectively mitigate the UHI effect. However, as cities grow and become increasingly heterogeneous, targeted solutions are required. LCZ solutions can be classified into different types based on surface materials, ground cover, and the influence of human activities. A study by Zhang et al. (67) on the temporal and spatial variability of UHI and urbanization in Beijing showed that LCZ conversion had a significant impact on surface UHII. In addition, Quan et al. (68) conducted an LCZ classification of Beijing, combining MODIS data with wind and cloud data at 100 m; the results showed significant differences in the LCZ diurnal thermal response with seasonal changes. It is therefore important to use higher resolution data to study diurnal differences and seasonal variations in urban thermal environments from the perspective of the LCZ. In addition, as a core area of Beijing, the Fifth Ring Road area was divided into LCZ by pixel-based method, and the whole study area was divided into 13 types. Compared with the method of LCZ division based on community units, this pixel-based method could show the LST differences of each LCZ more clearly. Further understanding of the spatial heterogeneity of urban LST caused by the complex intra-city landscape is required to provide certain references to improve local climate and for reasonable planning practice.

Use of ECOSTRESS data

The change of urban environment has an important impact on the improvement of human settlements. Therefore, we used LCZ scheme combined with ECOSTRESS LST data to study the urban thermal environment and analyze its changes during different seasons and between day and night. ECOSTRESS data can obtain the surface temperature of most parts of the world from different time periods with the advantages of multi time points and high resolution. It makes up for the deficiency of traditional ASTER and MODIS data timing observations. Taking the Fifth Ring Road in Beijing as an example, we show the unique advantages of ECOSTRESS LST data in analyzing the urban thermal environment, and provide a new perspective for the study of urban thermal environment. When there are data from multiple time periods from the same area, we can study the diurnal variation of surface temperature in urban areas more accurately; such as the diurnal variation in surface temperature and surface UHII in three cities in India was analyzed by Siddiqui et al. (69) using MODIS LST data. Lu et al. (70) combined MODIS and Landsat images to analyze diurnal differences and seasonal characteristics of surface UHII variability in Hefei, China. Compared with MODIS LST data, ECOSTRESS LST data show higher temporal and spatial resolution and can more accurately reflect temperature differences. Our study shows that LST spatial distribution in urban areas varied between day and night, which is consistent with the findings of previous studies (71, 72). The daytime differences in LST are mainly related to the type of ground cover and material; for instance, building materials and impermeable surfaces tend to absorb more energy than vegetation. The difference in nocturnal LST is mainly caused by the discharge of accumulated energy during the day (73); water bodies that absorb large amounts of heat during the day release it at night, leading to higher temperatures at night than during the day.

Limitations

This study has some limitations. We used the ECOSTRESS LST data and LCZ framework to study the seasonal and diurnal differences in LST in Beijing. First, when LCZ segmented building vector data, only existing data were used for segmentation because the latest building data was not available at that time. There may be some differences with existing building forms. In addition, although ECOSTRESS can perform repeated observations of the same area within 3–5 days, due to the impact on data quality, the day and night LST data are not guaranteed to belong to the same day, so there may be some uncertainty in the data accuracy. At the same time, in order to avoid the influence of extreme weather and diurnal variation of LCZs, high-quality and time-consistent images should be used in future studies.

Conclusions

We analyzed the thermal characteristics of different LCZs in the Fifth Ring Road area of Beijing on both diurnal and seasonal time scales, constructed LCZs for the study area using GIS methods, and downloaded diurnal ECOSTRESS LST data for all seasons to analyze the diurnal and seasonal LST variations within and between the LCZ classes. The main conclusions can be summarized in three points.

(1) Overall, the Fifth Ring Road area of Beijing is mainly composed of building-type LCZs, while natural-type LCZs are scarce. LCZ9 (sparse low-rise buildings) is an important part of the built-up LCZs. In addition, natural LCZs, such as LCZA/B (woodland), LCZD (grassland), and LCZG (water body), mainly comprise park landscapes, as determined in combination with Google Earth satellite images.

(2) There were significant differences in LSTs between the seasons and between day and night; specifically, daytime LST showed a summer > spring > autumn > winter trend, while the night-time trend was summer > autumn > spring > winter. All LST results were highest during summer and lowest during winter. In addition, high-temperature areas during the day were concentrated in building areas, while low-temperature areas were concentrated in natural landscape areas comprising trees and water bodies, most of which included park landscapes. At night, the temperature in the study area was lower than the daytime temperature in all the seasons.

(3) The spatial distribution of LST and LCZ was highly consistent. In addition, the average temperature of the LCZs was ranked according to the seasonal and diurnal LSTs, and the highest LSTs found during the four seasons were in LCZ2 (spring), LCZ2 (summer), LCZ3 (autumn), and LCZ1 (winter). The LSTs of building-type LCZs were higher than those of natural-type LCZs, while the LST of LCZG (water body) was lowest in all seasons except winter. At night, there was no obvious pattern of LST change in building-type LCZs; in contrast, LCZD ranked last among the natural-type LCZs in all seasons, indicating that its average LST was the lowest.

Therefore, natural landscapes, such as woodland, grassland, and water bodies, should be reasonably laid out in urban planning to improve the urban environment and quality of life.

Based on the LCZ framework, this paper analyzes the diurnal surface temperature changes in the Fifth Ring Road area of Beijing, and has a more comprehensive understanding of the surface temperature changes under different ground covers during different seasons and day and night. With the continuous development of the night economy, while studying the changes of the urban thermal environment during the day, the changes in the urban thermal environment at night should also be paid more attention. The ECOSTRESS LST product, It can observe the change of night surface temperature with higher resolution, and use the advantage of high time resolution to obtain the surface temperature at multiple time points in a certain area. In future research, the understanding of diurnal surface temperature changes in urban areas can be further improved. Extensive ECOSTRESS data and more detailed LCZ classification will deepen the understanding of diurnal changes in urban thermal environment in the future, and shall provide references for future urban planning and the formulation of heat mitigation strategies.

Data availability statement

The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding author/s.

Author contributions

JY contributed to all aspects of this work. ZS wrote the main manuscript text. LW, FL, GW, XX, and JX conducted the experiment and analyzed the data. All authors reviewed the manuscript. All authors contributed to the article and approved the submitted version.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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Intergenerational differences in the urban vibrancy of TOD: Impacts of the built environment on the activities of different age groups

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Transit-oriented development (TOD) has been regarded as an effective way to improve urban vibrancy and facilitate affordable, equitable, and livable communities in metro station areas (MSAs). Previous studies placed great attention on the interplay between the MSA-level built environment and overall human activities while neglecting the heterogeneity among different age groups. To address this gap, we leverage the mobile phone signaling data to quantify the spatio-temporal distribution of the MSA-level human activities among different age groups as measured by the vibrancy index (VI). Furthermore, we investigate the impact of the MSA-level built environment on the VI and its intergenerational differences by employing multiple linear regressions based on multi-sourced data. To this end, Chengdu—a TOD-thriving megacity in China—is chosen as a case study. The results indicate that: (1) Residential and bus stop density are positively associated with the VI. And the magnitudes of the correlation coefficients are similar among different age groups. (2) Distance to CBD is negatively associated with the VI of teenagers (12–18 years), middle-aged adults (40–59 years), and older adults (above 60 years) but unrelated to the VI of young adults (19–39 years). (3) Employment density is positively associated with the VI of young and middle-aged adults but insignificantly associated with the VI of teenagers and older adults. (4) The correlations between the floor area ratio and the VI are positive for all age groups. As age increases, the significance of such correlations becomes more pronounced. (5) Streetscape greenery shows a more significant positive correlation with the VI of teenagers and older adults as compared to those of young and middle-aged adults. (6) Significant negative correlations exist between housing price and the VI of different age groups. The findings can inform the development and design of vibrant TOD communities.

KEYWORDS

mobile phone signaling data, intergenerational differences, urban vibrancy, TOD, metro, built environment

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Introduction

In today's society, where urban life is highly socialized, the value of space is determined by its usage frequency, i.e., urban vibrancy (1). The concept of urban vibrancy was first introduced by Jacobs in her seminal text - *The Death and Life of Great American Cities* (2). She regarded urban vibrancy as the intensity and diversity of human activities in urban space. Moreover, she argued that the interaction processes of activities and living places form the diversity of cities. Urban vibrancy reflects the attractiveness, accessibility, and spatial quality of urban areas (3). It can facilitate social interactions (4), enhance cities' competitiveness, promote cities' economic growth and thus contribute to achieving sustainable urban development goals (5). Hence, how to stimulate urban vibrancy and improve the efficiency of space use in urban areas by leveraging built environment interventions is of great importance to the urban planning and construction process.

Under the green transport and new-type urbanization development strategies, urban rail transit is moving from the basic function of "meeting travel demand" toward the strategic function of "guiding urban development" (6). Given metro systems are the backbone of urban public transportation systems and attract millions of rail commuters every day, metro station areas (MSA) act as substantial transportation nodes for cities (7) and the impetus shaping the vibrancy of urban areas (8). The high density of passenger flows and businesses around metro stations generates considerable agglomeration and spillover effects, which in turn frame the MSA to be the hotspot area for urban activities and interactions (9). Therefore, research on the relationship between the built environment of MSA and urban vibrancy will have significant implications for informing the planning and design process of transit-oriented development (TOD).

Transit-oriented development concept aims to build vibrant communities and drive sustainable city development through high-capacity public transport, mixed land-use, and high-intensity construction (10). In recent years, the burgeoning development of information and communication technologies (ICT) has accelerated the emergence and prevalence of multi-sourced spatio-temporal data, which possesses great potential for measuring and quantifying urban vibrancy (11). Besides, the study of urban vibrancy has received wide scholarly attention from several disciplines, including urban planning (3), transportation (12), and urban geography (13). Also, the focus of integrated transport and land use planning has shifted from "providing amenities and facilities" toward "accommodating the needs of residents" (14). Against this background, MSA, as one of the most important carriers of urban vibrancy with intensive human activities, is attracting more and more attention among practitioners and scholars. For example, Chengdu - a TOD-informed megacity in China - has carried out initiatives for building 24-h vibrant communities in the MSA in its recently-released planning guidelines such as "Land Management Measures for Comprehensive Development of Chengdu Metro Rail Transit Stations" and "15-Minute Living Service Circle of TOD". In addition, previous studies also show that the rational design of pedestrian systems (15) and appropriate layout of functional facilities and land use (12) can help enhance the intensity of human activities in the MSA.

It is worth noting that most of the existing studies use social media data (16), the heat map of mobile applications (17), economic activity data, and point-of-interest (POI) data to measure TOD vibrancy. However, these data fail to record the staying time and activity trajectories of individuals/groups due to their transient and cross-sectional features, leading to inaccurate identifications. Besides, previous studies extensively explore the impact of 5D built environment factors (i.e., density, diversity, design, distance to transit, and destination accessibility) (18, 19). However, it remains uncertain how refined built environment factors such as the streetscape and street network topology contribute to TOD vibrancy. Moreover, there are variation of different age groups in mobility. Although previous studies placed great attention on the interplay between the MSA-level built environment and overall human activities, the heterogeneity among different age groups has been neglected. This may result in the homogenization of the construction and residential population structure in the TOD.

To address these gaps, we set out to investigate the impact of the MSA-level built environment on the VI and its intergenerational differences using Chengdu as a case study based on multi-sourced data. To be specific, we first take advantage of the cellular signaling data to quantify the spatio-temporal distribution of the MSA-level human activities among different age groups as measured by the vibrancy index (VI). Then, we measure a wide range of refined built environment factors by leveraging various spatial data such as the POI data, street view data, and parcel-level land use data. Finally, we employ multiple linear regressions to model the relationship between the MSA-level built environment and the VI of different age groups. The empirical findings are expected to provide evidence-based guidance for the planning and design of TOD vibrant communities. The main contributions of this study are as follows: (1) quantifying the spatio-temporal distribution of the MSA-level VI among different age groups; (2) deciphering the impact of the MSA-level built environment on the VI and its intergenerational differences; (3) providing policy recommendations for accommodating affordable, livable, and equitable communities around metro stations.

The following of this paper is structured as follows: Section "Literature review" reviews and analyzes the literature on the urban vibrancy and its built environment determinants. Section "Study area and data" introduces the study area, data, and methodologies. Section "Results" presents the spatio-temporal

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distribution of the MSA-level human activities among different age groups and the results of regression analysis. Section “Discussion” interprets the results and carries out discussions. Section “Conclusions” concludes and provides evidence-based policy implications.

Literature review

Definition and measurement of urban vibrancy

Urban vibrancy is derived from Jacobs' (2) concept of street vibrancy. It means the intensity and type of people and their activities in a given space, which reflects the attractiveness and diversity of a city. Lynch (20) argued that urban vibrancy consists of three components: urban spatial form, functional composition, and social activities. Landry (21) considered that measures of urban vibrancy reflect the social-economic situation, physical environment, and interactions between society and the economy. Montgomery (22) provided a more comprehensive explanation of urban vibrancy. He treated urban vibrancy as a continuous and compact flow of people, efficient space use, and vibrant street cultural life. Moreover, Chhetri et al. (23) further suggested that urban vibrancy is an external manifestation of the interaction between residents and their surrounding space. From the above scholars' definitions of urban vibrancy, it can be seen that although the concept of urban vibrancy is under development, it is always based on human activities and interactions.

However, there are no uniform standards to measure or evaluate urban vibrancy. Some previous studies have used static data sources, including population censuses, interview surveys, housing prices, and Nighttime light (NTL) to characterize urban vibrancy (24–29), while these traditional data only reflect the static, rather than the dynamic, urban vibrancy. Besides, there are disadvantages of the traditional vibrancy characterization data, such as insufficient precision and small spatial coverage (30, 31). In recent years, with the rapid development of information and communication technology (ICT), multi-source big data provides the data basis for calculable and quantitative analysis of urban vibrancy (32). In this era of big data, mobile internet users are both the recipients and producers of data. The “digital geographic footprint” of cell phone users (33, 34) and social network information form a huge amount of big data on human spatio-temporal activities. Compared to traditional community census and survey data, big data has the advantages of timeliness, high penetration, large sample size, and abundant activity information (35). In this regard, many studies have used mobile phone signaling data (36), social media data (37), smartcard data (38), and POIs (34, 39) to explore the urban vibrancy. For instance, Chen et al. (1) used Facebook API to obtain the activity characteristics of residents in Hong Kong. They found that the north coast of Hong Kong Island and the south coast of Kowloon Peninsula were the most vibrant areas of the city. Yue et al. (40) used the diversity of POIs to measure the spatial vibrancy of the city. Guo et al. (41) analyzed the 24-h neighborhood vibrancy distribution in Xining, China, based on mobile base station communication records of 560,000 cell phone users. They found that the spatial and temporal street vibrancy is basically consistent with the rhythm of residents' daily life. Plus, other scholars aggregate a variety of data to reflect the comprehensive urban vibrancy (34). Xiao et al. (42) constructed a TOD vibrancy aggregation index using Sina Weibo data, Dianping data, subway smartcards, and Baidu heat maps. Huang et al. (35) measured pedestrian density, economic activity intensity, and social activity intensity in Shanghai through cell phone GPS, public service comments data, and social media data.

It is worth noting that the studies above all used multiple sources of big data to reflect urban vibrancy. However, these data sources are mostly transient, such as online check-in data (Sina Weibo). Data sources like this are limited in coverage and fail to reflect the staying time and activity trajectory of individuals/groups in MSAs due to being transient, which may lead to inaccurate identification of urban vibrancy. So large numbers of pass-through and short-time staying people flow being recorded as urban vibrancy. Meanwhile, these people do not consume, relax, live or work in MSAs, which cannot simply be defined as urban vibrancy. Secondly, little has been done to distinguish the heterogeneity of human activities by age in these studies. According to related research (43, 44), there are differences in the activity ability, activity scope, and activity purpose of different age groups. For example, the main activity spaces of teenagers are schools and home, the main activity spaces of youth are mainly home and employment places, while the main activity spaces of older adults are mostly home and community parks. Therefore, if we ignore the intergenerational differences in the impact of MSA-level built environment features on vibrancy, it may lead to overestimation/underestimation of the comprehensive influence of built environment elements on TOD vibrancy.

Impact of the built environment on TOD vibrancy

The transport-oriented development policies are considered as the important impetus that enhances urban vibrancy (10). Related studies indicate that 5Ds built environment indicators affect the vibrancy of TOD (9, 12, 17, 39, 45). Scholars have conducted studies on the relationship between the built environment and TOD vibrancy in cities with developed rail transit, such as Shenzhen (9, 12, 42, 45), Hong Kong (15, 46), Shanghai (17), Singapore (9), and Montreal (47). For example, Ye et al. (17) explored the linkage mechanisms between the built environment of Shanghai's MSA and the Baidu heat map. They found that the vibrancy of TOD has a significant relationship with FAR, land-use mix, and bus station density. Zhou and Yang's (45) study pointed out that the service ability of TOD network influences the number of public facilities (POI density). In Xiao et al.'s (42) work, gradient boosting decision trees were used to explore the nonlinear synergistic effects of the built environment and TOD vibrancy in Shenzhen's MSAs. The study showed that the adequate transit service system, building density, and land-use mix were the most important drive factors of TOD vibrancy. They also found that different built environment indicators had synergistic promotion effects on TOD vibrancy. Similarly, a study by Yang et al. (12) revealed a non-linear trend in the impact of the metro station's proximity on urban vibrancy in Shenzhen. In the range of 0–810 m to the station, the station proximity negatively correlated with human activities, and there is no effect when beyond a threshold. The conclusion is consistent with the basic explanation of the ground rent theory curve. Moreover, Tu et al. (9) used multi-source big data such as smartcard data, Weibo check-in data, Twitter tweets, and EZ-link transaction tweet data as the characterization of the metro station vibrancy in three cities: Shenzhen, London, and Singapore. The study showed that the metro station vibrancy in central urban areas is higher than that in suburban areas and that cities with higher GDP have higher vibrancy. They also concluded that built environment factors such as road density, bus station density, land-use mix, and gross building area have a significant impact on the urban vibrancy aggregative indicators. Jacobs-Crisioni et al. (48) pointed out that built environment indicators, including metro station, railway station, and business density, have a positive effect on vibrancy intensity. In addition to the study of human activities at the ground level of metro stations, some scholars have conducted studies on a microscopic scale. They study the interaction among pedestrian systems, spatial structure, facility distribution, and human activities in the underground space of metro stations (15, 46, 47).

Most previous studies that have explored the linkage mechanisms of the built environment in MSAs and vibrancy are based on 5Ds (18, 19). However, the mechanisms by which the refined built environment of MSAs affects vibrancy are unclear. For example, the current residential and employment density data of the MSA are mainly derived from government census data (street level, TAZ) (49). However, the range of TAZ is much larger than that of MSA. It can lead to coarse measures of population density indicators and biased estimations. Moreover, the influence of three-dimensional built environment visual perception indicators such as green view index and sky rate on vibrancy remains to be explored. Therefore, it is necessary to extract and quantify more refined built environment elements in MSAs and analyze their relationship with vibrancy.

Study area and data

Study area

Chengdu, the capital of Sichuan Province, China, located in the Sichuan Basin, is an important central city in the western region. Chengdu is also an important national high-tech industrial base and integrated transportation hub. From 2010 to 2021, Chengdu's total population increased from 14 to 21 million, and the urbanization rate increased from 65% to 77%. Under the high population growth and urbanization process, Chengdu has become one of the cities in the world with the fastest urban rail transit construction. From the first line (Line 1) in Chengdu officially opened in September 2010 to the latest "five lines" of Chengdu Metro launched in December 2020, Chengdu metro soon became the fourth longest railway network in China in operation (only after Shanghai, Beijing, and Guangzhou). However, in the era of rapid population, economic development, and rapid urban rail transit construction, Chengdu's MSA construction and TOD vibrancy creation are significantly behind the speed of rail construction. In addition, since 2021, Chengdu has enacted urban development strategies, including the "*metropolitan area on the rail*" and "*TOD city*", TOD has become an important urban development concept in Chengdu. Therefore, Chengdu-a TOD-informed megacity in China-is chosen as a case study.

As of November 2019, there are six lines with a total of 156 stations (Figure 1). The rail lines in the study area cover a total of 10 districts in Chengdu, including five districts in the central area (Chenghua, Qingyang, Jinniu, Jinjiang, and Wuhou) and five districts in the periphery (Xindu, Pidu, Shuangliu, Wenjiang, and Longquanyi). To solve the buffer overlay problem of MSAs, our study on MSAs follows the work of Li et al. (50), and we use the 800 m buffer zone of stations as well as the Tyson polygon to determine the range of MSAs.

Data sources

Considering that the COVID-19 epidemic broke out in December 2019, the mobile signaling data used in this study was dated November 2019.The mobile phone signaling data are obtained from DASS platform of SmartSteps, and we handle these data through Python and GIS. With the rapid spread of mobile communication and the Internet, individual/group mobile user activities generate continuous and abundant spatial position information. All the information forms the Mobile Positioning Big Data (MPBD), which records individual travel chains as well as massive crowd activity trajectories. Mobile phones have become one of the most important tools in residents' daily lives, and mobile communication networks in major cities have basically achieved full coverage (41). In 2019, the total number of mobile communication users of

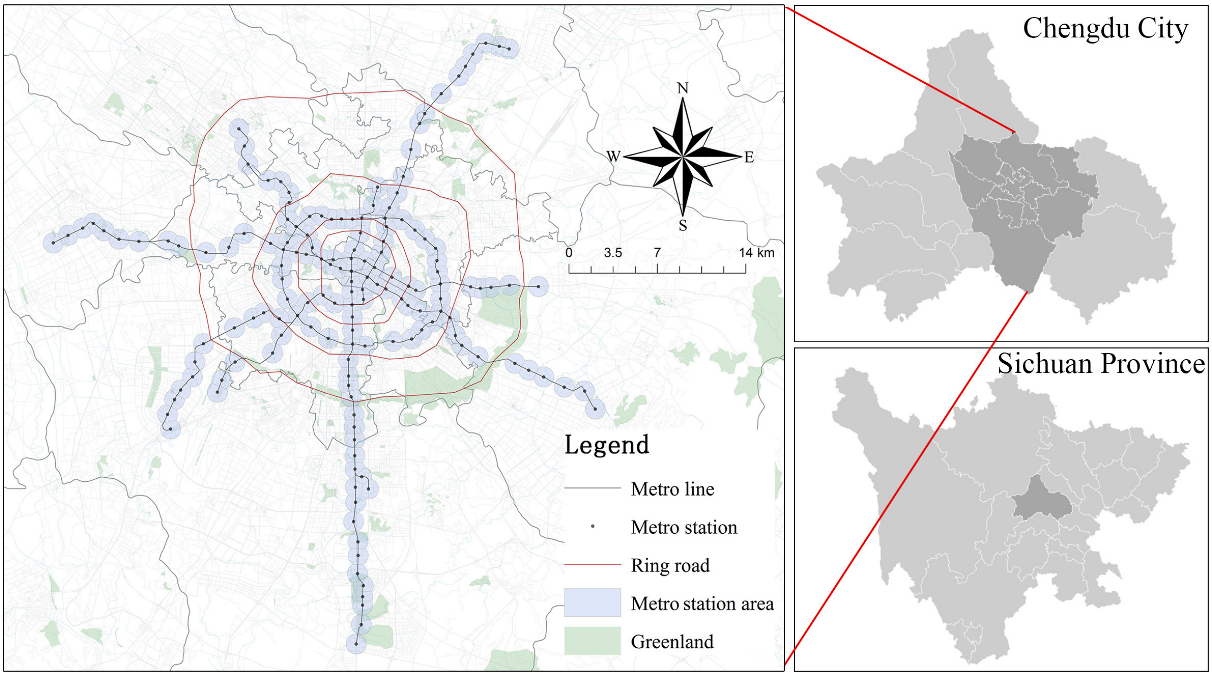

FIGURE 1
The study area and metro station area.

China's three major operators (China Mobile, China Telecom, and China Unicom) reached 1.6 billion. Given that mobile phone signaling data can reflect the spatio-temporal gathering patterns of the crowd (e.g., the distribution of working and living populations, user activity patterns), it is an important data basis for analyzing urban human activities. Compared with social network data such as Weibo and Facebook, mobile phone signaling data have larger data volume, more general coverage, and higher point density. It can accurately reflect the population attributes of users (age, gender, etc.). In this study, in order to ensure privacy and security, the mobile phone signaling data we obtain do not contain personal information. Moreover, our study divides the population structure into four levels based on the age classification standard of the World Health Organization (WHO) and the relevant regulations (e.g., *Chinese Law on the Protection of the Rights and Interests of the Elderly*). The classification in this work is as follows: (1) 12–18 years old (teenagers), (2) 19–39 years old (young adults), (3) 40–59 years old (middle-aged adults), and (4) 60+ (older adults).

According to the base station coverage of cell phones and the scale of neighborhoods (based on literature studies and the Chinese Ministry of Housing and Urban-Rural Development's 2022 "Annual report on road network density and traffic operation in major Chinese cities," the average street density in Chengdu has reached 8.4 km/km^2 and the street spacing is 250 m), in order to present street-level activity travel trajectories, we divided the study area into a grid of 250*250 m (Figure 2).

Firstly, based on the method of Xiao et al. (51), we used mobile phone signaling data to calculate the number of residential and employment populations in each grid (Figure 3). Compared with the traditional census data, these data carved by mobile phone signaling are more refined. Secondly, we recorded the change in the population data within each grid, 24 h per day from November 11 to 17. It is worth noting that almost all previous studies based on transient tweets, hotspots, and other data, which recorded instantaneous population and integrated this into vibrancy. However, instantaneous population distributions are highly mobile, and many of the flows only pass through the area. For example, a person who drives through an MSA, even if he/she doesn't work or consume in the MSA, is still recorded as a vibrant individual. Thus, to extract the real vibrant users who generate consumption and staying time in the MSAs, we counted users who stayed in the MSA for more than 30 min and defined them as people with vibrancy. Finally, we aggregated the number of people with vibrancy in each grid to the MSA and calculated the average number of people with vibrancy per hour for each age group, recording the average TOD vibrancy index (VI) for each age group.

In recent years, POI data become an important representation of the distribution of facilities in the built

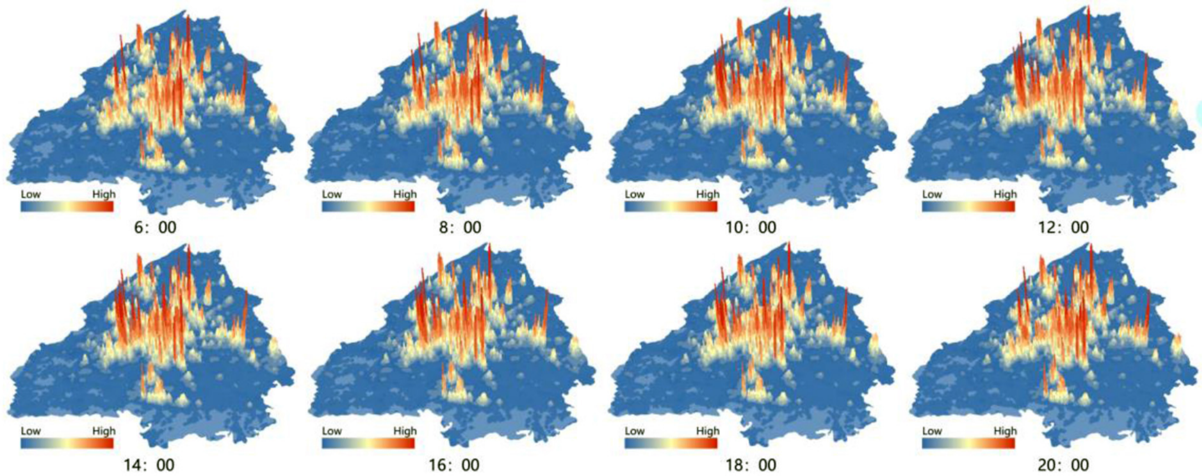

FIGURE 2
The heat map of population distribution in Chengdu.

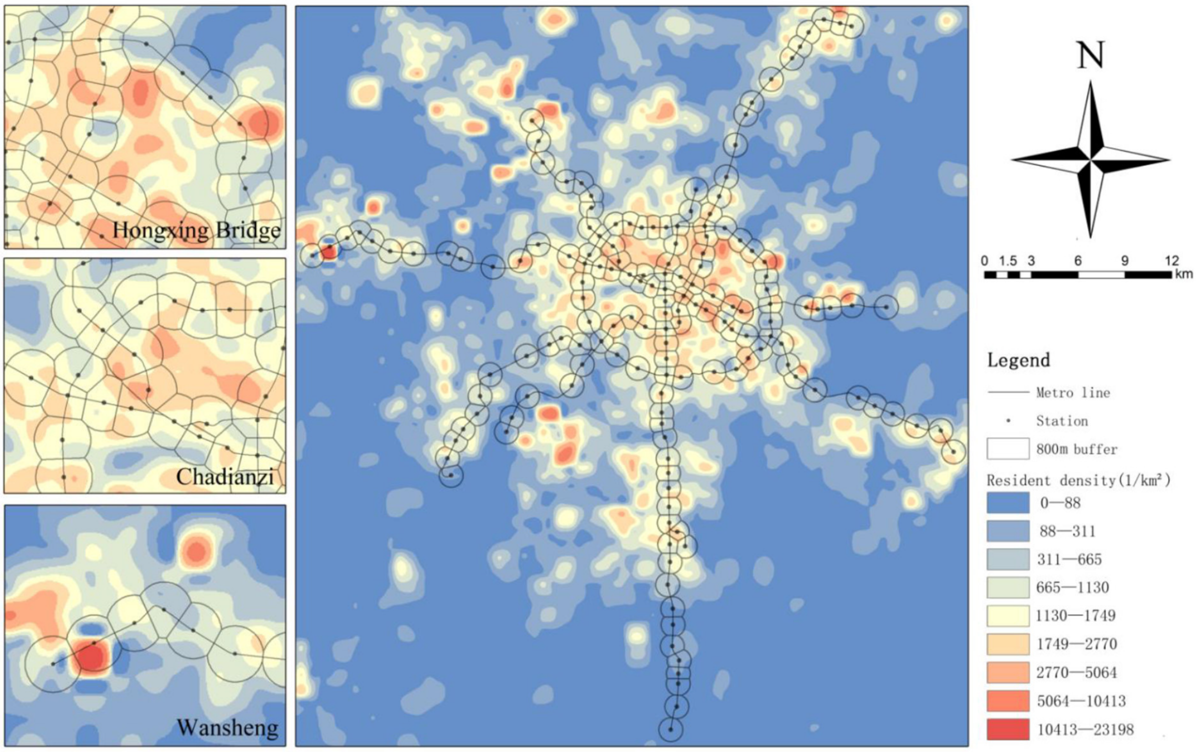

FIGURE 3
The identification and distribution of residential density in Chengdu based on mobile phone data.

environment. POI data record a series of information such as facility classification, name, and address. Compared with traditional land-use data, POI data (https://www.amap.com/) can fully reflect the characteristics of functional urban facilities' layout. The POI data we used in this study includes shopping facilities (Supermarkets, convenient stores, groceries, and so on), park facilities (plazas, parks, scenic areas, and ancillary facilities). Then we calculate the density of shopping facilities

FIGURE 4
Street view point distribution in MSA and identification of green view rate.

and park facilities. The CBD of Chengdu is Tianfu Square, so we calculate the distance to Tianfu Square of each metro station as the distance to CBD. The above indicators serve as destination accessibility of MSA-level built environment.

In addition to POI data, the study also used urban spatial and economic data such as building footprint data (https://www.baidu.com/), road network data (https://www.openstreetmap.org/), housing prices (https://cd.lianjia.com), and bus routes and stops in Chengdu. Using These data, we calculated the FAR, road network integration index, average housing price, and bus stop density of MSA. We also calculated the land-use mix of MSA based on the POI data of Chengdu. Finally, we obtained the street view map of each MSA sampling point by calling the interface of Baidu API (Figure 4). Moreover, we calculated the street green view index of MSA by using a semantic image recognition tool. The green view index is calculated by

$$VGI_i = \frac{\sum_{i=1}^{4} GreeneryPixels_i}{\sum_{i=1}^{4} Total\ Pixels_i} \quad (1)$$

where VGI is the green view rate and takes values in the range [0, 1), $GreeneryPixels_i$ is the area of green pixel points of the i-th position in the street view map, and $TotalPixels_i$ is the area of the observed street view image of the i-th position.

Variables

The VI of TOD in this study is used as the dependent variable. Based on the 5Ds principle, and previous research (12, 17, 37, 42, 50), we selected built environment independent variables that may affect VI. The independent variables are as follow: density (residential density, employment density, and FAR), design (green view index and road network integration index), diversity (land-use mix), destination accessibility (distance to CBD, park density, and shopping facility density), and distance to transit (bus stop density). In addition, considering the economic attributes of MSA, we added the indicator of housing price as an independent variable. The descriptive statistics of the independent variables are shown in Table 1.

Methodology

Our study explains the intergenerational differences in the impact of MSA built environment on VI employing a multiple linear regression model which illustrate the relationship between the independent and dependent variables (33), and the model is calculated by

$$\log y = \beta_0 + \beta X + \varepsilon \quad (2)$$

TABLE 1 Descriptive statistics of independent variables.

Variables		SD	Mean	Min	Max
Density	Residential density (10^4/km^2)	2.87	4.00	0.10	12.83
	Employment density (10^4/km^2)	4.67	3.51	0.11	29.75
	FAR (floor area ratio)	0.61	1.22	0.03	2.93
Diversity	Land-use mix	0.08	0.76	0.27	0.89
Design	Road network integration index	0.19	0.64	0.08	1.23
	Green view index (%)	0.05	0.19	0.05	0.32
Distance to transit	Bus stop density (1/km^2)	4.74	8.51	0.57	27.36
Destination accessibility	Distance to CBD (km)	6.79	9.52	0.00	28.70
	Park density (1/km^2)	5.50	3.08	0.00	39.13
	Shopping facility density (1/km^2)	491.56	335.32	0.00	4,258.33
Economic attribute	Housing price (10^4 yuan/m^2)	0.49	1.56	0.38	3.54

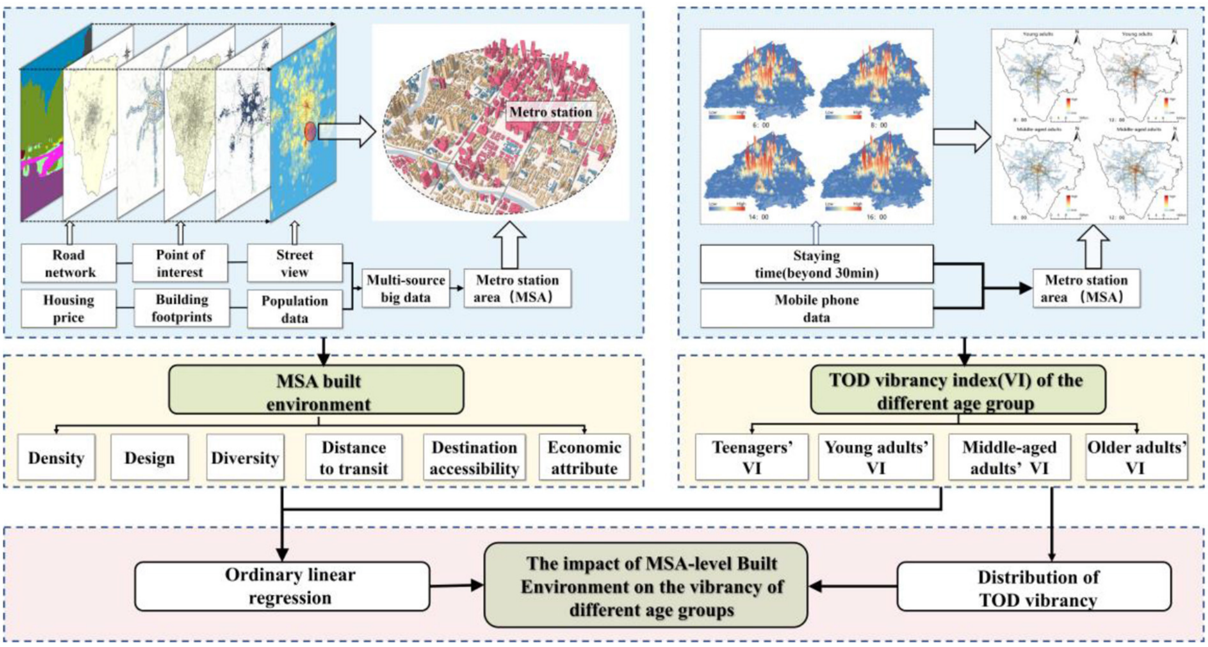

FIGURE 5
Methodological framework.

where y is the VI, X is a vector representing the independent variables, β_0 is a constant, and β is the vector of estimated coefficients,ε is the residual. To investigate the intergenerational differences in the impact of the MSA-level built environment on VI, we employed five multiple linear regression model. Model 1 is a model of the impact on VI of all age groups, and Models 2–5 are models of the impact on the vibrancy of teenagers, young adults, middle-aged adults, and older adults, respectively. Separate models were constructed to explain the relationship between the MSA-level built environment and each age group's activities. The research framework of this paper is shown in Figure 5.

Results

Spatial distribution of all age group VI (Vibrancy Index) in MSA

(1) For teenagers (Figure 6), the MSAs in the central districts within the 3rd Ring Road of the city are not the main concentration areas. Rather, it is the vocational-technical schools in the outer areas of the city that are the hotspots of teenagers' VI. We believe that two reasons may contribute to the spatio-temporal different characteristics of the teenagers' activities hotspots. Firstly, cell phones are banned in most

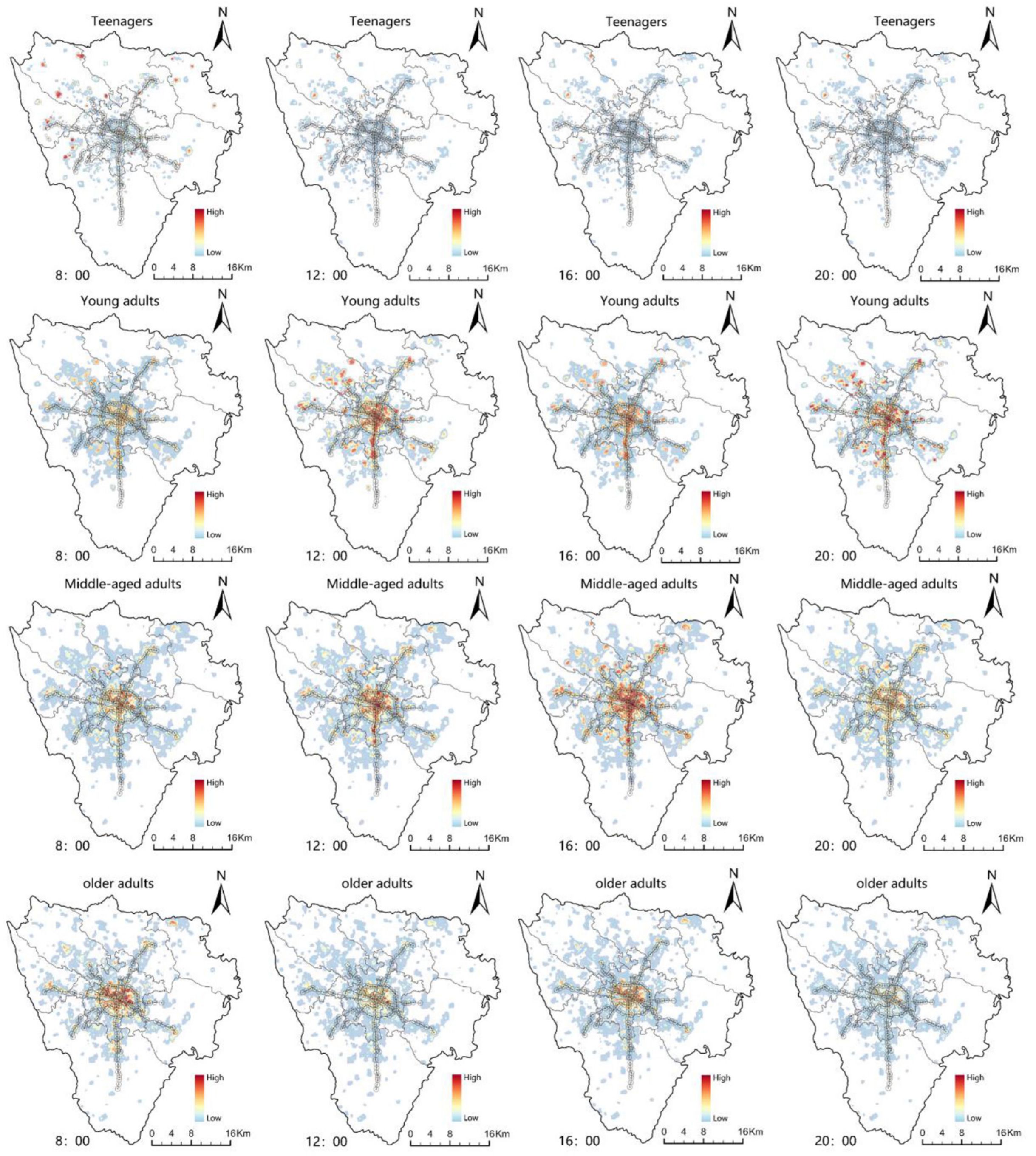

FIGURE 6
The distribution of TOD vibrancy for each age group (teenagers, young adults, middle-aged adults, and older adults).

Chinese primary, middle and high schools during school hours, while they are not in vocational-technical schools. Therefore, the recorded mobile phone signaling data of students in vocational-technical schools are likely to be more active. Secondly, due to vocational-technical schools' large student population and floor area, they are generally set up around MSAs in suburban areas. Thus, teenagers' VI is higher in the outer areas of the city. (2) For young adults, the Gaoxin South, Tianfu Square, and the Gaoxin West are the three major concentration areas. Tianfu 3rd Street Station, Tianfu 5th Street Station, Financial City Station, Chunxi Road Station, and Century City Station, which are located in these areas, combine the highest employment density in the city. Secondly, the central towns of the satellite cities are also secondary hotspots of young adults' VI. The end stations of several metro lines set near these towns (Xipu Station, Longquanyi Station, Science City Station, Wansheng Station, etc.) are highly attractive to the surrounding employment population, driving the employment of youth in rural. (3) There is some similarity in the distribution of VI between middle-aged adults and young adults, while middle-aged adults' VI is significantly higher in the city center than in several other age groups. The result may be strongly related to housing affordability and the consumption level of the middle-aged adults. (4) The older adults' VI is mainly located in the core metro stations in the city's central areas. Given that the MSAs within the 3rd Ring Road have a huge number of old neighborhoods and high-quality medical services (e. g. Huaxi Hospital, Sichuan Provincial People's Hospital, etc.), the distribution of older adults' activities reveals a pattern of high in the center and low in the periphery.

Results of the multiple linear regression model

Prior to the regression model calculations, we analyze the correlations between the built environment indicators through Stata (Figure 7). The results show that the correlation coefficients between indicators were all below 0.7, implying that there is no multicollinearity between these indicators. The results of the regression model reveal that the R^2 of the overall model is 0.755 and the R^2 of each age group model is 0.587 (teenagers), 0.719 (young adults), 0.758 (middle-aged adults), and 0.799 (older adults), respectively (Table 2). Plus, the model is relatively good with a high goodness-of-fit. In terms of VI for all ages, indicators including residential density, employment density, FAR, bus stop density, and green view index are significantly and positively correlated. The results of Zhang et al. (3) and Wu et al. (37) also support these findings. Meanwhile, indicators such as distance to the CBD and housing prices are significantly and negatively related to the VI. Surprisingly, land-use mix is not remarkably related to VI, which is different from the study by Yue et al. (40).

The model results of each age group show that residential density (p-value < 0.01) and bus stop density contribute significantly to VI for teenagers, young adults, middle-aged adults, and older adults. There is little difference in the size of the coefficients. For example, bus stop density is significantly and positively correlated with VI for all ages, with coefficients ranging from 0.028 to 0.045. This suggests that residential density and transportation accessibility have a dominant effect on TOD vibrancy of all age groups. However, distance to CBD, FAR, housing price, employment density, green view index, shopping facility density, and road network integration index varies significantly on VI across all age groups. This finding suggests that there are considerably intergenerational differences in the impact of spatial construction intensity, street space design, and economic attributes of MSAs on TOD vibrancy.

Discussion

Density

Convincingly, residential density is significantly and positively correlated with VI for all ages. This is consistent with the conclusion of Yue et al. (40) and Wu et al. (52). Currently, most schools and companies in China institute an 8-h working model. For most people, apart from travel activities such as working, going to school, and hanging out, the remaining time of daily activities are spent around their living places, including consumption and leisure. Thus, compared to development density and employment density, residential density is the core of human activities that guarantee the basic source of TOD vibrancy. As we expected, employment density is not correlated with the older adults' and the teenagers' VI but is positively correlated with young adults' and middle-aged adults' VI. Moreover, the influence coefficient of young adults' VI is 0.065 (p-value < 0.01), which is higher than that of middle-aged adults' VI (0.023, p-value < 0.05). Consistent with the employment density distribution in Shanghai, Tokyo, Seoul, and Hong Kong (7, 53–55), Chengdu's MSA is the area with the highest employment density in the city. And both the young adults and the middle-aged adults are the main population currently employed. In this regard, it is reasonable to assume that VI for these two age groups are positively correlated with MSA employment density. In addition, the working model of "996" (work from 9 am to 9 pm per day, 6 days per week) is now common in companies (51). Compared to the middle-aged adults, "generation oppression" at the workplace (56) usually extends more overtime work for young adults. So, the population and gathering time of young adults are more than other age groups in MSAs with higher employment density. To be sure, this phenomenon is also common in other East Asian countries such as Korea and Japan (56). Then, as for the impact of FAR on VI, there is also a notable intergenerational difference. And the impact of FAR on VI continued to increase with age. We believe that this may be strongly related to the urban spatial and population structure of Chengdu: Firstly, TOD development in the central areas of Chengdu is earlier, resulting in a considerably higher MSA development intensity (FAR) than that in the peripheral areas. Secondly according to data from the "*The seventh census of China,*" old neighborhoods around city center are now the main settlement areas for the older adults. Therefore, MSAs with a high FAR in the central part of the city are more active for older adults.

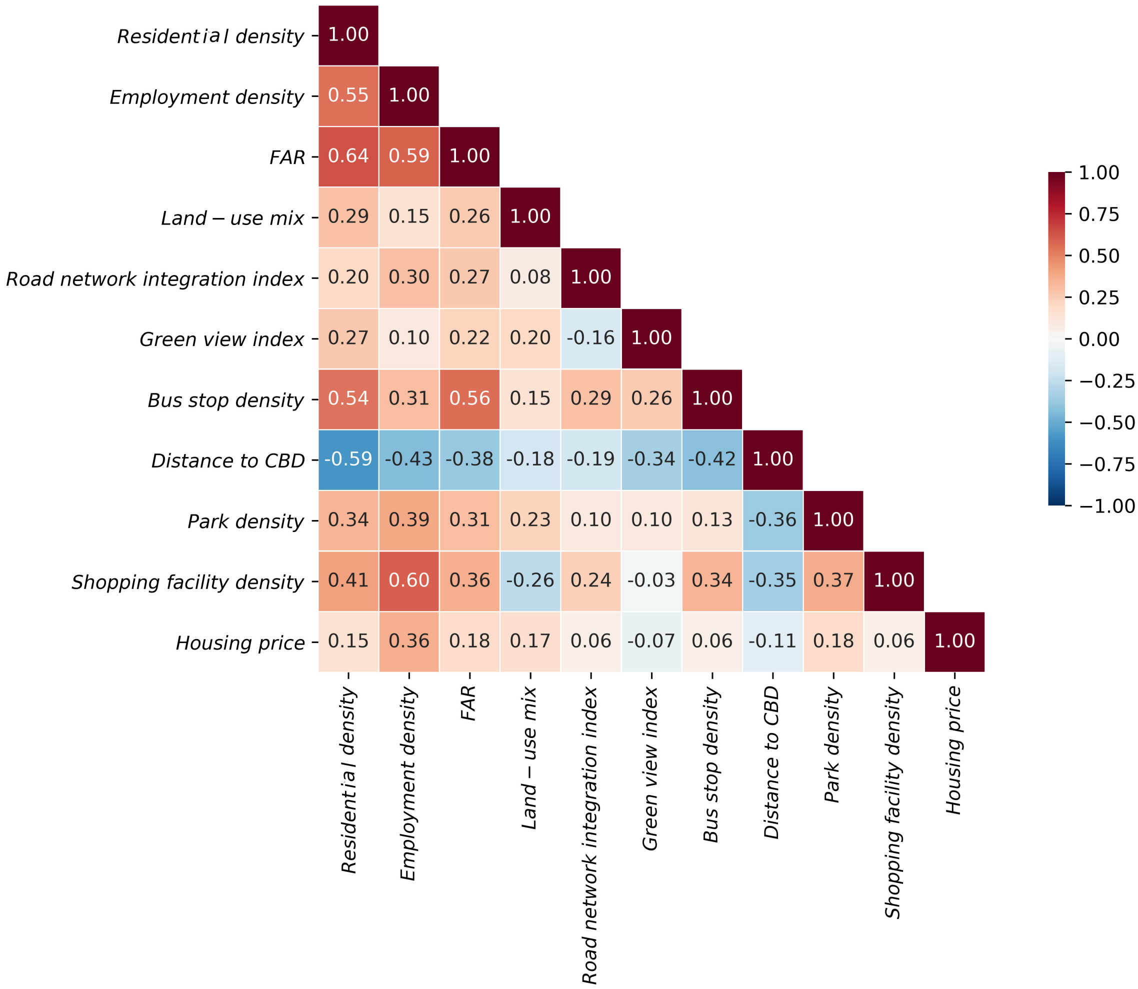

FIGURE 7
Pair-wise correlation analysis result.

Diversity

According to the New Urbanism and Smart Growth, the land-use mix model is important to enhance urban vibrancy (3, 57, 58). Meanwhile, it is surprising that land-use mix is not associated with VI in either the overall model or the models for each age group, which is remarkably different from previous studies. For instance, some empirical studies in cities such as Shenzhen and Seoul show that land-use mix and spatial interaction diversity have a significant contribution to urban vibrancy (40, 59, 60). The reason may be as follow: People are able to accomplish their travel purposes in a relatively small range in TOD with a high land-use mix, which may restrict the mobility and redistribution of people. The study by De Nadai, Staiano (36) based on cities in Italy also finds that there is no significant relationship between land diversity and urban vibrancy. Thus, the mixed development model advocated by New Urbanism should base on the high quality of space.

Destination accessibility

Distance to CBD is significantly and negatively related to teenagers', middle-aged adults', and older adults' activities, and the coefficients vary little. The geographic decay function for urban human activities is also evidenced in studies by Tu et al. (34) and Yang et al. (61). It is worth noting that young adults' activities are less influenced by distance, and there is no remarkable relationship. We believe that this may be related to the polycentric development pattern of Chengdu and the spatial movement patterns of the young adults. Firstly, the employment centers in Chengdu are located in the MSAs of new urban areas such as the Gaoxin South, the Gaoxin West, and Tianfu New

TABLE 2 Results of the multiple linear regression model.

Variables	Model 1 (overall)		Model 2 (teenagers)		Model 3 (young adults)		Model 4 (middle-aged adults)		Model 5 (older adults)	
	Coefficient	SE	Coefficient	SE	Coefficient	SE	Coefficient	SE	Coefficient	SE
CONSTANT	9.916***	0.47	4.499***	1.066	9.342***	0.521	8.724***	0.426	7.756***	0.481
Residential density	0.123***	0.019	0.143***	0.044	0.137***	0.022	0.083***	0.018	0.121***	0.02
Employment density	0.044***	0.013	0.033	0.029	0.065***	0.014	0.023**	0.011	−0.007	0.013
Distance to CBD	−0.017**	0.007	−0.039**	0.016	−0.011	0.008	−0.024***	0.006	−0.034***	0.007
FAR	0.187**	0.089	0.147	0.201	0.121	0.098	0.241***	0.08	0.332***	0.091
Housing price	−0.466***	0.079	−1.073***	0.18	−0.48***	0.088	−0.393***	0.072	−0.495***	0.081
Bus stop density	0.031***	0.01	0.045*	0.023	0.028**	0.011	0.034***	0.009	0.040***	0.01
Shopping facility density	−0.001	0.001	0	0.003	−0.002*	0.001	0	0.001	0.001	0.001
Land-use mix	−0.163	0.534	−0.478	1.213	−0.112	0.593	−0.494	0.484	0.249	0.547
Road network integration index	0.111	0.212	0.926*	0.482	0.149	0.236	0.15	0.192	0.046	0.217
Park density	0.006	0.008	0.011	0.018	0.004	0.009	0.008	0.007	0.012	0.008
Green view index	1.459*	0.85	5.563***	1.931	1.098	0.944	1.592**	0.771	2.301***	0.871
Performance statistics										
F-statistic	40.416		18.588		33.452		40.930		52.184	
R-squared	0.755		0.587		0.719		0.758		0.799	
Number of observations	156		156		156		156		156	
Akaike crit. (AIC)	195.696		451.599		228.268		165.020		203.085	

***$p < 0.01$.
**$p < 0.05$.
*$p < 0.1$.

District, while the commercial centers (consumption centers) are located in the MSAs of old urban areas such as Tianfu Square and Chunxi Road Station. Secondly, young adults are more active and mobile compared to other age groups. As the main population of employment and consumption in the city, their activities pattern presents a homogeneous distribution throughout the day. This results in the fact that the young adults are less influenced by the geographic decay function of "center-periphery" distance in the city.

Design

The green view index is significantly and positively correlated with VI for teenagers, middle-aged adults, and older adults. With coefficients of 5.56, 1.59, and 2.30, respectively. The existing literature shows that the green view index is an important impetus to enrich human activities, as greenery can improve the pedestrian walking experience by increasing shade and reducing stress (62). Older adults have a more flexible activity schedule and are more focused on physical health and physical activities. Thus, MSAs with a high green view rate are attractive to senior citizens. As for the teenagers, green space makes up a large part of campus spaces in China, so teenagers' VI is also significantly and positively correlated with MSA green view index rates. Meanwhile, the effect of the green view index on the young adults' VI was not remarkable. This is a very interesting result, and we think the possible reasons are as follows: (1) Due to economic pressure, the young adult group is more concerned with the economic benefits of TOD rather than spatial quality. (2) Given that MSAs with high employment density and high development intensity, which highly attract young adults, are generally new urban areas. The green view rate of street space in new areas is relatively lower because of the wider streets and the shorter planting time of greenery. Therefore, under the combined influence of group activity preferences and MSA place-making differences, the use of green space in TOD is "spatially inequity" for young adults.

The road network integration index is an important spatial design indicator of TOD street networks. Hillier et al. (63) argued that healthy urban spaces attract pedestrian flows and further attract specific functional spaces to grow in density, which in turn leads to a high consistency in the scale of pedestrian flows and the structure of the street network. So, integration is the core of functions and pedestrian flows aggregation. However, the model results show that the road network integration index is only positively related to teenagers' VI, but not significantly related to VI for other age groups. We believe that this may be related to the spatial structure of road networks in Chengdu. The road network structure within the 3rd

Ring Road in Chengdu has retained small-scale neighborhoods and complex road networks, resulting in low road network integration index of MSAs. By contrast, the new areas outside the 3rd Ring Road have grid-like and highly integrated road network structures. The road network integration index of MSA in the periphery area of the city is higher than that in the central of the city. The distribution of VI for different age groups shows a spatial pattern that is high in the center and low in the periphery, except that the distribution of teenagers' VI was on the contrary. In this regard, it is understandable that the other age group activities do not correlate with the road network integration index of the MSA.

Distance to transit

The bus stop density is highly consistent for all age group models, with little intergenerational differences. Compared to the metro system, bus transit has much greater coverage and is important for connecting other areas of the city to the MSA. Besides, transit accessibility has been noted in many studies to increase metro ridership (64), which is the most important source of human activities in MSAs. Therefore, MSAs with higher bus stop density have a greater capability to radiate and attract people from surrounding areas.

Housing price

Housing prices are negatively correlated with VI for all age groups, suggesting that high housing prices in MSAs may inhibit the TOD vibrancy. We think that this may be related to the "spatial squeezing effect" of high housing costs. High housing prices in TOD can "squeeze" out non-housing affordable people from MSAs and urban centers (65). Then, under the constraints of market choice and payment capability, low- and middle-income people often have to give up accessibility for relatively affordable houses. This social phenomenon results in a spatial mismatch between work and housing and a significant time spent on commuting. So, it can be explained that "spatial squeeze" and "jobs-housing imbalance" generates negative externalities, which in turn inhibit the time and density of people gathering in MSAs.

Previous studies have shown that urban rail transit has a positive impact on housing prices (66). On one hand, according to classical land economics and ground rent theory, urban metro construction enhances the spatial accessibility of stations and areas along the rail lines, rising land and housing prices (67). On the other hand, TOD-related facilities are easily capitalized into neighboring property values. Because people are willing to pay a higher price for convenient and efficient access to public services and infrastructure. Some scholars refer to this effect as "transit capitalization effects" or the "value capture" of rail transport. Similarly, in countries such as India, Korea, and China, where rapid urbanization is taking place, TODs are more used as a tool for real estate development to promote urban development and land taxation. In short, this process of TOD-based real estate appreciation is accompanied by a continuous division of classes and generations, coming into "Transit-Induced Gentrification" (68). Chava et al. (69) have pointed out that the gentrification of MSAs has a significant relationship with people's usage frequency of rail transport.

Surprisingly, MSA housing prices have the most impact on the suppression of teenagers' VI. We suggest that this may be closely associated with the "school district housing" and "squeeze of land value." For one reason, China's policy of the School District System (70) results in the housing price rising in MSAs with better educational resources in central areas. This leads to a large number of teenagers moving with their parents to study in city peripherals. For another reason, the abundant added value of land in MSAs with high housing prices will lead to a tendency to develop commercial and residential facilities, which will squeeze out space for larger public infrastructure such as education and sports. This cycle further exacerbates the suppression on teenagers' VI in MSAs with high housing prices.

Conclusions

Transit-oriented development has been touted as an important integrated transport and urban planning concept for enhancing urban vibrancy and realizing sustainable urban development. In this study, we use cellular signaling data to quantify the spatio-temporal distribution of the MSA-level VI among different age groups. Meanwhile, multi-sourced spatial data such as streetscape, parcel-level land use, and POI data are adopted to measure the MSA-level refined built environment. Based on these data, we apply multiple linear regressions to scrutinize the impact of the MSA-level built environment on the VI and its intergenerational differences.

The findings of the study are conducive to understand the mechanisms of how the MSA-level built environment affects urban vibrancy and to inform urban planners on how to create vibrant TOD communities. Specifically, the visualization results show that there are evident intergenerational differences in the spatial distribution of the MSA-level VI. The MSA in new urban areas, in which plenty of firms are concentrated, accommodates a large number of activities of young and middle-aged adults. In contrast, the hotspots of the MSA-level activities of older adults are mainly located in the well-developed city center with premium accessibility to public service facilities. Regarding the impact of the MSA-level built environment factors, the results of regression analysis indicate that (1) Residential and bus stop density are positively associated with the VI. Furthermore, most of the correlation coefficients are similar among different age groups. (2) Distance to CBD is negatively associated with the VI of teenagers, middle-aged, and older adults, while it is unrelated to the VI of young adults. (3) Employment density is positively associated with the VI of young and middle-aged adults but not significantly associated with those of teenagers and older adults. (4) The correlations between the FAR and the VI are positive for all age groups. As age increases, the significance of such correlations becomes more pronounced. (5) Green view index shows a more significant positive correlation with the VI of teenagers and older adults as compared to those of young and middle-aged adults. (6) Significant negative correlations exist between housing price and VI of different age groups. Teenagers are influenced the most by such spatial-squeezing effects, i.e., transit-induced gentrification.

Based on these findings, we propose the following planning recommendations for enhancing TOD vibrancy. First, the planning and design of the TOD living circle need to take the intergenerational differences in human activities into consideration. For instance, TOD communities with a high fraction of older adults are supposed to provide sufficient elderly-friendly facilities and improve the streetscape design, thereby facilitating the mobility and activity of the older adults in the MSA. Second, to address the adverse effects of "Transit-Induced Gentrification" on urban vibrancy, we call for efforts to develop and improve the multi-level housing support system (e.g., government-subsidized and affordable rental housing) in the MSA to achieve a systematic spatial match for the "housing-transportation" system. This will help reduce the "Spatial Deprivation" suffered by low-and middle-income residents due to high housing prices (71), thus contributing to the development of equitable, accessible, and vibrant TOD communities. Finally, to accommodate the daily activities of young adults, urban planners need to improve the quality of public space in the high employment density MSA by providing adequate leisure facilities like small community parks.

However, there are limitations in this study. First, Meng and Xing (5) and Xiao et al. (42) considered urban vibrancy as an aggregative index, so they aggregated data from social media, smartcards, and POIs to form a comprehensive urban vibrancy index. Meanwhile, our study uses mobile phone signaling data, which mainly responds to the density and duration of people aggregation. Thus, the calculation of the vibrancy index for each age group based on this dataset may lead to an incomplete characterization of urban vibrancy. Secondly, although we use Tyson polygons to reduce the effect of MSA spatial proximity on the model results, it is still difficult to solve the problem of spatial heterogeneity. In this regard, the next study should employ a geographically weighted regression model (GWR) or a geographically temporally weighted regression model (GTWR) to reduce the effect of spatio-temporal nonstationary on the model results.

Data availability statement

The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding authors.

Author contributions

BY, XC, and FT: conceptualization. BY and XC: funding acquisition. BY: supervision and writing—original draft. XC and FT: methodology. RL and FT: formal analysis. XC, RL, FT, TY, and PL: writing—review and editing. PL, TY, and FT: validation. All authors contributed to the article and approved the submitted version.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Publisher's note

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Impact of urban green space on self-rated health: Evidence from Beijing

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As a crucial component of urban green space (UGS), urban parks have been found to be closely associated with the health of urban residents. Drawing on a large-scale survey, "International First-class Harmonious and Livable Capital", in Beijing conducted in 2018, this paper examines the impact of subjective and objective characteristics of UGS on residents' self-rated health (SRH) by using a binary logistic regression model. The results indicate that the overall SRH status of urban residents in Beijing is relatively good, with 73.8% of the respondents reporting good SRH. The perceived quality of UGS and objectively measured accessibility to UGS are positively associated with residents' SRH, but the subjective indicator of UGS has a greater impact on SRH than the objective indicator of UGS. In terms of influencing mechanisms, social interaction and air quality perception were the two major mediators of UGS that affected residents' SRH. The heterogeneity analysis suggests that objective accessibility to different types of urban parks has mixed effects on residents' SRH. Access to high-quality parks is positively associated with residents' SRH, whereas access to common parks has a negative impact on residents' SRH. Our findings provide important policy implications for optimizing urban park design and improving the quality of urban park provision according to human needs in the Beijing Metropolitan Area.

KEYWORDS

urban green space, self-rated health, influencing mechanism, binary logistic model, Beijing

Introduction

Urbanization is advancing rapidly worldwide, with more than 60% of the global population living in cities. However, rapid, extensive urbanization in some developing countries such as China has been accompanied by serious environmental pollution and a high incidence of chronic diseases (1, 2). Since Healthy China 2030 was proposed in 2016 by the Chinese government, public health concerns have received widespread attention from interdisciplinary scholars (3). Most health studies have focused on either objective health (i.e. mortality and morbidity due to various diseases) or subjective health (i.e. self-rated health [SRH]) (4, 5). More recently, a growing body of health studies has considered SRH a useful measurement indicator of public health because of data availability at a fine spatial scale and its satisfactory prediction of mortality (6).

The factors that influence individuals' health in the research community comprise both intrinsic and extrinsic factors. Intrinsic factors are some physiological factors and behaviors, for example, daily health behaviors and genetic factors that are potential determinants affecting individuals' health. For instance, health behaviors such as individual dietary habits and physical activity may directly affect human health (7). Health tends to vary according to individuals' behavior and socioeconomic status (8). External factors such as the natural environment, social capital, level of economic development, and the built environment are also associated with health and can be broadly classified into three levels. At the macro level, factors such as urbanization level, socioeconomic development level, and availability of medical facilities exert different degrees of impact on residents' health (9). To build a healthy city, the residential environment is also of substantial concern in recent health-related research at the meso level (10). Evidence has suggested that neighborhood social capital, community cohesion, and perceived neighborhood deprivation play important roles in determining the physical and psychological health of residents (11, 12). Other scholars have focused on health at the micro level and analyzed the effect of environmental exposure on residents' health through individual spatiotemporal behaviors, such as residents' travel mode and commuting time (13). However, most health-related studies at the micro level have been conducted in developed countries, such as the United States and the United Kingdom (14, 15), and there has been scant research on the association between individuals' residential environments and their health in China.

Urban green space (UGS) is green infrastructure, namely, for example, urban parks, urban forests, public green spaces, school playgrounds, public rest areas, city squares, and vacant lots (16), among which urban parks are one of the most critical components and are widely used by nearby residents. In recent years, urban construction land has expanded rapidly due to rapid urbanization, especially in developing countries (17), encroaching on natural resources and ecological land within the city limits. The continuous reduction of UGS, has increased the incidence of various mental illnesses and chronic diseases (18, 19). With the increasing human demand and numerous health benefits of green spaces, UGS has also become an emerging research focus in health studies. However, most of the urban greenery and health literature has been conducted in the western context on relatively low-density cities, and their findings cannot be generalized to Chinese cities that have a higher population density.

UGS provides a wide variety of social, economic, and environmental benefits (20, 21). Existing health-related studies have found that UGS is positively associated with residents' health through various mechanisms in the physical, psychological, and social dimensions (22). The typical theories linking UGS and health are stress reduction theory and attention restoration theory (23, 24), and the health effects of UGS are mainly composed of three mediated paths (21). The first mediated path is the reduction of environmental stress, which means that UGS can effectively mitigate the harmful impact of air pollution, noise pollution, and other types of deleterious environmental exposures in the living environment (25). The second mediated path is restoring capacity, which shows that UGS can relieve residents' physical and psychological stress and restore their attention, reducing the prevalence of chronic diseases (26). The third mediated path is building capacity, through which UGS can improve the living environment for physical exercise and thus enhance residents' physical fitness (27). Additionally, UGS, considered a high-quality social activity space, can also promote social interaction, which enhances residents' social well-being and mental health (28). Although burgeoning literature has focused on the relationship between UGS and residents' health, few studies have examined the impact of both objectively measured access to UGS and the perceived quality of UGS on residents' SRH.

Research has provided evidence of the UGS-health association. However, most of the health-related literature has measured UGS only from an objective perspective, such as the quantity and accessibility of UGS (29). Widely used accessibility measurement methods are, for example, the buffer zone method, shortest distance method, Gaussian two-step floating catchment area method, and gravity model method (30, 31). However, evidence showed that proximity to UGS has a mixed effect on residents' health. For instance, some studies have found that the increasing quantity of UGS near the residence tends to relieve residents' psychological stress and thus promote their mental health (32); other studies have found a negative association between UGS and residents' health after controlling for their individual characteristics (33). This is in part due to the fact that there are limitations to only consider the quantity or accessability of the UGS while neglecting their quality. Numerous previous studies have reported the varied health enhancing effects of the UGS among diffent types of urban parks (e.g., size and quality) (34, 35). Another possible reason for the inconsistent results may be induced by spatial mismatch between the distribution of UGS and local residents' real needs (36), because utilizing only objectively measured accessibility to UGS may ignore the actual needs of residents related to UGS. Therefore, examining residents' perceived quality of UGS from an environmental psychological perspective is necessary.

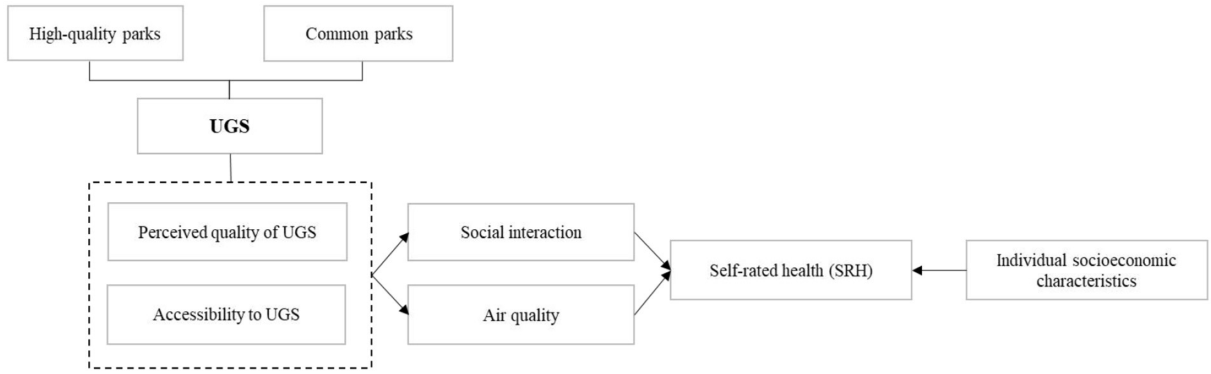

FIGURE 1
Research framework for the association between UGS and residents' SRH.

With the popularity of individual-centered urban development, the relationship between individuals' perceptions of UGS and their health has received increasing attention, and the concept of perceived accessibility has been widely used. Perceived accessibility generally refers to an individual's subjective perception of and satisfaction with the accessibility to public facilities in the physical environment (37), indicating a comprehensive understanding of objective accessibility, quality, and other use processes of the UGS. Although both objective and subjective characteristics of UGS could potentially affect residents' actual use behavior of UGS and further affect their health (38), few studies have focused on the impact of both subjective and objective measurement indicators of UGS on residents' health.

In filling these research gaps, exploring the association between UGS and residents' SRH using both subjective and objective perspectives is necessary. As an influential component of UGS, urban parks have a close relationship with residents' daily lives and health. Thus, exploring the impact and influence mechanisms of urban parks on residents' health to promote the construction of UGS as well as sustainable and healthy urban development is important. Drawing on a large-scale questionnaire survey, "International First-class Harmonious and Livable Capital", conducted in Beijing in 2018, this study combined both objective accessibility indicators and subjective perceptions of UGS to examine the relationship between UGS and urban residents' SRH in Beijing using a binary logistic regression model while controlling for residents' socioeconomic attributes.

More specifically, the objectives of this study are to (1) compare the impact intensity of both objectively and subjectively measured indicators of UGS in influencing residents' SRH; (2) explore the mediating paths through which UGS affects the SRH of urban residents; and (3) examine the heterogeneous effects of different types of urban parks on residents' SRH. Our findings provide policy insights into optimizing the allocation of UGS and improving human health through improved UGS provision.

Materials and methods

Research framework

As shown in Figure 1, this study takes Beijing as a case study and constructs a research framework for examining the impact of UGS on residents' SRH from both objective and subjective perspectives, in which subjective perceptions of UGS reflect respondents' satisfaction with UGS quality and objective UGS accessibility (distance from the respondents' residence to the nearest urban park). By referring to the literature (21) and considering data availability, this study focuses primarily on the mediating mechanisms of both social interaction and air quality for UGS in influencing residents' SRH, and socioeconomic characteristics are also included as control variables in the analytical framework (34).Since high-quality parks generally provide healthier and more enjoyable environmental elements than common parks, thus the heterogenous effects of different types of urban parks (e.g., high-quality parks and common parks) on residents' SRH is also considered in our study.

Study area and data sources

The questionnaire survey "International First-class Harmonious and Livable Capital" was conducted in the urban areas in Beijing in April 2018. It was performed by the Institute of Geographic Sciences and Natural Resource Research of the Chinese Academy of Sciences and covered 184 streets within the sixth ring road. Surveyed respondents were randomly selected from the streets with support from the local community council, and a face-to-face questionnaire survey was conducted with trained investigators. Because our survey covered many streets,

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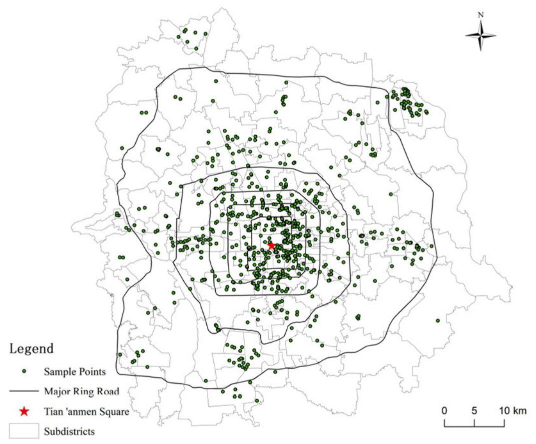

FIGURE 2
Spatial distribution of study area and surveyed respondents in Beijing.

it is representative of all types of urban residents' perceived living environment quality and SRH in Beijing. The spatial distribution of the study area and the surveyed respondents are shown in Figure 2.

The survey covered seven dimensions of living environment quality (urban safety, life convenience, comfort of the natural environment, comfort of the human environment, convenient transport, openness and innovation, and urban management) and respondents' socioeconomic characteristics such as age, gender, marital status, educational attainment, annual household income, car ownership, household registration, and occupation type. The survey also included residents' SRH and perceived quality of the park near the residential area. At the same time, in order to explore the mediating role of social interaction and air quality in the process of park affecting residents' health, we also investigated respondents' satisfaction with these two items.Our survey also collected the geographic coordinates of respondents' residences, with the support of a location-based service, which can be applied to accurately identify respondents' accessibility to UGS. The total number of questionnaires obtained in our survey was 10,651. After removing questionnaires with missing data, we finally have 10,011 effective surveys, with an effective rate of 93.99%.

Variables

Self-rated health

SRH is a widely used indicator of public health because of its easy availability in large-scale surveys (39) and its importance in predicting mortality (40). Hence, SRH was measured using a five-point Likert scale to assess the overall perceived physical and psychological health of the respondents in this study. All respondents were asked, "How do you feel about your health compared with your peers?" The response items comprised five options related to residents' health: "very good", "good", "fair", "bad", and "very bad". To avoid the potential bias caused by sparse data (41), the original five-point Likert scale data were dichotomised into good SRH (i.e. "very good" and "good") and poor SRH (i.e. "fair", "bad", "very bad"). In our model, good SRH was coded as 1, and poor SRH was coded as 0.

Indicators of urban green space

In this study, UGS indicators comprised objective and subjective aspects (42). Because urban parks are a typical UGS closely related to residents' daily lives, this study selected urban parks as a proxy variable for UGS and examined 384 registered parks in the urban areas of Beijing. The objective indicator of UGS, focusing on its accessibility, was defined as the shortest distance to the UGS, measuring the spatial distance obstacle from a person's residence to the nearest park. Notably, objectively measured accessibility was an inverse index, where a shorter distance indicated higher accessibility. Because urban parks are daily recreational spaces for residents and essential green infrastructure in the city, most urban parks are located within 1 km of residential areas, leading to a low travel resistance for urban residents to nearby urban parks. The minimum distance method is suitable for measuring accessibility to a UGS (Nielsen and Hansen, 2007). For the subjective indicator of UGS, we used a special question in the questionnaire to measure participants perceived quality of UGSs. The question uses a five-point Likert scale, and the respondents were asked, "How satisfied are you with your surrounding parks and UGS?" The response items comprised "very dissatisfied", "dissatisfied", "average", "satisfied" and "very satisfied", and their values were 1 to 5 points, respectively.

Mediator variables

In this study, social interaction and air quality were used as mediator variables, both of which were measured through respondents' perceived evaluations of living environment quality. In terms of social interaction, respondents were asked, "How satisfied are you with your social interactions in the community?" As for air quality, respondents were asked, "How satisfied are you with the air quality around your residential area?" For both survey questions, response items such as "strongly dissatisfied", "dissatisfied", "fair", "satisfied", and "very satisfied" were assigned a score from 1 to 5, respectively.

Socioeconomic characteristics

The control variables in this study were the socioeconomic characteristics of the respondents, such as age, gender, marital

TABLE 1 Descriptive statistics of all variables.

Variables	Definition	Mean	S.D.	Min.	Max.
SRH	Self-rated health	3.928	0.738	1	5
Perceived quality of UGS	Respondents' subjective perception of UGS quality	3.982	0.703	1	5
Accessibility to UGS	Distance to the nearest urban park from the respondents' residence	1.373	1.084	0.024	8.656
Accessibility to high-quality park	Distance from the respondents' residence to the nearest urban high-quality park	2.778	2.612	0.066	15.16
Accessibility to common park	Distance from the respondents' residence to the nearest urban common park	1.817	1.235	0.024	8.656
Mediating variables					
Social interaction	Satisfaction with social interactions in the community	3.849	0.680	1	5
Air quality	Satisfaction with air quality around the residential area	3.342	0.904	1	5
Socioeconomic characteristicss					
DisCBD	Distance to city center	15.210	8.150	0.694	40.36
Male	Dummy: 1 = Male, 0 = else	0.480	0.500	0	1
Female	Dummy: 1 = Female, 0 = else	0.520	0.500	0	1
Age 1	Dummy: 1 = Under 20 years old, 0 = else	0.040	0.197	0	1
Age 2	Dummy: 1 = 20–29 years old, 0 = else	0.189	0.391	0	1
Age 3	Dummy: 1 = 30–39 years old, 0 = else	0.237	0.425	0	1
Age 4	Dummy: 1 = 40–49 years old, 0 = else	0.182	0.386	0	1
Age 5	Dummy: 1 = 50–59 years old, 0 = else	0.169	0.374	0	1
Age 6	Dummy: 1 = 60–69 years old, 0 = else	0.143	0.350	0	1
Age 7	Dummy: 1 = 70 years and above, 0 = else	0.040	0.195	0	1
Married	Dummy: 1 = Married, 0 = else	0.765	0.424	0	1
Unmarried	Dummy: 1 = Unmarried, 0 = else	0.235	0.424	0	1
Edu 1	Dummy: 1 = Middle school and below, 0 = else	0.165	0.371	0	1
Edu 2	Dummy: 1 = High School, 0 = else	0.299	0.458	0	1
Edu 3	Dummy: 1 = College, 0 = else	0.284	0.451	0	1
Edu 4	Dummy: 1 = University, 0 = else	0.201	0.401	0	1
Edu 5	Dummy: 1 = Graduate student and above, 0 = else	0.051	0.220	0	1
Occupation 1	Dummy: 1 = State-owned enterprises, 0 = else	0.156	0.363	0	1
Occupation 2	Dummy: 1 = Non-state-owned enterprises, 0 = else	0.844	0.363	0	1
Income 1	Dummy: 1 = Below 30,000 CNY, 0 = else	0.055	0.228	0	1
Income 2	Dummy: 1 = 30,000–50,000 CNY, 0 = else	0.087	0.282	0	1
Income 3	Dummy: 1 = 50,000–100,000 CNY, 0 = else	0.188	0.390	0	1
Income 4	Dummy: 1 = 100,000–200,000 CNY, 0 = else	0.502	0.500	0	1
Income 5	Dummy: 1 = 200,000–300,000 CNY, 0 = else	0.111	0.315	0	1
Income 6	Dummy: 1 = 300,000–500,000 CNY, 0 = else	0.039	0.195	0	1
Income 7	Dummy: 1 = 500,000–1,000,000 CNY, 0 = else	0.015	0.120	0	1
Income 8	Dummy: 1 = Above 1,000,000 CNY, 0 = else	0.002	0.045	0	1
Car 1	Dummy: 1 = Owning at least one car, 0 = else	0.531	0.499	0	1
Car 2	Dummy: 1 = Owning no car, 0 = else	0.469	0.499	0	1
Hukou 1	Dummy: 1 = Beijing Hukou, 0 = else	0.681	0.466	0	1
Hukou 2	Dummy: 1 = Non-Beijing Hukou, 0 = else	0.319	0.466	0	1

status, educational attainment, annual household income, car ownership, household registration, and occupation type. The distance to the city center from the respondents' residence was also controlled, which can reflect residents' residential location. Table 1 lists descriptive statistics of all variables.

Research method

In this study, a binary logistic regression model was used to examine the effects of UGS on urban residents' SRH in Beijing. First, the subjective indicator (respondents' perceived UGS quality) was included in the model as the key explanatory variable (Model 1a). Second, the objective indicator of UGS, measured by accessibility (the distance to the nearest urban park from the respondent's residence), was included as the key explanatory variable in the model (Model 1b). Finally, both accessibility to UGS and residents' perceptions of UGS were included in the model (Model 1c), to test the joint effect of the subjective and objective measures of UGS on individuals' SRH.

The control variables were the distance to the city center and repondents' socioeconomic characteristics, such as gender, age, marital status, educational attainment, occupation type, total annual household income, car ownership, and *hukou*. The logistic regression model equation is as follows:

$$\text{Logit P} = \text{Ln}\left(\frac{P}{1-P}\right) = \alpha + \beta_i x_i + \beta_j x_j$$

where P denotes Y = 1, the probability of occurrence of respondents having good SRH; 1-P denotes Y = 0, the probability of occurrence of respondents with poor SRH; α is the intercept; x_i and β_i are UGS variables and the corresponding regression coefficients; x_j and β_j are control variables and the corresponding regression coefficients.

TABLE 2 Demographic and socioeconomic characteristics of respondents.

Factors	Percentage (%)	Factors	Percentage (%)
Gender		**Occupation type**	
Male	47.9	State-owned enterprises	15.6
Female	52.1	Non-state-owned enterprises	84.4
Age		**Household income**	
<20 years old	4.0	<30,000 CNY	5.5
20–29 years old	18.9	30,000–50,000 CNY	8.7
30–39 years old	23.7	50,000–100,000 CNY	18.8
40–49 years old	18.2	100,000–200,000 CNY	50.2
50–59 years old	16.9	200,000–300,000 CNY	11.1
60–69 years old	14.3	300,000–500,000 CNY	3.9
≥70 years old	4.0	500,000–1,000,000 CNY	1.5
Marriage status		>1,000,000 CNY	0.2
Married	76.5	**Car ownership**	
Unmarried	23.5	Yes	53.1
Education		No	46.9
Middle school and below	16.5	**Household registration**	
High school	29.9	Beijing *Hukou*	68.1
College	28.4	Non-Beijing *Hukou*	31.9
University	20.1		
Graduate student and above	5.1		

Results

Socioeconomic characteristics and self-rated health outcome of respondents

Table 2 summarizes respondents' demographic and socioeconomic characteristics. The respondents were mainly young and middle-aged (20–49 years old): these two groups accounted for approximately 60% of all respondents. The gender of the respondents showed little difference: male and female respondents accounted for 47.9 and 52.1%, respectively. The percentage of married and unmarried respondents was 76.5 and 23.5%, respectively. In terms of educational attainment, 53.6% had a college education or above, indicating high educational attainment among the respondents. Regarding occupation type, 15.6% of respondents worked in state-owned enterprises. Additionally, 66.9% of the respondents reported an annual household income of 100,000 CNY or above, and 53.1% of the respondents had private cars. Residents of Beijing with hukou accounted for 68.1% of the respondents, and 31.9% of the respondents were migrants. Overall, the demographic and socioeconomic characteristics of the respondents in our investigation are similar to the characteristics of the general population in Beijing.

Figure 3 shows the spatial distribution of the respondents' SRH outcomes. According to the descriptive statistics of participants' SRH, the mean score of their SRH is 3.93 with a standard deviation of 0.703, indicating that urban residents in Beijing generally have good SRH. After the original SRH variable was dichotomised, 73.8% of respondents had good SRH and 26.2% had poor SRH.

Objective and subjective characteristic of urban green space attributes

Table 3 shows the descriptive statistics of participants' perceived quality of and accessibility to UGS. Their average distances to the nearest UGS, such as all urban parks, high-quality parks, and common parks, are 1.37, 2.78, and 1.82 km, respectively. The mean score of respondents' perceived quality of the UGS was 3.98, suggesting that they were generally satisfied with the UGS in Beijing.

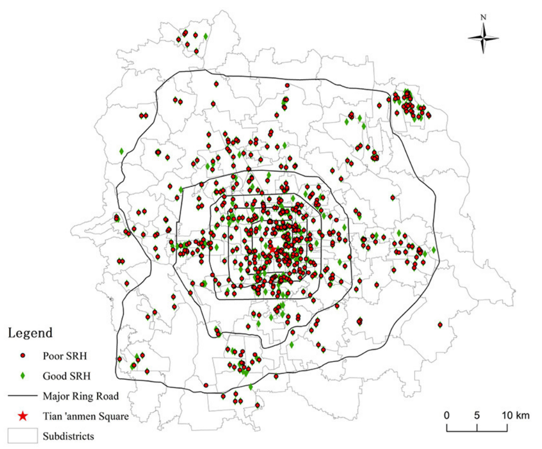

FIGURE 3
Spatial distribution of SRH among respondents.

TABLE 3 Descriptive statistic of perceived quality and accessibility to UGS.

Variables	Mean	St. Dev.
Perceived quality of UGS	3.98 points	0.703
Accessibility to UGS	1.37 km	1.084
Accessibility to high-quality park	2.78 km	2.612
Accessibility to common park	1.82 km	1.235

Impacts of urban green space on residents' self-rated health

A binary logistic regression model was used to examine the effect of UGS on participants' SRH. In order to compare the effects of influencing factors, all explanatory variables were standardized before being introduced into the model. The results of the multicollinearity test showed that the variance inflation factor (VIF) values of all independent variables were below 5, indicating that multicollinearity is not a problem. The results of the regression model are shown in Table 4. Model 1a shows the relationship between the perceived quality of UGS and respondents' SRH from a subjective perspective. The odds of participants reporting good SRH is positively associated with their perceived quality of UGS, with regression coefficients and odds ratios of 0.329 and 1.390, indicating that a one-unit increase in participants' satisfaction with the surrounding parks and UGSs increases the odds of reporting good SRH by 39.0%. Model 1b shows the relationship between accessibility to UGS and participants' SRH from an objective perspective. The odds of respondents reporting good SRH are positively associated with accessibility to UGS, with coefficients and odds ratios of 0.049 and 1.050, respectively, indicating that the odds of participants reporting good SRH increase by 5.0% for each unit increase in distance to the nearest urban park. Model 1c shows the effects of the perceived quality of UGS and accessibility of UGS on SRH from a combined subjective and objective perspective. Despite the smaller regression coefficient in Model 1c, both perceived quality of UGS and accessibility to UGS exerted significant and positive effects on the odds of reporting good SRH among respondents, with odds ratios of 1.389 and 1.048, respectively. By contrast, the impact intensity of perceived quality of UGS on participants' SRH is much greater than that of accessibility to UGS.

In addition, the results of Model 1c show that some socioeconomic attributes are also associated with respondents' SRH. Middle-aged and elderly residents had lower odds of reporting good SRH than residents aged under 20 years. Respondents with a graduate education or above had a poorer SRH than residents with a below middle school education, with a 31.7% lower odds ratio reporting good SRH. Residents with a higher annual household income had better SRH than the reference group with annual household income below 30,000 CNY, with the odds ratio ranging from 1.565 in the 300,000–500,000 CNY group to 2.835 in the 500,000–1,000,000 CNY group. Regarding household registration, respondents with a Beijing hukou had worse SRH than non-hukou residents, with a 31.4% decrease in the odds of residents reporting good SRH.

To explore the specific influencing mechanisms of the effects of UGS on respondents' SRH, social interaction and air quality were added as mediating variables in the model. The results are shown in Table 5. Models 2a and 2b examine the effects of the subjective and objective indicators of UGS on the mediating variables of social interaction and air quality, which are also new dependent variables. The modeling results showed that respondents' perceived quality of UGS was significantly and positively associated with social interaction and air quality, with regression coefficients of 0.433 and 0.561, respectively. However, accessibility to UGS was positively associated only with air quality, with a regression coefficient of 0.203.

Model 2c included two mediating variables, social interaction and air quality, in the regression analysis based on the baseline model. The results showed that social interaction and air quality were significantly and positively associated with residents' SRH, with regression coefficients of 0.060 and 0.196, respectively. The mediating analysis results reveal that social interaction and air quality are important mediator variables for the UGS effect on respondents' SRH, and UGS affects respondents' SRH directly or indirectly by increasing their satisfaction with social interaction and air quality.

Heterogeneity effects of types of urban green space

Following the high-quality parks rating standard issued in Beijing, local authorities have differentiated urban parks

TABLE 4 Regression model results of the association between UGS and respondents' SRH.

	Model 1a			Model 1b			Model 1c		
Variables	**Coefficient**	**OR**	**S.E.**	**Coefficient**	**OR**	**S.E.**	**Coefficient**	**OR**	**S.E.**
Perceived quality of UGS	0.329***	1.390	0.046				0.329***	1.389	0.046
Accessibility to UGS				0.049**	1.050	0.024	0.047**	1.048	0.024
DisCBD	0.036	1.036	0.038	0.013	1.013	0.037	0.028	1.029	0.038
Male	0.075	1.078	0.051	0.081*	1.084	0.051	0.074	1.077	0.051
Age 1	Reference			Reference			Reference		
Age 2	−0.463***	0.629	0.104	−0.479***	0.619	0.102	−0.464***	0.629	0.104
Age 3	−0.467***	0.627	0.108	−0.502***	0.606	0.104	−0.467***	0.627	0.108
Age 4	−0.694***	0.499	0.086	−0.714***	0.490	0.084	−0.692***	0.500	0.087
Age 5	−0.789***	0.454	0.079	−0.832***	0.435	0.075	−0.791***	0.453	0.079
Age 6	−1.313***	0.269	0.047	−1.363***	0.256	0.044	−1.308***	0.270	0.047
Age 7	−1.406***	0.245	0.047	−1.511***	0.221	0.042	−1.400***	0.247	0.048
Married	−0.020	0.981	0.074	−0.028	0.972	0.073	−0.023	0.978	0.074
Edu 2	−0.028	0.973	0.070	−0.014	0.986	0.070	−0.024	0.976	0.070
Edu 3	0.101	1.106	0.091	0.113	1.120	0.091	0.102	1.108	0.092
Edu 4	−0.049	0.952	0.093	−0.032	0.969	0.094	−0.045	0.956	0.093
Edu 5	−0.383***	0.682	0.098	−0.410***	0.664	0.095	−0.382***	0.683	0.098
Occupation type 2	−0.082	0.921	0.063	−0.055	0.947	0.065	−0.076	0.927	0.064
Income 2	0.482***	1.620	0.192	0.461***	1.585	0.186	0.484***	1.622	0.192
Income 3	0.724***	2.062	0.220	0.710***	2.033	0.215	0.725***	2.064	0.220
Income 4	0.718***	2.051	0.235	0.714***	2.042	0.232	0.723***	2.060	0.236
Income 5	0.945***	2.574	0.354	0.948***	2.581	0.354	0.954***	2.596	0.357
Income 6	1.042***	2.835	0.499	1.019***	2.770	0.485	1.058***	2.879	0.508
Income 7	0.448*	1.565	0.353	0.459*	1.582	0.355	0.457*	1.579	0.357
Income 8	−0.001	0.999	0.485	−0.085	0.919	0.441	0.013	1.013	0.492
Car 1	−0.079	0.924	0.068	−0.083	0.920	0.067	−0.085	0.918	0.067
hukou 1	−0.377***	0.686	0.038	−0.378***	0.685	0.038	−0.377***	0.686	0.038

***$p < 0.01$, **$p < 0.05$, *$p < 0.1$; reference groups are Age 1, unmarried, edu 1, Occupation type 1, income 1, car 2, and hukou 2.

TABLE 5 Mediating effect of the association between UGS and respondents' SRH.

	Model 2a			Model 2b			Model 2c		
	Social interaction			Air quality			SRH		
	Coefficient	**OR**	**Std. Err.**	**Coefficient**	**OR**	**Std. Err.**	**Coefficient**	**OR**	**Std. Err.**
Social interaction							0.060*	1.062	0.036
Air quality							0.196***	1.216	0.028
Perceived quality of UGS	0.433***	1.542	0.085	0.561***	1.753	0.167	0.269***	1.309	0.036
Accessibility to UGS	0.026	1.026	0.075	0.203*	1.225	0.114	0.044	1.044	0.022
Covariates	controlled			controlled			controlled		

***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

into high-quality parks and common parks based on a set of criteria since 2002, such as planning and construction, greening and maintenance, supporting facilities, and order maintenance. Specifically, high-quality parks must fulfill the following criteria: (1) a park green space cover rate of over 70%; (2) a satisfaction ratio among the visitors that exceeds 90%; (3) the loess in the park is not open to air; (4) neat, standardized signage; two-star or higher toilets; (5) no advertising umbrellas or other facilities that hinder the landscape; (6) no stagnant water, dirt, spitting, or cigarette butts; no vending stalls within 50 m of the park

TABLE 6 Heterogeneous effects of urban park types on respondents' SRH.

	Model 3a Park type = high-quality parks Dependent variable: SRH			Model 3b Park type = common parks Dependent variable: SRH		
	Coefficient	OR	Std. Err.	Coefficient	OR	Std. Err.
Perceived quality of UGS	0.377***	1.458	0.046	0.375***	1.455	0.046
Accessibility to UGS	0.085***	1.089	0.028	−0.057*	0.944	0.028
Covariates	controlled			controlled		

***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

entrance; (7) good order in the park; (8) no major complaints or safety accidents. High-quality parks generally provide healthier and more liveable environmental elements than common parks.

To examine the heterogeneous effects of types of urban parks on respondents' SRH, we differentiated urban parks into high-quality and common parks for further analysis. Table 6 shows the model results for high-quality parks (Model 3a) and common parks (Model 3b). The results of Model 3a show that the accessibility to UGS for high-quality parks is significantly and positively associated with respondents' SRH, with a regression coefficient of 0.085, indicating that the odds of reporting good SRH increase by 8.9% when the distance to a high-quality park increases by one unit for residents. The results of Model 3b show that accessibility to UGS for common parks is negatively associated with respondents' SRH, with a regression coefficient of −0.057, indicating that the odds of residents reporting good SRH decreases by 5.6% when the distance to common parks increases by one unit.

Discussion

Main findings and contributions to existing work

This study explored the relationship between UGS and respondents' SRH using data collected in a large-scale survey in Beijing: the International First-class Harmonious and Liveable Capital. Our study contributes to the literature on UGS and health in at least three aspects. First, we combine the objective and subjective characteristics of UGS in the research framework. Second, mediating mechanisms such as social interaction and air quality between the UGS and residents' health are examined. Finally, our study adds new empirical evidence on the health impacts of UGS in developing countries with rapid urbanization, using Beijing as a case study.

Our study found that the mean value of respondents' SRH in Beijing was 3.93 and 73.8% of residents reported good SRH, indicating that the overall SRH of urban residents in Beijing was good. This finding is similar to that in many studies (43): Beijing, the capital of China, has many beneficial conditions such as a high level of economic development, satisfactory medical facilities, and conveniently access to UGS. In addition, urban residents in Beijing, characterized by good education in general, have a healthy lifestyle and good health knowledge, which contribute to their reporting a good SRH.

The binary logistic regression model results indicated that the perceived quality of UGS was positively associated with respondents' SRH. This finding occurs because residents' perceived quality or satisfaction with urban parks originates from their experience (37), and residents' physiological health can be improved by using UGS (44), enhancing their SRH. Unexpectedly, accessibility to UGS was positively associated with residents' SRH in this study, indicating that residents with a longer distance from the nearest urban park have better SRH than those with a shorter distance, which was different from the results in the literature (45). A possible reason is that park facilities will crowd out the spatial layout of other public service facilities. Thus, the park layout should consider avoiding crowding other public service facilities. Different residents have different perceptions of and satisfaction with the same environment, and objective UGS accessibility indicators cannot fully reflect residents' subjective perceptions of UGS and their health benefits. Therefore, in the design of park UGS, the perception factors of residents should be fully considered to improve the role of park UGS in promoting health.

In line with the literature (46, 47), our findings showed that social interaction and air quality are important pathways through which UGS affects respondents' SRH. Specifically, the perceived quality of UGS positively contributes to respondents' SRH by enhancing their satisfaction with both social interaction and air quality, and accessibility to UGS was only relevant for respondents' SRH through satisfaction with air quality. UGS was shown to abate PM2.5 concentrations and effectively reduce the health risks caused by air pollution (48). In addition, UGS, as an area for residents' daily activities, creates a good public space for social interaction among residents (49). Increased social interaction is conducive to improving residents' social identity and alleviating negative emotions, such as anxiety (50), and promoting residents' physical and mental health.

The results of the heterogeneity analysis revealed that the effects of high-quality and common parks on respondents'

SRH differed. Among them, accessibility to UGS for high-quality parks was positively correlated with respondents' SRH, indicating that respondents with a longer distance to the nearest high-quality park tend to report a good SRH. This result may be observed because high-quality parks generally occupy a large area, which, to a certain extent, compresses the space for other public service facilities, leading to other types of healthy living needs of residents not being fulfilled and, in turn, affecting respondents' SRH (51). By contrast, accessibility to UGS for common parks was negatively associated with respondents' SRH, suggesting that a longer distance to common parks for respondents tends to lead to poor SRH. These results conform to the results of Xie et al. (52), who also found that a shorter distance or better access to UGS is beneficial for the health of nearby residents. Thus, different optimisation measures should be implemented for high-quality parks and common parks to fulfill the diverse health needs of residents.

Implications for park planning

The findings of our study provide important policy implications for improving UGS construction. Firstly, because the perceived accessibility of UGS plays a significant role in promoting residents' self-rated health, the planning and design of urban parks should pay attention to residents' perception of use and regularly collect residents' feedback on their satisfaction with urban parks. In addition, the objective distance of UGS also significantly affects the self-rated health of residents. Landscape planning departments should give priority to increasing urban parks with appropriate scale and high accessibility according to the distribution of residential areas and the urban road network system without crowding out other public service facilities.

Second, social interaction and air quality are important ways in which UGS affects SRH of respondents. Therefore, when designing urban parks, landscape design departments should not only provide good internal environment design and comfortable and pleasant green landscape to purify the air, but also create a comfortable atmosphere and provide convenient and diverse activity facilities to promote residents' social activities.

Finally, in view of the difference in the impact of high-quality parks and common parks on the SRH of respondents, the government departments in Beijing should take corresponding optimization measures for different types of parks. Specifically, the focus of optimisation for high-quality parks is to improve their quality, promote the transformation of high-quality parks into high-quality spaces, and fulfill the demands of some residents for high-end UGS. For common parks, the spatial quality and micro design of UGS in parks should be improved, based on not occupying land for other types of public service facilities. The area of park UGS should be appropriately expanded to increase fitness facilities and public spaces to fulfill the diversified needs of different groups with different social attribute.

Limitations and future studies

This study has several limitations. First, this study used cross-sectional data, which cannot fully reveal the causal relationship and changing linkage between UGS and SRH among respondents. Second, the specific mediating mechanisms of UGS on respondents' SRH in our study only considered their perceived social interaction and air quality. Other potential mediating mechanisms (e.g., physical activity) were not explored and should also be included in further research. Finally, the accessibility to UGS in this study was measured only by the shortest road network distance without consideration of actual traffic speed in different grades of road segments and individuals' transport modes. Further research should focus on the impact of travel time accessibility to the UGS on residents' SRH. In addition, the areas of the original urban parks were aggregated into points according to their geometric gravity center, which could also cause some measurement bias in accessibility when encountering urban parks with a large area.

Conclusions

Unlike developed western countries that have explored the health benefits of green space under the background of low population density, empirical evidence of green space and human health in developing countries with high population density is still relatively limited, and existing studies tend to focus only on the objective attributes of green space. Drawing on a large-scale survey and the spatial distribution of UGS in Beijing, this study quantified the association between UGS and residents' SRH by using a binary logistic regression model. It focused on the role of objectively measured accessibility to UGS in influencing residents' SRH, examined the relationship between perceived UGS quality and residents' SRH, and comprehensively measured the health benefits of UGS exposure levels from both the subjective and objective perspectives to mitigate the limitations of current research on the association between UGS and residents' health. In our study case, UGS is found to be associated with urban residents' SRH in Beijing. More specifically, both the perceived quality of UGS and objectively measured accessibility to UGS are positively related to residents' SRH, but the perceived quality of UGS has a much greater effect on residents' SRH. In addition, we identified that social interaction and air quality are important mediating paths through which UGS affects residents' SRH. Moreover, the effects of the types of urban parks on residents' SRH differed. Among these differences, accessibility to UGS for high-quality parks is positively associated with residents' SRH, and accessibility to UGS for common parks is negatively related to residents' SRH. Overall, this empirical evidence provides novel insights into optimizing green space,which could help guide planners and decision-makers to promote green space development for public health.

Data availability statement

The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding authors.

Author contributions

DZ, BZ, and WZ: conceptualization. DZ: writing and review. QZ: writing—original. M-PK: review and editing. JL: software. BZ and QZ: data analysis. WZ: investigation. All authors contributed to the article and approved the submitted version.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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Evaluating personnel evacuation risks under fire scenario of Airbus wide-body aircraft: A simulation study

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Airliner accidents are often accompanied by incidental aircraft fires, causing huge casualties and incalculable economic losses. The research on airliner fire and its emergency evacuation is the focus and difficulty of aviation safety research, but it is difficult to carry out the research through experiments, and the use of computer simulation is an effective method. This paper comprehensively studies the dynamic development of the cabin fire and the corresponding cabin evacuation when the wide-body airliner Airbus A350-900 is forced to land in two states: horizontal and forward. The spatial distribution of the remaining evacuation time at each seat is used to analyze and judge the safety evacuation risk of the airliner cabin. Finally, two evacuation optimization design ideas based on partition guidance and seat layout are proposed to improve the spatial distribution of the overall evacuation risk of passengers in the cabin and provide some reference suggestions for strengthening fire prevention in the design, manufacture, and use of airliner. Some targeted countermeasures are put forward for the emergency evacuation of passengers in the cabin in a fire situation.

KEYWORDS

Airbus aircraft, airliner environment, personal safety, evacuation risk, fire exposure

Highlights

- The influence of the capacity of aircraft emergency slides on passenger evacuation is considered.
- A spatial representation method of personnel evacuation risk is proposed.
- An unconventional working condition is analyzed when the aircraft is tilted forward.
- An optimization idea is proposed to optimize the distribution of remaining evacuation time.

Introduction

A survey of air accidents in the past 30 years found that in civil aviation, fires often occur near the landing gear, cabins, and hangars and are often extremely sudden. The causes of fire accidents generally include fuel leakage, landing impact fire of passenger aircraft, the fire of dangerous goods in luggage, short circuit fire of electrical system, and an engine fire caused by improper maintenance of passenger aircraft (1). If a fire occurs inside the cabin, such an accident is extremely unfavorable for the evacuation of passengers. For the research on cabin fire, most scholars often use empirical formulas to calculate the fire development process, use CFD technology to analyze the temperature field distribution, or use advanced fire extinguishing equipment to evaluate the fire extinguishing effect; at the same time, a few scholars use full-size or small-size aircraft to carry out In experimental research, some scholars use professional software numerical simulation tools to study fire. Most of these studies are based on simple physical models.

As early as 1976, the National Aeronautics and Space Administration carried out the physical fire resistance experiment on passenger aircraft (2). In 1979, the Federal Aviation Administration of the United States put aviation fuel outside the passenger cabin door to conduct combustion experiments to analyze the impact of fire on various parameters in the passenger cabin (3). The National Aeronautical Facility Test Center in the United States conducted a related aircraft fire experiment in 1996. Researchers used a full-size transport aircraft to transform its cabin into an airliner cabin (4).

Wang (1) selected the Airbus A330-300 civil passenger aircraft as the research object in 2016 and used the modeling method to simulate and analyze the dynamic development law of the fire of the Airbus A330-300 passenger aircraft. In 2019, Bai (5) conducted a risk assessment on a large passenger aircraft, the Airbus A330-300 passenger aircraft, and proposed a specific fire risk assessment method for passenger aircraft. Zhang et al. (6) used the fire simulation software PyroSim in 2012 to simulate the fire scene in an airtight passenger cabin and obtain the simulation results for further analysis.

Liu (7) researched and collected information such as the cabin's plane layout, established a mathematical model that restores the real situation as much as possible based on this information, and finally obtained the model with the fastest evacuation speed. Yu (8) and others established a passenger aircraft cabin evaluation system with 5 indicators and 23 influencing factors as the main content and blushed effective, comprehensive evaluation methods for evacuation capabilities. Fu (9) used Pathfinder software to simulate the evacuation of Boeing 777-200 aircraft by setting 5 specific scenarios.

From the above summary, it can be seen that domestic and foreign scholars have carried out extensive research on aircraft fires and personnel emergency evacuation, and the research has continued to deepen. The research mainly focuses on mathematical reasoning, simulation, and experimental analysis of aircraft fire and passenger evacuation.

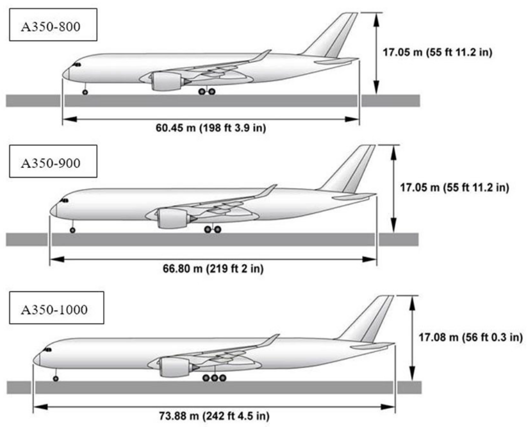

FIGURE 1
Airbus A350 series model appearance and size comparison.

Modeling

Airbus manufactures the A300, A310, A318, A319, A320, A321, A330, A340, A350, A380, and other aircraft. Among them, the A350 series consists of A350-800, A350-900, and A350-1000, which are small to large and carry 270, 312, and 350 passengers, respectively, as shown in Figure 1. In this paper, the Airbus A350-900, a large twin-engine ultra-long-range, two-aisle wide-body airliner, is selected as the object of study. The cabin layout of this type of airliner is shown in Figure 2.

Basic parameters of the model

After collecting and sorting out, the main basic parameters of Airbus A350-900, such as fuselage length, fuselage height, cabin length, and cabin width, are shown in Table 1.

In the passenger cabin of Airbus A350-900, the seating arrangement is a typical three-class cabin arrangement consisting of business class, super economy class, and economy class. Its seating arrangement is as follows: rows 11–18 are business class, with a total of 32 seats; rows 31–33 are super economy class, with a total of 24 seats; rows 34–63 are economy class, with a total of 256 seats. The basic parameters of specific cabin seats are shown in Table 2 below.

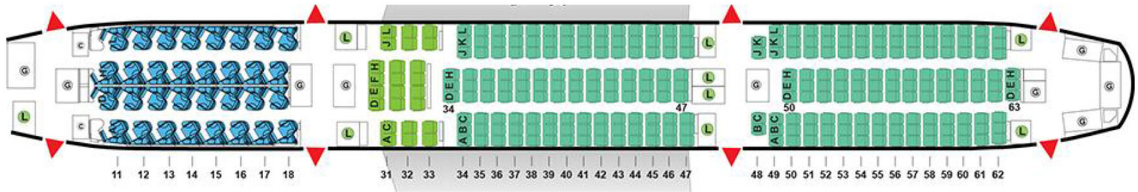

FIGURE 2
Plane layout of Airbus A350-900 passenger cabin.

TABLE 1 Main parameters of Airbus A350-900.

Parameter	Value	Parameter	Value
Length (m)	66.80	Length of cabin (m)	51.04
Height of fuselage (m)	6.09	Width of fuselage (m)	5.96
Height of cabin (m)	2.2	Width of cabin (m)	5.61
Height of airliner (m)	17.05	Number of doors	8
Wingspan (m)	64.75	Wheelbase (of a vehicle) (m)	28.66

TABLE 2 Basic parameters of cabin interior seats.

Class of cabin	Business class	Premium economy class	Economy class
Number of seats	32	24	256
Row of seats	8	3	30
Seat pitch (m)	1.09	0.97	0.81
Width of seat (m)	0.58	0.48	0.44
Maximum seat reclining angle (°)	180	120	100

Design of fire scene

When building a fire scenario, the known conditions and potential risks should be taken into account, the parameters of the airliner should be understood, the safety influencing factors in the cabin should be identified, and the location of the fire source should be reasonably set around the purpose of the study (10). Civilian airliners generally have a central fuel tank or additional central fuel tank near the center of gravity of the fuselage. As early as 1989, the Civil Aviation Administration of the United States carried out a physical simulation experiment of cabin fire (1). The simulation scenario is: after the plane fell, the huge impact force destroyed the structure of the plane, the fuel tank on one side of the wing ruptured, and the fuel leaked, causing the external fuel to form a pool fire and then cause a cabin fire through thermal radiation.

This paper investigates the fire caused by the impact of a civil airliner on the ground causing damage to the front section structure of the main body of the airliner, resulting in the spillage of aviation fuel carried in the additional central tank of the airliner due to the cracking of the cabin. Further, it investigates the impact of the fire on the evacuation of passengers in the passenger cabin of the airliner. The fire scenario is designed around the issue of cabin passenger evacuation, and the fire scenario is designed by considering the maximum probability principle and the least favorable principle through literature research on airliner fires.

The air pressure in the cabin was set to 1 standard atmosphere, and the initial temperature was set to 20°C. The Airbus A350-900 wide-body airliner studied in this paper is a large airliner with a long fuselage and a large cabin space. The passenger cabin is a relatively closed, narrow, and long cavity. The external environment affects only a small area near the door and does not significantly affect the fire development in the entire cabin. In the standard case, the property parameters of aviation fuel are in Table 3.

The cabin bulkhead structure of civil airliner is often composed of aluminum alloy, which is flame retardant. To simplify this paper, the passenger cabin bulkhead is set to aluminum, and other materials such as seats are also made flame-retardant, and in the standard case, the property parameters of aluminum are shown in Table 4.

The size of the fire source is set to a rectangular oil pool of 2.0 × 2.0 m. The fire location is in the middle of the second pair of evacuation exits connected to the passenger cabin near the front side of the nose, with the red square representing the fire source. In contrast, the 4 pairs of doors of the airliner are numbered for the convenience of description, with the doors near $Q_{\max} = m'' \Delta H_c \chi \pi D^2/4$ the nose side numbered Exit 1 and Exit 2, the doors in the middle section numbered Exit 3 to Exit 6, and the doors near the tail side numbered Exit 7 and Exit 8, as shown in Figure 3.

According to the plane layout of the Airbus A350-900 airliner, the three-dimensional model of the cabin can be established after reasonably simplifying the model, as shown in Figure 4.

TABLE 3 Main property parameters of aviation fuel (11, 12).

Parameter	Heat of combustion ($MJ \cdot kg^{-1}$)	Progressive combustion efficiency ($kg \cdot m^{-2} \cdot s^{-1}$)	Chemical combustion efficiency	Density ($kg \cdot m^{-3}$)	Effective absorption coefficient ($L \cdot m^{-1}$)
Aviation fuel	43	0.035	0.9	940	1.7

TABLE 4 Main property parameters of aluminum (13).

Parameter	Value	Parameter	Value
Density (kg/m^3)	2700	Thermal conductivity [W/(m·k)]	237
Specific heat capacity [J/(kg·°C)]	880	The heat of evaporation (J/kg)	1.05×10^7
Melting point (°C)	660.4	Boiling point (°C)	2467
The heat of dissolution (J/kg)	3.98×10^5	Emissivity	0.9

Fire source parameter settings

In aviation accidents, once the oil tank is damaged and leaked, it is easy to cause oil injection or dripping, and an oil pool will be formed. The fire caused by aircraft fuel leakage can be divided into oil vapor fire, jet fire, and oil pool fire according to the fuel combustion mode. In practice, the combustion mode of fuel oil may be single or composite, which constitutes the complexity of cabin fire. In this paper, to simplify the fire calculation, only pool fire is considered for calculation. The calculation formula for the maximum heat release rate of oil pool fire is as follows (11):

$$Q_{max} = m'' \Delta H_c \chi^{\pi} D^2/4 \quad (1)$$

Where, ΔH_c is the combustion heat, $kJ \cdot kg^{-1}$; χ is the combustion efficiency; D is the diameter of the oil pool, m; $m''$is the mass combustion efficiency per unit surface area, $kg \cdot m^{-2} \cdot s^{-1}$; The calculation formula is:

$$m'' = m_{\infty}''(1 - e^{K'D}) \quad (2)$$

In the formula, m_{∞}'' is the progressive mass burning rate of large-scale oil pool fire, $kg \cdot m^{-2} \cdot s^{-1}$; k' is the effective absorption coefficient.

The fire source in the model is set in the middle of the connecting line between the second pair of hatch doors (Exit 3 and Exit 4) on the front side of the airliner. The rectangle with the size of 2.0×2.0 m is regarded as pool fire combustion. The fuel volume is assumed to be 0.1 m^3, and the following formula can calculate its equivalent diameter:

$$D = \sqrt{4S/pi} \quad (3)$$

Where S is the area of the liquid pool, according to the above, it can be calculated that the maximum heat release rate of the oil pool fire in this paper is 5.3011 MW.

The model in this paper sets the fire type as a very fast-growing fire, and the corresponding fire growth coefficient $\alpha = 0.1878$ kW/s^2. According to the formula, it can be calculated that the time when the maximum heat release rate is reached is 168 s, and the combustion efficiency per unit surface area of the fuel is calculated to be 0.03424 $kg \cdot m^{-2} \cdot s^{-2}$, from the total volume of fuel in the pool fire and the mass combustion efficiency of the fuel, it can be calculated that the burning time of the pool fire is 686 s. The decline of sump burning is a relatively complex process. The time when the fire source begins to decline is affected by the fire structure and other factors, and it is difficult to obtain an accurate solution. The decay rate of most fuels is 0.0001 m/s, and at some point the fuel is consumed to the point where the combustion cannot support the maximum heat release rate and begins to decay. At this time, the heat radiation is generally higher, and the fire decay process is faster. The schematic diagram of the fire scene's heat release rate development curve in this paper is shown in Figure 5.

FDS software simulates and calculates the CO concentration and flue gas diffusion according to the chemical equivalent combustion reaction of the specified fuel. Setting the co-production rate, flue gas production rate, and other parameters is necessary. Aviation fuel is a complex mixture, and aviation kerosene was chosen as a typical fuel for simplicity. Under standard conditions, its thermophysical parameters are as follows (14). The contents in brackets are the interpretation of the command line:

&REAC ID = 'KEROSENE' (The fuel is called fuel oil)

FYI = 'Kerosene, C_14 H_30, SFPE Handbook' (The molecular formula is $C_{14}H_{30}$)

MW_FUEL = 198.0 (The molar mass is 198)

NU_O2 = 21.5 (The coefficient of O_2 is 21.5)

NU_CO2 = 14.0 (The coefficient of CO_2 is 14)

NU_H2O = 15.0 (The coefficient of H_2O is 15)

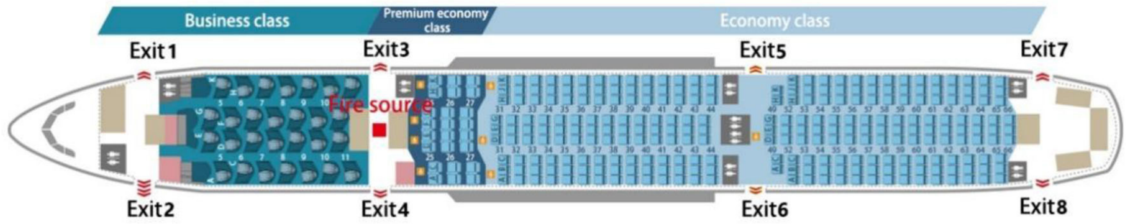

FIGURE 3
Diagram of each Exit number and the location of the fire source in the passenger compartment.

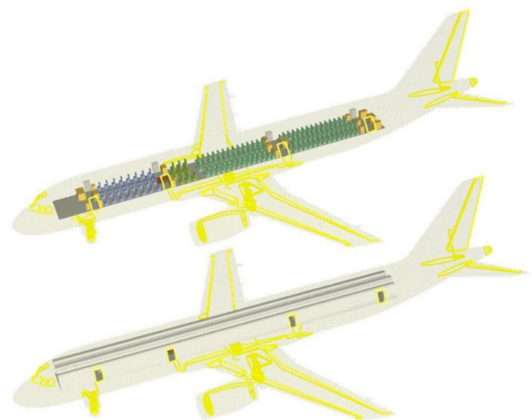

FIGURE 4
3D view of the PyroSim model of the Airbus A350-900 aircraft and cabin.

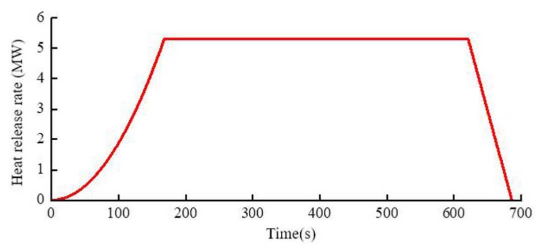

FIGURE 5
Growth curve of heat release rate.

EPUMO2 = 12700 (The energy released per unit mass of oxygen is 12700 kJ/kg)

CO_YIELD = 0.012 (The CO generation rate from combustion is 0.012)

SOOT_YIELD = 0.042/(The soot generation rate is 0.042)

The survey found that most passengers of medium and long-range wide-body airliners are adults. The average height of adults in China is about 1.70 m. It can be considered that the mouth and nose of passengers in the cabin during evacuation movement are about 1.65 m from the cabin ground. Therefore, this paper takes the cabin ground as the reference plane ($H = 0$ m), and the monitor is set at the height of $H = 1.65$ m, which is arranged concerning the layout of various types of seats in the cabin. A total of 312 observation points are set in the model. The positions of each observation point are shown in Figure 6. In the figure, the left side is the nose side of the aircraft, the observation points in business class are numbered from observation point 1 to observation point 32, and the observation points in super economy class are numbered from observation point 33 to observation point 56, and the observation points in economy class are numbered from observation point 57 to observation point 312. The numerical CO concentration, temperature, and visibility changes can be measured at each observation point. In the following chapters of this paper, these 312 observation points are selected to evaluate the safety indexes near all types of seats of the Airbus A350-900 wide-body airliner.

When a fire occurs, there will be many adverse factors that will cause harm to the human body. In this paper, the commonly used indicators in the fire are selected to analyze the available safe evacuation time of cabin fire. To ensure that passengers in the cabin can complete safe evacuation in the case of a cabin fire, the following specific quantitative standards are set as the critical value of danger for further analysis:

(1) The CO concentration in the passenger cabin at the height of 1.65 m from the ground is <50 ppm, which is converted into 0.00005 mol/mol commonly used in Pyrosim software;
(2) The flue gas temperature in the passenger cabin at the height of 1.65 m from the ground is <60°C;
(3) The visibility of the passenger cabin at the height of 1.65 m from the ground is >5 m.

Simulation and results

Fire simulation and analysis

After investigation, it is found that the forced landing of passenger aircraft is often accompanied by incidental fire

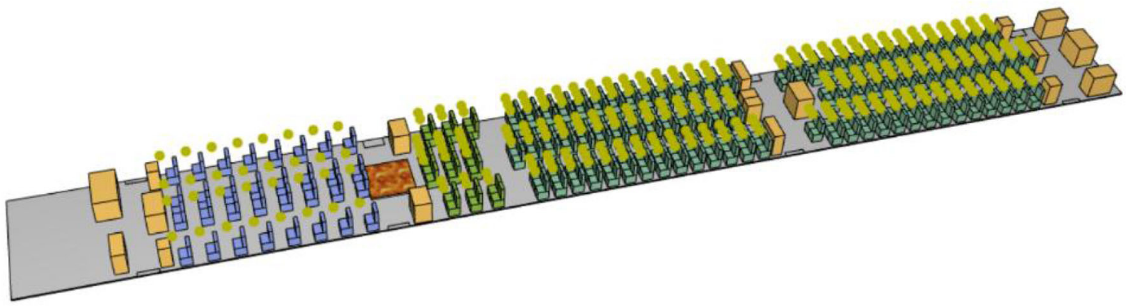

FIGURE 6
Location diagram of 312 observation points of the cabin model.

accidents, and the passenger aircraft is often in a horizontal and inclined state during the forced landing. Among them, the front landing gear of the passenger aircraft bears a huge impact force when landing, and the phenomenon of failure is not uncommon. When this happens, the passenger plane is often prone to lean forward, and the dynamic development of the fire at this time is also quite different from that when the passenger plane is in a horizontal and normal state. Therefore, it is necessary to carry out a comparative study of the two states.

When the airframe of the airliner is functioning normally, the front and rear landing gears are not damaged and can work normally, and the pilot drives the airliner properly so that the airliner is forced to land normally without tilting. As shown in Figure 7, the airliner remains horizontal after the forced landing. The length of the simulation time considers the specific simulation objects and scenarios. According to the relevant airworthiness regulations and practical experience of civil aviation aircraft, and this paper studies the passenger evacuation problem in the cabin fire scenario, the fire simulation time can be set as 200 s.

To obtain the ASET at each seat in the cabin, it is also necessary to calculate and analyze the time for the three indicators of CO concentration, temperature, and visibility to reach the dangerous critical value at the height of 1.65 m at the 312 observation points above the 312 seats under the two states of the airliner (15, 16). To select the time when any of the three safety evaluation indicators at each observation point first reaches the critical value of danger as the available safe evacuation time for the observation point.

When the airliner is in a horizontal state, the minimum time when any of the three safety indicators at each seat of the airliner reaches the critical value is calculated as the available safe evacuation time there, and the spatial distribution map of the airliner in the horizontal state is drawn, as shown in Figure 8.

From Figure 8, the distribution of ASET in the horizontal state of the passenger aircraft is analyzed as follows:

(1) Within the area of 6–12 m relative to the longitudinal position of the cabin: this area is mainly business class. Since this area is relatively close to the fire source, it is significantly affected by the fire, and the safe evacuation time is within 70 s. The seat temperature near the sidewall of the cabin reaches the critical value first, and the ASET is shorter;
(2) Within the 12–23 m area relative to the longitudinal position of the cabin: this area contains a small number of business class seats and all super economy class seats. The fire source is in this area, which is most affected by the fire. The available safe evacuation time of each seat is almost all within 60 s, and the temperature and visibility of most areas reach the critical value first;
(3) Within the area of 23–34 m relative to the longitudinal position of the cabin: this area includes all the economy class seats set in the middle of the cabin. The area affected by the fire gradually decreases from the front side to the rear side, the available safe evacuation time ranges from 60 to 90 s, and most areas are also the first to reach the critical value of temperature and visibility;
(4) Within the area 34 m behind the longitudinal relative position of the cabin: this area includes all the economy class seats arranged in the rear section of the cabin. Since this area is the farthest from the fire source, it is relatively less affected by the fire. Except for a few seats near the sidewall of the cabin, the available evacuation time is shorter, and the ASET of the rest of the seats is >90 s. The seats in this area are generally safe. The visibility index is the first to reach the critical value of danger.

When the airliner is forced to land, if the pilot does not operate properly and the uncertainty of the forced landing position is added, the probability of collision damage and failure of the nose landing gear is very high. The Airbus A350-900 aircraft studied in this paper adopts the front three-point landing gear design. The disadvantage of this landing gear design is that

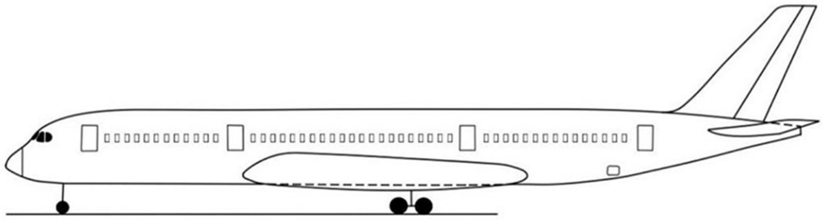

FIGURE 7
Schematic diagram of an airliner in the horizontal state.

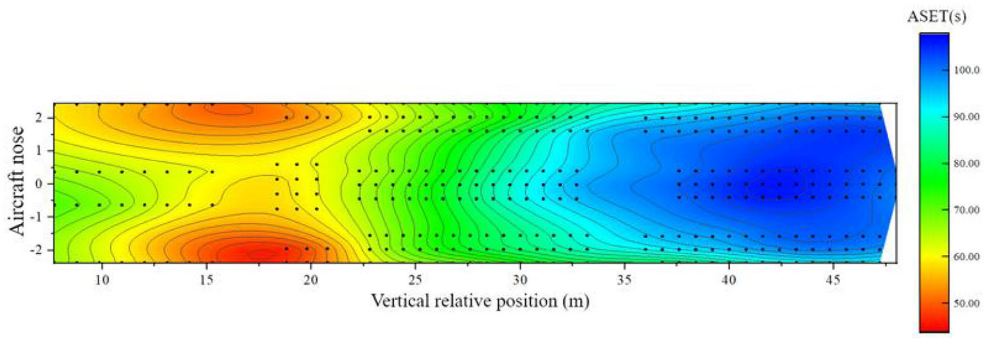

FIGURE 8
Distribution of available evacuation time under horizontal cabin state.

the front landing gear bears a large load. If the aircraft adopts an abnormal landing attitude, it can easily cause damage and failure. The passenger will lean forward, as shown in Figure 9.

Similarly, the distribution of ASETs around the cabin when the aircraft is tilted forward can be calculated, as shown in Figure 10.

From Figure 10, the analysis of the ASET distribution in the forward tilt state of the passenger aircraft is as follows:

(1) Within the 6–13 m area relative to the longitudinal position of the cabin: this area is mainly for most of the seats in business class. Although this area is relatively close to the fire source, under the influence of the forward tilt of the airliner, the available safe evacuation time is almost always >70 s, which is improved compared with the horizontal state. The available evacuation time for a small number of seats closest to the nose side is >100 s. The temperature of most seats in this part of the area is the first to reach the dangerous threshold;
(2) Within the 13–26 m area relative to the longitudinal position of the cabin: this area contains a small number of business class seats, all super economy class seats, and a small number of economy class seats set in the middle of the cabin. The fire source is located in this area, the most significant area in the cabin affected by the fire. Each seat's available safe evacuation time is mostly within 60 s, and the ASET of the seats near the bulkhead is <50 s. The indicator reaches the dangerous threshold very quickly;
(3) Within the 26–35 m area relative to the longitudinal position of the cabin: this area includes most of the economy class seats set in the middle of the cabin. The influence degree of the area affected by the fire from the front side to the backside is not obvious compared with the horizontal state, and the available safe evacuation time ranges from 60 to 80 s, and most areas are also the first to reach the critical value of temperature and visibility;
(4) Within the area 35 m behind the longitudinal relative position of the cabin: this area includes all the economy class seats set in the rear section of the cabin. Since this area is the farthest from the fire source, the available evacuation time is relatively long, almost all-around 80 s. Due to the influence of the forward tilt, it is reduced compared with the horizontal state, and the temperature and visibility are the first to reach the critical value of danger.

Evacuation simulation and analysis

1. Setting of evacuation scenarios

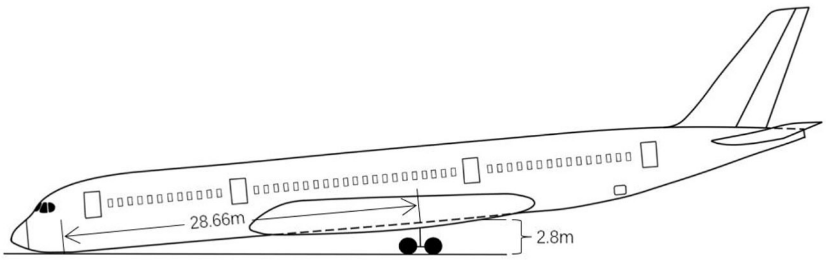

FIGURE 9
Schematic diagram of the passenger aircraft in a forward-tilted state.

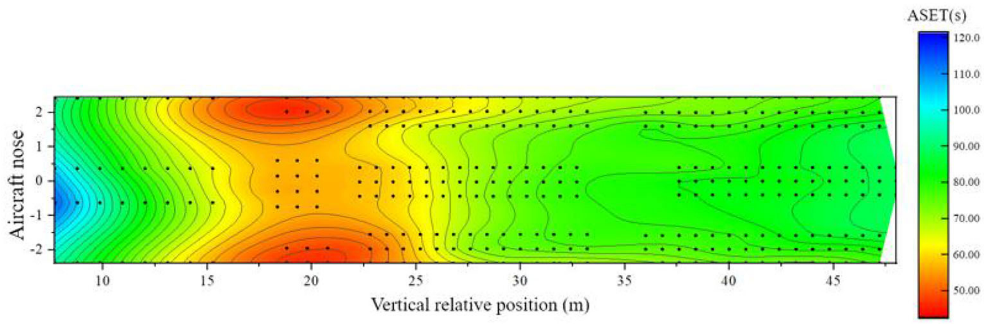

FIGURE 10
Distribution of available evacuation time when the cabin is tilted forward.

Through the analysis of the previous fire development results, it can be seen that after the emergency landing of the airliner and the fire occurs, the CO concentration, temperature, and visibility in the cabin are quite different when the cabin is horizontal and forward. Walking speed is also affected. When simulating cabin evacuation in this paper, two scenarios are set accordingly:

(1) Scenario 1: In the fire scenario when the cabin is in a horizontal state after a forced landing, the evacuation scenario in which all passengers are at their seats when the cabin is fully loaded;
(2) Scenario 2: In the fire situation when the cabin is in a forward-tilted state after the forced landing, the evacuation scene is in which all passengers are in their seats when the cabin is fully loaded.

2. Setting of cabin door conditions

In this paper, the forced landing of the passenger aircraft is considered to be in a horizontal forward-tilted state. Under this emergency evacuation condition, all cabin doors are considered to be able to open normally and immediately. In this model, the cabin is arranged with 8 cabin doors. However, corresponding to the maximum probability principle and the most unfavorable principle above, the fire occurred the Exit 3 and Exit 4 of the aircraft cabin near the nose side. It is assumed that people cannot be evacuated through Exit 3 and Exit 4, and the airliner is not level or forward. Cause other doors to fail, so this paper studies the situation where the other 6 Exits can be used for evacuation. For a large wide-body passenger aircraft with a huge passenger capacity, this situation is extremely unfavorable for evacuation. The default direction is the direction the seat is facing.

3. Setting of model personnel parameters

When using the software to simulate the evacuation of passengers in the cabin, the personnel attributes should be highlighted as much as possible to ensure that the simulation results are closer to reality. Generally, different genders and ages are often used in Pathfinder software to define different categories of personnel. In this paper Personnel, shoulder width is set to 40 cm. After a comparative analysis of the quarterly operating data and passenger turnover and other information released by a civil aviation airline, it was found that the ratio of male to female passengers was close to 6:4, and the age range: was 30–50 years old accounted for about 70%; under 30 years old accounted for 20% about 10%; the rest account

TABLE 5 Age and gender settings of evacuees.

Passenger category	Number of passengers	Proportion (%)
Women aged 29 and younger	25	8.01
Men aged 29 and younger	37	11.90
Women aged 30–50	87	27.90
Men aged 30–50	131	41.93
Women 51 and older	13	4.17
Men 51 and older	19	6.09
Total	312	100

TABLE 6 The empirical formula for the walking speed of personnel on the level ground (22).

Gender	Age (n)	Walking speed (m/s)
Women	2–8.3	0.06n + 0.5
	8.3–13.3	0.04n + 0.67
	13.3–22.25	0.02n + 0.94
	22.25–37.5	– 0.018n + 1.78
	37.5–70	– 0.01n + 1.45
Men	2.0–5.0	0.16n + 0.3
	5–12.5	0.06n + 0.8
	12.5–18.8	0.008n + 1.45
	18.8–39.2	– 0.01n + 1.78
	39.2–70	– 0.09n + 1.75

for about 10%. The maximum passenger capacity of the airliner is 312 people, according to which the personnel is divided as follows. See Table 5 for details.

This paper believes that the main factors affecting the walking speed of people on the ground in the cabin are age and gender. After consulting, it was found that there is no official approved clear regulation on the walking speed of evacuees in China. Therefore, this paper refers to the relevant empirical formulas summarized by some foreign scholars for estimation (17–21). Scholars summarized the relationship between people's walking speed on flat ground and age and gender. Generally speaking, people aged 29 and below walk faster. When the age is the same, the walking speed of men is often higher than that of women. The specific empirical formula of walking speed on flat ground is shown in Table 6.

Referring to the above empirical formula, the walking speeds of people of different ages and genders in the passenger cabin passageway can be approximately estimated, respectively, as shown in Table 7.

In the evacuation situation when the airliner is tilted forward by 5.6°, due to the complicated cabin conditions, how to change the overall speed of the personnel has

TABLE 7 The walking speed of different groups of people in the aisle when the cabin is horizontal (23).

Passenger category	Cabin aisle personnel walking speed		
	Minimum speed	Maximum speed	Average speed
Women aged 29 and younger	0.91	1.63	1.27
Men aged 29 and younger	1.08	1.81	1.45
Women aged 30–50	0.78	1.28	1.03
Men aged 30–50	0.92	1.66	1.29
Women 51 and older	0.58	0.97	0.78
Men 51 and older	0.88	1.45	1.17

TABLE 8 The walking speed of different groups of people in the aisle when the cabin is tilted forward.

Passenger category	Cabin aisle personnel walking speed		
	Minimum speed	Maximum speed	Average speed
Women aged 29 and younger	0.82	1.71	1.22
Men aged 29 and younger	0.97	1.90	1.39
Women aged 30–50	0.70	1.34	0.99
Men aged 30–50	0.83	1.74	1.25
Women 51 and older	0.52	1.02	0.74
Men 51 and older	0.79	1.52	1.12

become a more complicated problem. In this article, we reduce the minimum individual speed by 10%, increase the maximum individual speed by 5%, and the average moving speed of passengers is appropriately reduced to simplify processing, as shown in Table 8.

4. Cabin exit settings considering the capacity of aircraft slides

   The passenger cabin of a passenger aircraft is a long and narrow cavity, the ground in the cabin is flat, and the evacuation path is relatively simple. It's the dual aisle in the cabin. The evacuation Exits are symmetrically distributed on the left and right sides of the cabin, with a total of 8, and the width of each Exit is 0.9 m.

In the emergency evacuation scenario of a real aircraft forced landing, passengers need to be evacuated from the Exit of the cabin door through the escape slide. Therefore, the evacuation efficiency of passengers is closely related to the capacity of the escape slide. The evacuation flow of the escape slide is generally smaller than that of the cabin door, which will cause passengers to wait at the cabin door and

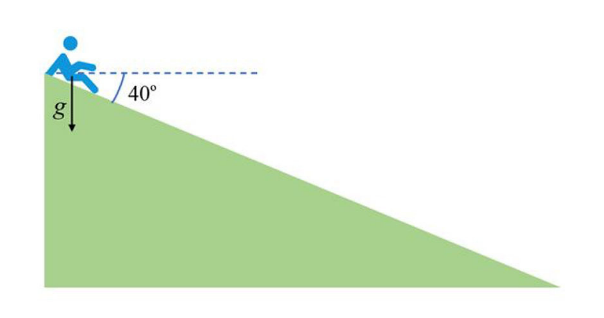

FIGURE 11
Equivalent schematic diagram of the escape slides at each Exit when the airliner is level.

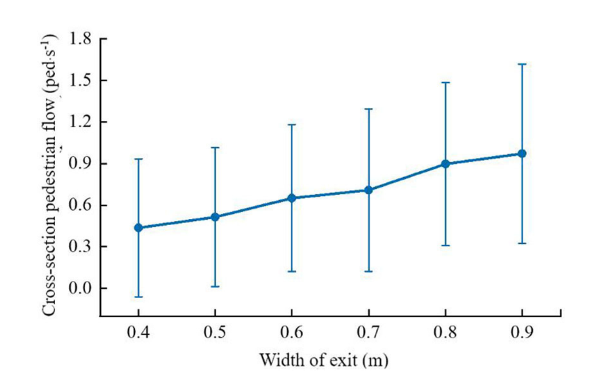

FIGURE 12
Outlet section flow corresponding to different outlet widths (mean ± standard deviation).

reduce the evacuation efficiency of the people in the cabin. Therefore, it is necessary to analyze the evacuation capacity of the escape slide, but the Pathfinder software does not support pedestrians escaping by The slide carries out the motion simulation of evacuation behavior by sliding down, and there are few evacuation experiments on aircraft escape slides, so the relevant slide flow experimental data has not been obtained yet. In the actual situation, there is a large section in the process of people sliding down the slide in the suspended state and doing parabolic motion, so the actual friction force is ∼0. Based on this, when the passenger cabin is in a horizontal state, this paper takes the aircraft escape slide equivalent to a smooth slope with a depression angle of 40° to carry out the ideal calculation, and its equivalent schematic diagram is shown in Figure 11.

In this paper, it is assumed that the length of the slide is fixed at 7 m, and the pedestrian is accelerated by gravity from the top of the slide with an initial velocity of 0 at the exit of the passenger cabin at a height of 4.5 m from the ground, and its sliding acceleration $a = g \times \sin[(40 \times \pi)/180]$, from this, it is calculated that the time for the passenger to fall from the top of the slide to the bottom is about 1.49 s. Assuming that the next passenger immediately falls from the top after the previous passenger leaves the slide, ignoring the influence of other factors, it is calculated that The corresponding flow is 1 divided by 1.49 equals 0.68 ped/s. When the cabin is tilted forward, the calculation method of the evacuation flow of slides with different angles from the ground is the same.

In this paper, it is assumed that the length of the slide is fixed at 7 m, and the pedestrian is accelerated by gravity at the exit of the passenger cabin at the height of 4.5 m from the ground at the top of the slide with an initial velocity of 0. From this, it is calculated that the time for a passenger to fall from the top to the bottom of the slide is about 1.49 s. Assuming that the next passenger immediately falls from the top after the previous passenger leaves the slide, ignoring the influence of other factors, the corresponding flow rate is calculated to be 0.68 ped/s. Therefore, to consider the influence of the evacuation capacity of the slide on the evacuation efficiency of the aircraft, it is necessary to perform an equivalent calculation on the width of the hatch according to the calculated flow of the slide. In this section, a single-exit room scenario is established to analyze the evacuation flow of pedestrians under different Exit width conditions. The room size is 10 × 10 m, the personnel density is uniformly set to 2 ped/m^2, and other personnel parameter settings are consistent with the above.

By setting different outlet widths (the width is shortened from 0.9 to 0.4 m in turn), the changes in the point section flow under the condition of different outlet widths are obtained, and the average evacuation section flow of different outlet widths is obtained according to the statistics of the outlet flow distribution, as shown in Figure 12.

It can be seen from the figure that when the width of the exit is 0.7 m, the average flow rate of the evacuation is close to 0.68 ped/s. Therefore, in this paper, considering the evacuation flow of passengers via the evacuation slide, the width of the exit of the passenger door is revised to 0.7. The equivalent width of m is used to carry out the evacuation simulation of the passenger aircraft when it is horizontal.

In the same way, after the airliner tilts forward, the distance between Exit 1 and Exit 2 from the ground is reduced to about 3 m. After calculation, the angle between the slide and the ground is 26°, and the time it takes for passengers to slide from the top to the bottom of the slide is About 1.80 s, the corresponding flow is calculated to be about 0.56 ped/s. The distance from Exit 7 and Exit 8 to the ground increases, about 5.8 m. After calculation, the angle between the slide and the ground is 56°, and the time for passengers to slide from the top of the slide to the bottom

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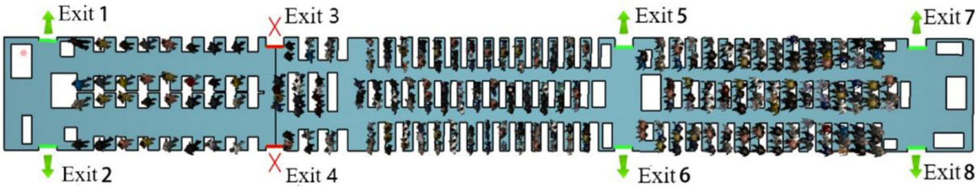

FIGURE 13
Schematic diagram of passenger cabin evacuation model.

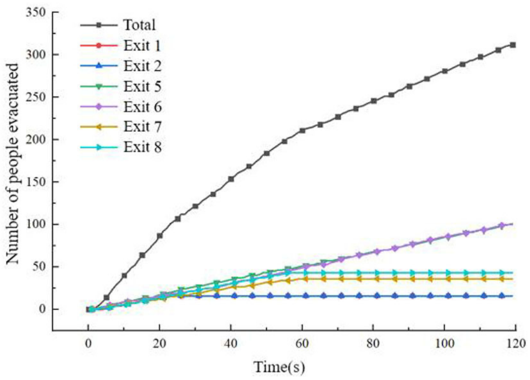

FIGURE 14
Statistics of the number of evacuees when the cabin is horizontal.

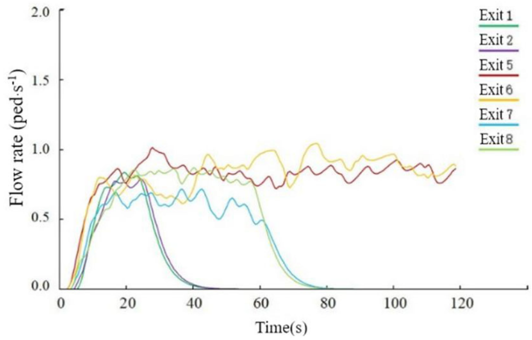

FIGURE 15
The flow of each outlet when the cabin is in a horizontal state.

is about 1.31 s. Calculate the corresponding flow rate of About 0.80 ped/s. Therefore, this paper also considers the evacuation flow of passengers through the evacuation slide when the passenger aircraft is tilted forward, and the width of the passenger door Exit 1 and Exit 2 is corrected to an equivalent width of 0.5 m, and the width of the passenger door Exit 7 and Exit 8 is corrected to an equivalent width of 0.8 m, and the height of Exit 5 and Exit 6 does not change significantly when the passenger aircraft tilts forward, so the equivalent width of 0.7 m is still selected, and the following is the case after the passenger aircraft tilts forward? Personnel evacuation simulation.

By studying the internal structure of Airbus A350-900 wide-body passenger aircraft, evacuation dual aisles, door position and passenger seat distribution information, and related parameters, combined with other parameter settings above, the construction of the cabin personnel evacuation model is completed. The schematic diagram of the model is shown in Figure 13.

When the passenger cabin is in a horizontal state, the evacuation speed of personnel decreases to a certain extent in the middle of the evacuation, and the evacuation efficiency of passengers in the cabin is not high during some periods. The specific evacuation situation is shown in Figure 14.

As seen from Figure 14, in the middle of the evacuation, all passengers moved to the evacuation channel or near the evacuation exit, which caused a certain congestion phenomenon, resulting in a decrease in the evacuation rate. At about 25 s, the number of people evacuated at Exit 1 and Exit 2 no longer increased, and at about 55 s, The number of evacuees at Exit 7 and Exit 8 no longer increased, indicating that the above four exits were idle at the corresponding time, and the average utilization rate of the exits was not high. In the later evacuation period, the remaining passengers were evacuated only through Exits 5 and 6. The flow at the exit is shown in Figure 15. After 119.8 s, all 312 passengers were evacuated.

The necessary evacuation time consists of three parts: early warning time, passenger response time, and movement time (24–26). Figure 16 shows the distribution of the necessary evacuation time for passengers at different seats in the passenger cabin when the passenger cabin is in a horizontal state under the condition of full load. The higher the evacuation efficiency of the individual, the shorter the time required for evacuation and the smaller the safety risk borne by the movement of the safety exit.

Combined with the analysis of the evacuation situation in the horizontal state of the aircraft, it can be seen from Figure 16 that:

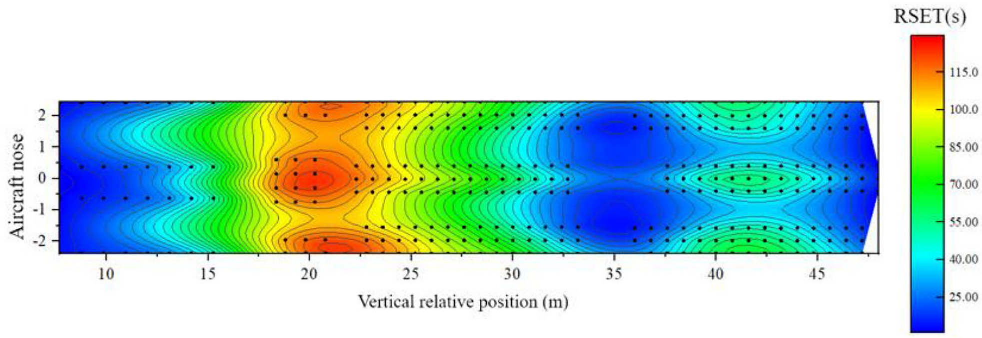

FIGURE 16
Distribution of necessary evacuation time when the cabin is horizontal.

(1) The RSET of passengers in business class is the smallest. All passengers use Exit 1 and Exit 2 for evacuation. The RSET of passengers in the cabin is basically within 25 s, which is the safest class in the passenger cabin, and the evacuation risk is relatively low;
(2) Passengers in the super economy class have the largest RSET. Under the most unfavorable evacuation conditions set in this paper, since exits 3 and 4 cannot be used for evacuation and escape, the super economy class is the farthest from the evacuation exit, and the people on the evacuation path are the farthest. The dense and crowded phenomenon is serious, and the RSET of a small number of passengers has even reached several times that of passengers in business class, which is the most dangerous class in the cabin, and the risk of evacuation is the highest;
(3) The main reason for the short RSET of business class is that business class with a passenger capacity of 32 people in the class with the most sparse distribution of people, and there are many evacuations exits available per capita. At the same time, the RSET of passengers in seats close to the exits also be significantly smaller than in other locations;
(4) Passengers in the middle seats of the same class in the cabin, especially those not adjacent to the aisle, have unfavorable factors for evacuation, such as long evacuation paths, dense distribution of people in the area, and small movement space, which lead to the evacuation of these passengers. It is easier to be congested, the evacuation time is longer, the evacuation efficiency is lower, and the evacuation risk is relatively higher.

Corresponding to the PyroSim fire model of the passenger aircraft cabin in the forward tilt state, the cabin is tilted forward 5.6°, the nose side touches the ground, and the schematic diagram of the cabin model in the forward tilt state is shown in Figure 17.

Figure 18 shows the distribution of necessary evacuation time for passengers at different seats in the cabin under full load when the passenger cabin is tilted forward.

Combined with the analysis of the evacuation situation when the passenger aircraft is tilted forward, it can be seen from Figure 18 that:

(1) The forward tilt angle of the cabin is 5.6°, which has little effect on the spatial distribution of the overall available evacuation time. Passengers in business class have the smallest RSET, which is basically within 25 s. Similar to when the cabin is in a horizontal state, business class is still a relatively safer class in the passenger cabin, with the lowest evacuation risk;
(2) Super economy class and close to fire sources Some passengers in economy class seats have the longest RSET, most of which are several times more than the RSET of passengers in business class. The necessary evacuation time for a small number of passengers is about 130 s. This part of the area is the most dangerous area in the passenger cabin. Evacuation risk is the highest.
(3) There is little difference between other evacuation conditions and when the cabin is in a horizontal state.

Risk analysis of personnel safety evacuation

When ASET > RSET, that is, ASET-RSET > 0, personnel can evacuate safely before suffering adverse effects from emergencies. Define T_{rem} (T_{rem} = ASET – RSET) as the remaining evacuation time. When $T_{rem} > 0$, passengers can evacuate the area before being affected by the fire accident. The smaller T_{rem} is, the longer the passenger is exposed to the fire risk, and the greater the risk; the greater the T_{rem}, the earlier the

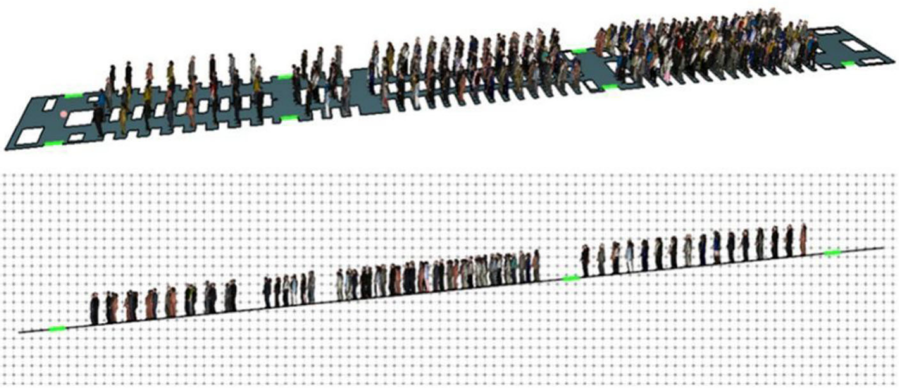

FIGURE 17
Schematic diagram of the model when the cabin is tilted forward.

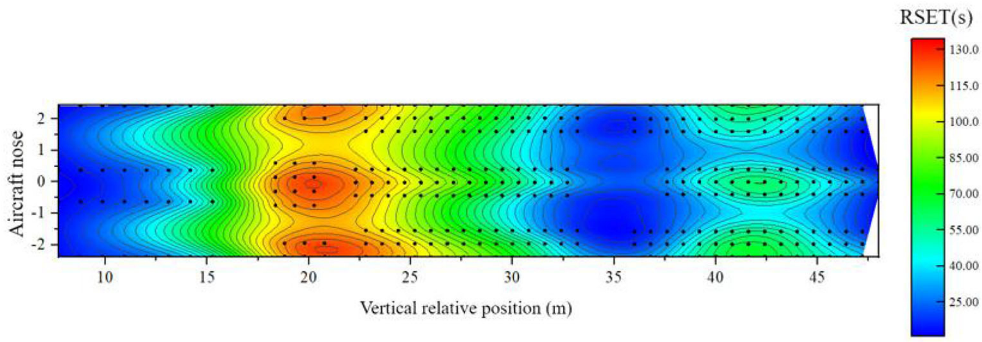

FIGURE 18
Distribution of necessary evacuation time when the cabin is tilted forward.

passenger is away from the danger brought by the fire, and the smaller the risk (27, 28).

Distribution of remaining evacuation time

When the airliner is in a horizontal state, there are 86 seats in the three classes of cabins, and the risk of safe evacuation is high. Figure 19 shows the distribution of the remaining evacuation time of passengers at different positions in the fully-loaded cabin.

Combined with the previous analysis of the cabin in a horizontal state, it can be seen from Figure 19 that:

(1) In the area of 6–16 m relative to the longitudinal position of the cabin: this area is the area where the business class seats are located, and the remaining evacuation time is about 15–55 s. between. Although the fire source is close to this area, the overall safe evacuation time is short, but the distribution of people is relatively sparse and there are many evacuation exits available per person, and the evacuation of people is faster and the RSET is shorter, so the overall safety is relatively low. There are 6 passengers in this area with a high risk of safe evacuation;

(2) In the 16–30 m area relative to the longitudinal position of the cabin: this area is the area where the super economy class and the economy class seats set in the middle of the cabin is located. The remaining evacuation time is <0 s, and the remaining evacuation time at some seats is even lower than − 65 s. It is the most unsafe area in the entire cabin. The main reason is that the area is close to the fire source, the ASET of most seats is short, and the failure of exit 4 resulted in a significant increase in the RSET of passengers in this area. There are 73 passengers in this area with a high risk of safe evacuation;

(3) In the area 30 m behind the relative longitudinal position of the cabin: this area is the area where the remaining economy class seats in the cabin are located, and some

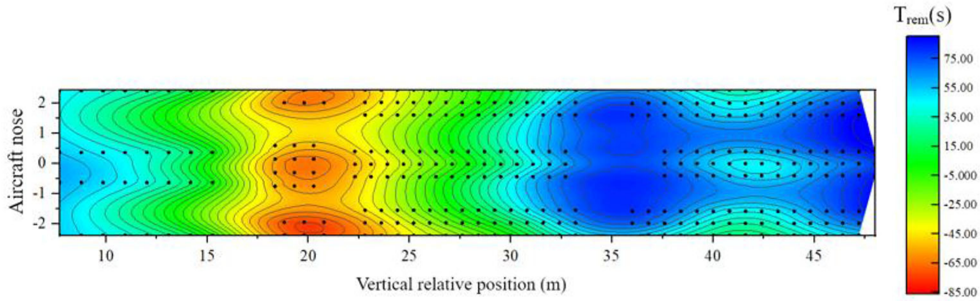

FIGURE 19
Distribution of remaining evacuation time when the cabin is horizontal.

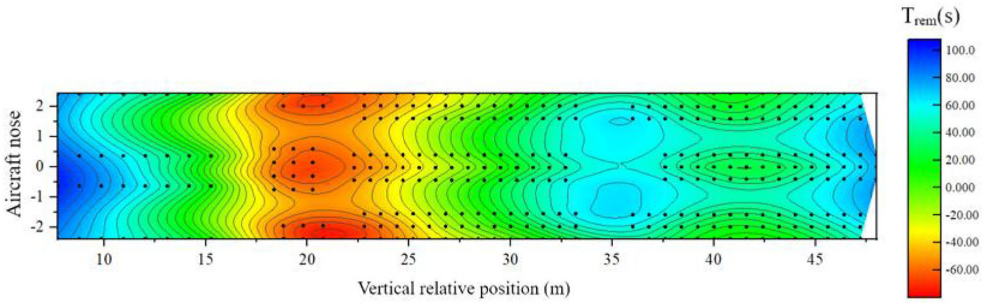

FIGURE 20
Distribution of remaining evacuation time when the cabin is tilted forward.

seats in this area are not adjacent to the aisle. The remaining evacuation time of the passengers is about –5 s. Although this area is far from the fire source, the density of people is higher than that of other classes, resulting in a large load at the evacuation exit and clear congestion, resulting in a longer RSET for passengers in the middle. This layout The lower passenger ASET near the bulkhead is relatively short and more vulnerable to fire. Seven passengers in the area are at high risk for safe evacuation.

When the airliner is tilted forward, there are 97 seats in the three classes of cabins, with a high risk of safe evacuation. Figure 20 shows the distribution of the remaining evacuation time for passengers at different positions in the fully-loaded cabin.

(1) In the area of 6–13 m relative to the longitudinal position of the cabin: this area is the area where most of the business class seats are located near the nose side, and the remaining evacuation time of passengers is more than 40 s. Although the fire source is close to the area, the overall available safe evacuation time is short, but the distribution of people in this area is relatively sparse, and there are many evacuation exits available per person, which makes the evacuation of people fast. Spread, the seat ASET on the nose side away from the fire source is extended compared to the horizontal state. There are 4 passengers in this area with a high risk of safe evacuation;
(2) Within the 13–35 m area relative to the longitudinal position of the cabin: this area includes business class seats, super economy class seats, and economy class seats set in the middle of the cabin, which is close to the fire source. The remaining evacuation time in the area near the fire source is less than -the 40 s, and some seats are even less than -the 60 s. Passengers close to the bulkhead are affected by the fire more quickly. This area is the most unsafe in the entire cabin. There are 83 passengers in this area with a high risk of safe evacuation;
(3) In the area 35 m behind the relative longitudinal position of the cabin: this area is the area where the economy class seats are located in the rear section of the cabin, and the remaining evacuation time for passengers in the middle section of this section is About - 10 s, although the area is far away from the fire source, the speed of the smoke reaching the area is accelerated under the action of the forward tilt of the passenger aircraft, which leads to the shortening of ASET. Similarly, under the "3-3-3"

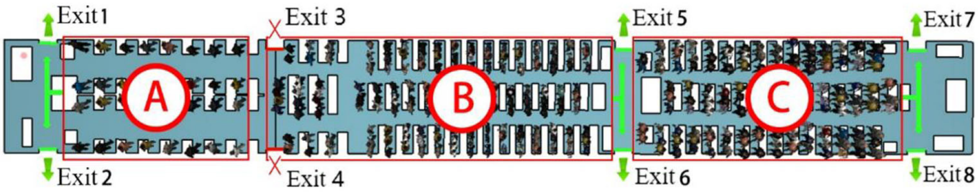

FIGURE 21
Schematic diagram of the evacuation optimization scheme for adding guidance.

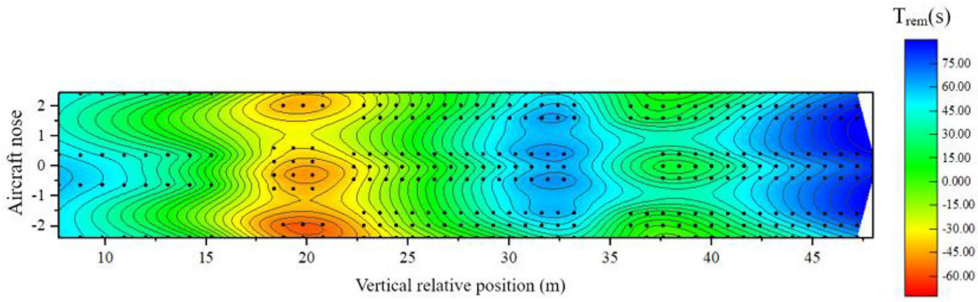

FIGURE 22
Distribution of remaining evacuation time after adding guidance.

horizontal layout of the seats. The area is a den, densely populated, the evacuation exit is heavily loaded, and the congestion is also obvious, resulting in a longer RSET for passengers far from the exit in the middle of the area. There are 10 passengers in the area with a high risk of safe evacuation.

To sum up, when the cabin is tilted forward, the safe evacuation risk in the cabin is higher than the risk when the cabin is in a horizontal state, and the evacuation situation when the cabin is tilted forward, and a fire occurs is a more dangerous situation than the conventional horizontal state. Therefore, putting forward a targeted cabin evacuation optimization scheme has important reference significance in the engineering practice in the field of aircraft safety.

Optimal design scheme for evacuation

The evacuation pressure of Exit 5 and Exit 6 in the middle is high, and the utilization rate of the four cabin doors available for economy class passengers is uneven, resulting in different degrees of congestion, resulting in low overall evacuation efficiency. Given the above situation, it is proposed to add zoning guidance to rationally allocate the use of available evacuation exits instead of using the overall passenger to select exits based on the nearest principle. In two states, horizontal and forward, this section analyzes the optimization method in the horizontal state of the cabin.

The specific method is to divide the business class into area A, and guide all passengers in this area to evacuate to Exit 1 and Exit 2 during evacuation; divide the super economy class and the economy class set in the middle of the cabin into area B, and guide all passengers in this area during evacuation. Evacuate to Exit 5 and Exit 6; divide the remaining economy class into area C, and guide all passengers in this area to evacuate to Exit 7 and Exit 8 during evacuation. The specific guidance optimization scheme is shown in Figure 21.

The distribution of the remaining evacuation time after optimization is as follows:

It can be seen from Figure 22 that this scheme improves the evacuation efficiency of this part of the passengers by alleviating the congestion in the middle section of the cabin where the risk of cabin evacuation is the highest, effectively reducing the evacuation risk of passengers in area B, and optimizing the remaining cabin. Evacuation time distribution. The optimized cabin evacuation situation is shown in Figures 23, 24:

After adding evacuation guidance, the overall evacuation time of the cabin is reduced to 111.3 s compared with 119.8 s before optimization, and the reduction is 8.5 s. As seen from the above figure, the evacuation flow of Exit 5, Exit 6, Exit 7, and Exit 8 is more balanced, and the utilization rate of available exports improved. Passengers in area C no longer use Exit 5 and Exit 6 for evacuation, which reduces the evacuation pressure on the

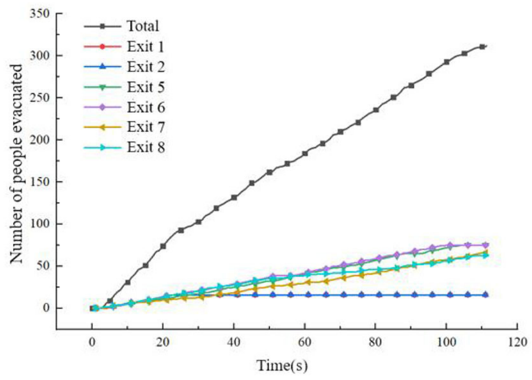

FIGURE 23
Statistics of evacuated people after adding guidance.

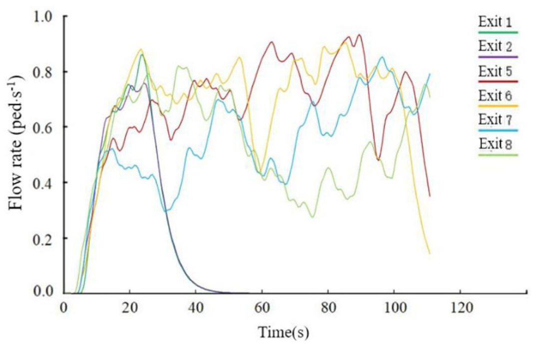

FIGURE 24
Each outlet flow after optimization.

pair of exits and reduces the congestion of people near the pair of exits. After optimization, the evacuation situation in area A has not changed from the previous one. There are 6 passengers with a high risk of safe evacuation; 64 passengers in area B have a high risk of safe evacuation; 8 passengers in area C have a high risk of safe evacuation, with a total of 63 passengers. The risk of safe evacuation is high, a total of 8 people have been reduced compared with before optimization, and the reduction ratio is 9.3%.

Conclusion

In this paper, by setting the fire scene in the cabin of the wide-body dual-aisle civil airliner Airbus A350-900, FDS software is used to simulate the fire development process caused by the second pair of mid-section aviation fuel leakage, and the impact of changes in relevant parameters on the cabin evacuation risk is analyzed. According to the time when the 312 observation points corresponding to each seat reach the critical value of any safety evaluation index, the available safe evacuation time of all seats is calculated, and the ASET distribution of the entire cockpit is obtained. Then, the Pathfinder software is used to simulate the evacuation process of passengers in both horizontal and forward states. When the passenger plane is fully loaded, the necessary safe evacuation time for passengers with 312 seats is calculated, and the RSET distribution of the entire cabin is obtained. According to the distribution of ASET and RSET, the distribution of the remaining evacuation time in the cabin is calculated, the safety risks of passengers in different positions in the cabin are analyzed, and an evacuation optimization design scheme for optimizing the distribution of the remaining evacuation time is proposed.

According to the above model simulation results and analysis, it can be seen that the safety hazards of the Airbus A350-900 wide-body passenger aircraft mainly include: when a serious fire occurs in the cabin, passengers may not be able to complete safety before a certain safety level index reaches a critical value. The main reasons for this phenomenon are: in the worst case, the passengers in the cabin far away from the available evacuation exits have long evacuation paths, long evacuation time, and long RSETs for these passengers. Passengers in the cabin close to the bulkhead are more vulnerable to fire in a fire situation, resulting in their short ASET.

The study found that the forward tilt of the cabin caused the effects of the fire to spread more quickly into the rear space of the cabin, and the tilt of the cabin also affected the evacuation of passengers. The cabin's forward tilt can significantly adversely affect safe evacuation.

Data availability statement

The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding author/s.

Author contributions

WL and CZ: funding acquisition. WL, CZ, and YY: validation. WL: conceptualization and writing—original draft. LX and JL: formal analysis, methodology, and revising. CZ: supervision. CZ and YY: revision discussion. CZ, YY, LX, and JL: writing—review and editing. All authors contributed to the article and approved the submitted version.

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Conflict of interest

Author YY was employed by Saifeite Engineering Technology Group Co., Ltd.

The remaining authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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Exploring built environment factors on e-bike travel behavior in urban China: A case study of Jinan

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E-bike, characterized as a low-carbon and health-beneficial active travel mode, is gradually becoming popular in China. Although built environment factors are considered to be key parameters that can facilitate or hinder active transportation, such as cycling or walking, few studies have explored the impact of built environment on e-bikes. To fill this gap, this study was the first to explore the relationship between e-bike usage and built environment factors based on population level travel survey in central Jinan, China. Both macro and micro levels of built environment were measured using multi-source data. We employed ordinary least squares (OLS) and geographically weighted regression (GWR) models to explore the aggregation patterns of e-bike trips. Besides, the local Moran's I was employed to classify the aggregation patterns of e-bike trips into four types. The results from OLS model showed that eye-level greenery, building floor area, road density and public service POI were positive significantly related to e-bike trips, while open sky index and NDVI had negative association with e-bike trips. The usage of GWR model provided more subtle results, which revealed significant spatial heterogeneity on the impacts of different built environment parameters. Road density and public service POI posed positive effects on e-bike travel while NDVI and open sky index were found mainly pose negative impacts on e-bike travel. Moreover, we found similar coefficient distribution patterns of eye-level greenery, building floor area and distance to bus stop. Therefore, tailored planning interventions and policies can be developed to facilitate e-bike travel and promote individual's health level.

KEYWORDS

built environment, e-bike usage, multi-source data, geographical weighted regression, LISA, spatial heterogeneity, Jinan

Introduction

The prevalence of e-bike and its advantages

For the past few years, the built environment which is suitable for active transportation have attracted interests from various of fields including urban design, public health and transportation. Global economic development has been driven by the fossil energy consumption which improved human living conditions but caused air pollution and global warming and a series of environmental problems (1). Energy-saving, low-carbon, healthy lifestyle have become the common will of the government and citizens (2). Governments have implemented policies including improving energy efficiency, developing fossil energy substitution technologies, and using biocarbon sink technologies to reduce carbon emissions (3). In addition, it is a key intervention to maintain physical activity level and reduce chronic disease by encouraging residents to adopt active transportation (i.e., walking and cycling, e-bike) rather than apply motorized vehicles (4). Therefore, it is vital to understand the characteristics of active transportation and its driving factors for planning department and policy makers (5).

As an emerging active transportation mode, the advantages of e-bike are embodied in several ways. First, compared to traditional cycling, e-bike is time efficient (6) and aging-friendly which can help users to overcome obstacles of long distance and climbing (7). Meanwhile, e-bike travel also combines the advantages of promoting personal physical fitness and well-being (8). Specifically, e-bike travel can benefit those who are unwilling to engage in physical activity (i.e., overweight, disabled, and elderly) by helping them achieve moderate vigorous of physical activity (9, 10), which is known to support individual's social interaction (11) and mental health (8). Some studies have shown that e-bike travel improves metabolism (12), cardiovascular health (13) and allows riders to have lower level of perceived exercise and higher level of enjoyment (14). Moreover, e-bike is more economically efficient with lower purchase price, less operating and maintenance cost than automobile, thus is becoming a competitive alternative (15). In addition, some studies have shown that using an e-bike can reduce CO_2 emission by about 460 kg per year, which is an impressive social benefit (16).

The numerous benefits of e-bikes have made them popular with residents in many countries. It is expected that more than 40 million e-bikes will be sold worldwide in 2023 generating approximately 20 billion dollars in revenue (17). In some low-density Western countries such as Italy, Germany and Canada, residents ride e-bikes primarily for leisure and exercise (18). These countries often have a unique cycling culture, with sophisticated cycling facilities and fewer safety barriers. In the last few years, several countries, e.g., Belgium, Norway, Netherlands, have started to subsidize the purchase of e-bikes to support e-bike assisted commuting (19). Furthermore, majority cities in Asia are still in the rapid development stage. The high-density urban environment and high-intensity economic pressure have raised the great demand for e-bikes. According to statistics, the sales of e-bikes in countries including China, Vietnam and Japan are rising year by year, occupying more than half of the global market share (20). China, in particular, is a global leader in the manufacture of e-bikes as well as in the annual and total number of e-bikes sales. By the end of 2019, China had over 300 million e-bikes and the market size reached trillions (21). Rising gasoline price, declining e-bike technology cost and deteriorating road congestion and parking problem are the main reasons for the tremendous demands of e-bike (22). As housing price continually rises and the imbalance between job-housing relationship increases, residents' commuting distance has increased, thus e-bike is gradually regarded as a comfortable and efficient way for daily transportation (23).

Relationship between built environment and e-bike usage

Built environment is usually defined as man-made buildings and places which involve physical facilities as well as abstract elements such as human spatial perception (24). Built environment is measured in various ways. The macro-level built environment was first characterized by 3-Ds element (3Ds), namely density, design and diversity (25). Later studies added distance to public transportation and destination accessibility to form the 5Ds assessment framework (26). In addition, micro-level factors such as open sky, buildings, and greenery visibility perceived by residents were also included in the studies related to built environment (27).

Active travel behavior, as a fundamental travel mode of daily life, has been proven to have strong correlation with built environment elements. For example, proximity to commercial facility and low noise level were prove to be benefit for residents' walking and cycling (28). Pronounced building density and mixed land use had a positive influence on promoting active travel instead of automobile travel (29). Moreover, more residents would choose to travel by bicycle in the areas with high road density, proximity to green space and abundant bicycle parking facilities (30).

Currently, few studies have been conducted by scholars on e-bikes in relation to the built environment. Some studies showed that e-bike is an alternative vehicle in many Chinese cities (31). An empirical study revealed a non-linear association between built environment characteristics and e-bike holdings (32). E-bike holding has negative correlation to residence density while is positively related to distance to public transportation (32). The e-bike usage in China was different among various urban scales. Longer commuting distance in metropolis made e-bike less competitive that public transportation, while e-bike travel was found to be more attractive in middle-size cities (33). In addition, some studies showed that the travel patterns of residents in the rural area differ from those of urban residents. Certain road level (i.e., major trunk road or city road without bike lane) have positive effects in facilitating e-bike usage for rural residents (34).

Multi-source urban big data to assess built environments

Urban information collection plays a vital role in urban studies and travel behavior research. In the past, traditional urban research has long been constrained by field observation characterized as time-consumption, inefficiency, and small simple size (35). With the rapid development of big data, studies on built environment and travel behavior broke through the limitations of traditional data by applying emerging technologies which can obtain real-time and accurate data to quantify complex built environment factors. New urban data, such as social media data (36), heatmap (37), street view image (38), point of interest (POI) (39) and building footprint data (40), provide urban researchers with fine spatial and temporal granularity. However, the plenty advantages of urban big data cannot completely replace traditional data in some research. Urban big data and traditional data are complementary and the integration of the two is believed to be an inevitable trend (41). Currently, scholars are actively exploring methodologies and specific frameworks for urban research that combine traditional data with big data for the integration of data with various sources in city studies (42, 43).

Research gap and our study

Despite many studies exploring the relationship between traditional active transportation (i.e., walking, cycling) and the built environment, e-bike related studies were rarely emphasized (44, 45). Previous studies on e-bike travel mainly focused on the personal perception and travel preference of e-bike users (22, 46). Since e-bike is becoming a vital active travel mode in developing countries, clarifying the association between built environment and e-bike usage will enrich active transportation research and assist urban planners in developing more appropriate planning interventions.

In order to eliminate the research gap, e-bike usage was measured using 2019 residential travel characteristics survey in Jinan, China. We applied ordinary least squares (OLS) model, geographically weighted regression (GWR) and Moran's I to reveal the spatial distribution pattern of e-bike usage and the relationship between built environment factors and e-bike usage. This study makes contribution to the existing research from three aspects: (1) Using multi-source data, i.e., street view images and point-of-interest (POI) data to assess macro and micro built environment factors and expand 5D built environment framework. (2) Revealing the global and local effects of built environment on e-bike travel using OLS and GWR models. (3) To our knowledge, this study is among the first articles that attempts to reveal the mechanism of e-bike travel.

Materials and methods

Study area and spatial unit

Jinan, the capital of Shandong Province, is a mega-city with a long history. In the past 70 years, Jinan has developed rapidly with the built-up area expanding to 841.2 km^2 and the resident population growing to 9.336 million. Currently, Jinan has 12 county-level administrative districts (47). However, rapid urbanization has brought many problems to Jinan. The increasing number of urban motor vehicles aggravates the traffic pressure and exacerbates air pollution which has become a major source of urban environmental degradation. In 2020, Jinan ranked as the most congested city in China and the 11th most polluted city in terms of air pollution (48, 49). The drawbacks of motor vehicles have led to a surge in the number of e-bikes in recent years. According to the statistics, about 30.56% of Jinan residents choose e-bikes as their daily travel mode and there are more than 3.6 million e-bikes in Jinan and the number still grows (50). The growing demand for e-bikes places higher requirements on Jinan's future urban construction. Therefore, to unveil the relationship between urban built environment and e-bike travel can help to plan and build a better city.

The study area includes the central urban area of Jinan (116°51′36″-117°12′25″E, 36°32′51″-36°46′5″N) enclosed by the Jiguang Expressway, the Jingtai Expressway and the Jinan Bypass Expressway, with an area of 535.96 km^2 (Figure 1). Our study area is located at the central area of Jinan's master plan, and it serves as the core of Jinan's economic, political and cultural center. In the main urban area of Jinan, e-bikes as a flexible mode of travel play as a vital part in people's daily life. This study intends to unveil the relationship between built environment and e-bike usage in Jinan city.

With the increasing attention on active travel in various countries, the government is gradually promoting the construction of 15-minute city (51), where 500–800 m is considered proximity to neighborhood residents' activity and is therefore widely applied in walking- or cycling-related studies (52). In the study area, a 600 × 600 m rectangular grid was generated as the basic analytical unit which can facilitate the integration of urban built environment statistics with e-bike usage data (Table 1), and help to eliminate the effect of uneven administrative division (53). Then,

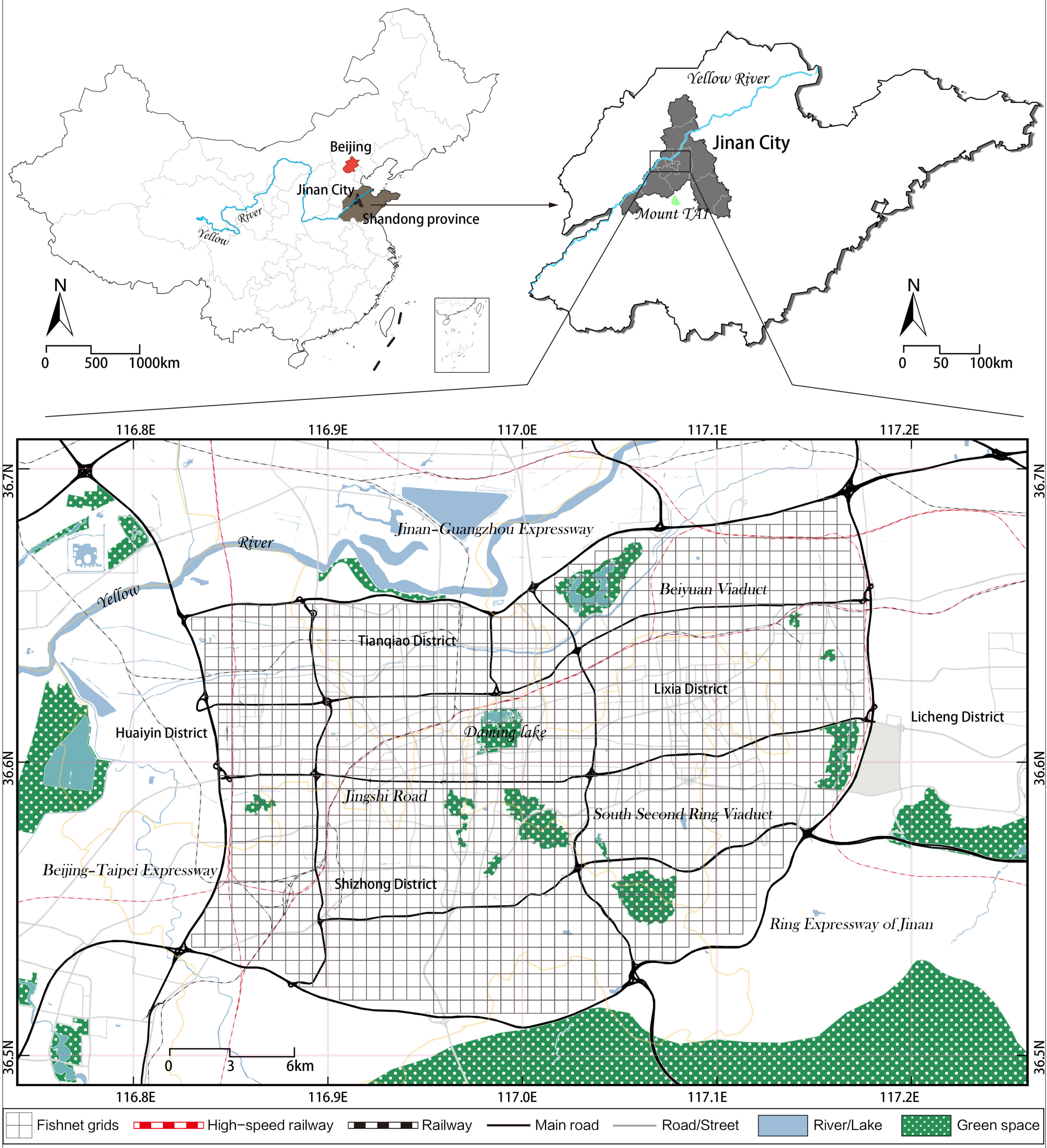

FIGURE 1
Location of the study area.

the data related to e-bike travel behavior and urban built environment were processed and imported into the mapping and analysis software ArcGIS (version 10.6) for geocoding, among which the grids that did not contain e-bike travel data were removed, leaving a total of 770 grids in the study area.

TABLE 1 Definitions of the dependent and independent variables.

Variables (unit)	Definition
Dependent variable	
Number of E-bike trips (N)	The total amount of e-bike trips (destination or origination) in each grid
Independent variable	
Micro scale built environment	
Eye-level greenery	The average ratio of greenery of all SVIs in each grid
Open sky index	The average ratio of open sky of all SVIs in each grid
Macro scale built environment	
Building floor area (m^2)	The total building floor areas in each grid
Land-use mix (≥0)	The ratio of different land-use types in each grid
Road density (m)	The total road length (m) in each grid
Commercial POI (N)	The number of corresponding POIs in each grid (acquired from http://map.baidu.com)
Public service POI (N)	
Distance to bus stop (m)	The distance from the nearest bus stop in each grid
NDVI	The average NDVI value of each grid

Data source and variables

Dependant variable

In this study, e-bike travel behavior data were obtained from the Jinan Resident's Travel Survey of 2019 (JNRTS 2019), which was conducted to study the travel behavior of Jinan citizens. In order to ensure the completeness and representativeness of the sample, the JNRTS 2019 was conducted in July 2019 by trained interviewers followed a proportional to population size (PPS) method to obtain the sample. Respondents were requested to offer one-day elaborate travel records. Taking e-bike travel as an example, respondents were asked to record personal travel message such as the start and end times, initial and final locations. In total, the survey recruited 44,084 adults from 698 communities in central Jinan. All locations of e-bike trips were geocoded and relocated in corresponding fishnets adopting ArcGIS 10.6. At last, the number of e-bike trips within a gird was used as the dependent variable.

Macro-level built environment features

The independent variables in this study, macro-level built environment factors, were assessed according to 5Ds framework, including density, design, diversity, destination accessibility and distance to public transportation (26). In addition, numerous studies have shown that urban greenery has a significant impact on active travel (54).

Density is measured based on the total building floor areas in every grid. Diversity is calculated by using land-use mix of five fundamental point of interest (POI) categories (i.e., commercial, residential, public service, tourism and education) in each grid (55). Land-use mix is calculated as follows:

$$E_j = \frac{-\sum_i \left(A_{ij} \ln\left(A_{ij}\right)\right)}{\ln\left(N_j\right)}$$

Where A_{ij} indicates the percentage of POIs of category i in grid j; N_j is the number of POI types in grid j.

Design is measured based on road density, namely the total road length (m) in each grid. We applied the number of POIs in each grid as destination accessibility. Distance to public transportation is calculated by the shortest physical distance to bus stop (56).

Finally, we employed normalized difference vegetation index (NDVI), a commonly used parameter for vegetation assessment, as indicator of urban greenery (57). NDVI is calculated by Landsat-8 remote-sensing image acquired in June 2018, the calculation formula is shown as follows:

$$NDVI = \frac{NIR - Red}{NIR + Red}$$

Where Red and NIR denote spectral reflectance measurements extracted from red and near infrared areas, respectively. The values of NDVI are between 0 to 1, a high NDVI value suggest a high level of vegetation.

Micro-level built environment features

We collected the pedestrian's eye-level streetscape features *via* street view image (SVI) as the micro-scale built environment characteristics (58). Sampling points were obtained every 50 meters along the urban roads by Open Street Map (OSM). Then four SVIs (1,024*1,024 pixels) with a 90° field of view were collected for each sampling point through Baidu Maps' API (https://lbsyun.baidu.com/). The heading parameters 0°, 90°, 180°, and 270° of the four pictures collected at each sampling site representing north, east, south, and west, respectively. In this study, 519,388 street view images were retrieved from 129,847 sampling sites in Jinan. We then performed a Pyramid Scene Parsing Network (PSPNet) with a Cityscapes model to classify the foreground objects in the image into 19 categories, calculate the pixel percentage of every streetscape feature in the image and finally obtain the average value of each streetscape feature at each sample point. Since the vegetation (eye-level greenery) and open sky index are widely used in active-transportation related studies (59–61), we selected them as micro-level built environment variables, which were measured by calculating the average value in each grid (Figure 2).

Statistical analysis

In the research, global Moran's I and local Moran's I were employed to characterize the global and local aggregation pattern of e-bike usage. We first tested the variance inflation factor (VIF) between the independent variables. All variables with VIF >4 were excluded from the subsequent analysis. Thus, education and residential POI were excluded. OLS and GWR model were used to better quantify the built environment elements-e-bike usage association. In addition, we combined the results of the GWR model with Local Indicators of Spatial Association (LISA) to further explore the local aggregation characteristics of e-bike trips (Figure 3).

Spatial autocorrelation

Spatial autocorrelation is an essential indicator to examine whether the attribute value of a factor is significantly associated with its value of non-boring unit (62). Global Moran's I indicates the overall distribution of data within the study area, while local Moran's I assesses the similarities and differences between neighboring units (63). Global and local Moran's I are calculated as follows:

$$Global\ Moran's\ I = \frac{n\sum_{i=1}^{n}\sum_{j=1}^{n}\omega_{ij}\left(x_i-\bar{x}\right)\left(x_j-\bar{x}\right)}{\sum_{i=1}^{n}\sum_{j=1}^{n}\omega_{ij}\sum_{i=1}^{n}\left(x_i-\bar{x}\right)^2}$$

$$Local\ Moran's\ I = \frac{x_i-\bar{x}}{S^2}\sum_{j=1}^{n}\omega_{ij}\left(x_j-\bar{x}\right)$$

$$S^2 = \frac{\sum_{j=1,j\neq i}^{n}\omega_{ij}\left(x_j-\bar{x}\right)}{(n-1)} - \bar{x}^2$$

where x_i and x_j denote the total e-bike trips of grid i and j, respectively; n denotes the total count of girds; $\bar{x}$ is the mean e-bike trips of n grids; ω_{ij} is the spatial weight matrix. The value of Moran's I is distributed between −1 and 1. When Moran's I index is above 0, it indicates that the attribute values of all girds have positive spatial correlation. While Moran's I index below 0 indicates that the attribute values of all girds have negative spatial correlation.

Local Indicators of Spatial Association (LISA) is a method based on local Moran's I proposed by Anselin, and this method can reveal the possible spatial heterogeneity (64). We applied LISA to distinguish the studies into four types i.e., high-high (H-H), low-low (L-L), high-low (H-L) and low-high (L-H). The H-H type represents high value clustering and the L-L type represents low value clustering. The units of H-L type denote high values surrounded by low values, while the L-H units denote low values surrounded by high values.

Regression analysis

In this study, OLS and GWR models were conducted to quantify the relationship between built environment and e-bike travel. The OLS model is a regression model commonly used to analyze linear relationships between variables (65). The OLS model is calculated as follows:

$$\mathbf{y} = \mathbf{X}\beta + \varepsilon$$

where y is the e-bike trips, X is the matrix of the independent variable, β is a vector of the coefficient, and ε is a vector of random error term (66).

The GWR model is a further extension of the OLS model, and this model can explore the spatial variation patterns of influencing factors in different geographical locations (67). The spatial relationship among multiple built environment variables can be effectively processed using the GWR model to better explain the variables affecting e-bike travel. The GWR model is expressed as follows:

$$\mathbf{y_i} = \beta_0\left(\mathbf{u_i},\mathbf{v_i}\right) + \sum_{\mathbf{k=1}}\beta_{\mathbf{k}}\left(\mathbf{u_i},\mathbf{v_i}\right)\mathbf{x_{ik}} + \varepsilon_{\mathbf{i}} \quad \mathbf{i=1,\ldots,n}$$

where (u_i, v_i) denotes the coordinates of unit i; $\beta_0(u_i, v_i)$ denotes the intercept value; and $\beta_k(u_i, v_i)$ is the set of parameter values at unit i. Different from the spatially fixed coefficient of OLS model, GWR model allows the parameter estimates to vary with units and therefore may capture local effects (68).

Results

Descriptive statistics

The descriptive statistics of e-bike ridership and built environment are shown in Table 2. The average value of e-bike usage in each grid is 43.30 (SD = 53.980), indicating that there was an average of ∼43 e-bike trips occurred in each unit. Besides the count span of e-bike usage between spatial units is substantial, ranging from 1 to 394.

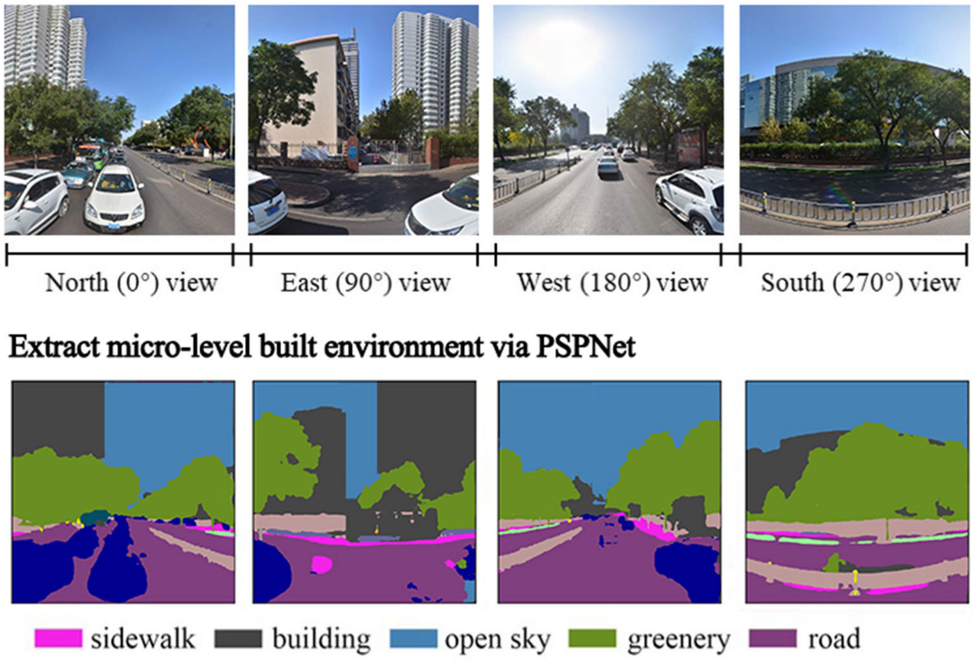

FIGURE 2
Assessing micro-level built environment from Baidu street view image *via* machine learning Technique (PSPNet).

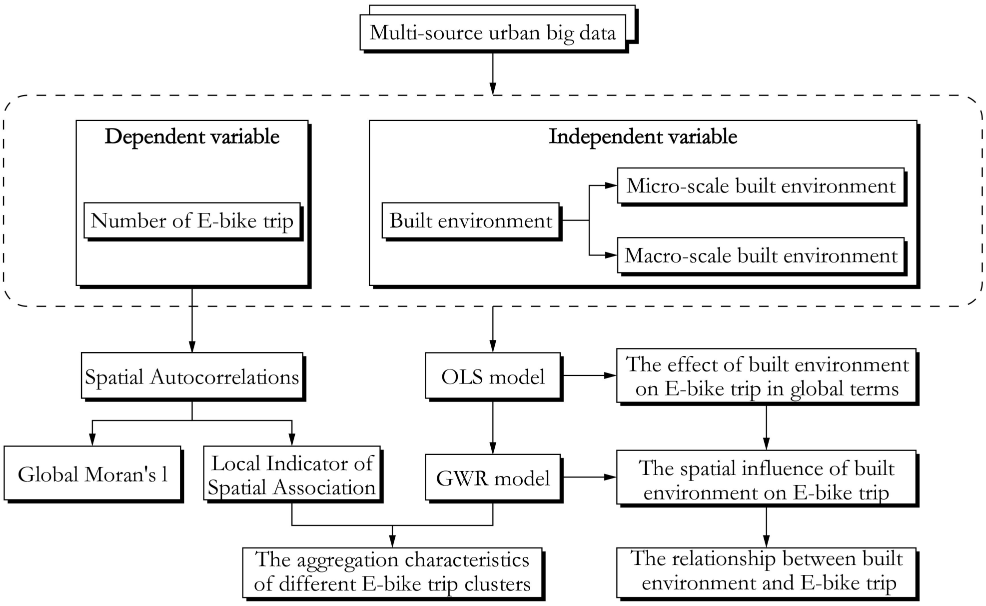

FIGURE 3
Technology roadmap.

For the micro-built environment, the standard deviation (SD) of both open sky index (Mean = 0.254, SD = 0.081) and eye-level greenery (Mean = 0.147, SD = 0.081) were the same. Open sky index had a greater average value than eye-level greenery, which indicated that the proportion of open sky was larger than that of greenery in most spatial units. In terms of

TABLE 2 Statistics for all variables within the Jinan study area, sampled in 2019 (fishnet = 600 × 600 m, $N = 770$).

Variables (unit)	Min.	Max.	Mean	SD
Dependent variable				
Number of E-bike trips (N)	1	394	43.300	53.980
Independent variable				
Micro scale built environment				
Eye-level greenery	0	0.552	0.147	0.081
Open sky index	0	0.440	0.254	0.081
Macro scale built environment				
Building floor area (m^2)	0	197,202.304	63,536.748	43,409.640
Land-use mix (≥0)	0	1.000	0.696	0.344
Road density (m)	0	17,255.150	3,997.850	2,402.737
Commercial POI (N)	0	189	18.030	25.651
Public service POI (N)	0	227	22.740	30.252
Distance to bus stop (m)	0	1,230	56.620	136.592
NDVI	0.061	0.338	0.164	0.047

N, number; Min., minimum; Max., maximum; SD, standard deviation; POI, point of interest; NDVI, normalized difference vegetation index.

macro-built environment, the study area had a relatively high building density (Mean = 63,536.748, SD = 43,409.640) and a highly mixed land use level (Mean = 0.696, SD = 0.344). In addition, the study area owned a well-connected transportation system with a high road density (Mean = 3,997.850, SD = 2,402.737) and convenient proximity of public transit (Mean = 56.620, SD = 136.592). Moreover, the mean value of public service POI (Mean = 22.740, SD = 30.252) was higher than that of commercial POI (Mean = 18.030, SD = 25.651).

Spatial distribution pattern of e-bike travel volume

The results of global Moran's I were presented in Figure 4A. There was a significant spatial autocorrelation (Moran's I = 0.579 and $p < 0.001$) in the distribution of e-bike usage in the study area.

Figure 4B presented the results of local Moran's I of e-bike trips. The results of LISA specifically reflected the local spatial correlation of e-bike travel volume. H-H clusters were concentrated in the central part of study area, which is a densely populated area with plenty of shopping areas. H-H areas were considered as the core development area of Jinan. Meanwhile, L-L clusters were distributed at the edge of the study area, which generally characterized by poor infrastructure configuration, complex terrain features, and relatively low population density. We also noticed an aggregated trend in the H-H and L-L units, respectively. In addition, L-H units were distributed in a fragmented form at the edge of the H-H units, while H-L units occurred randomly within the study area.

Regression results of OLS model

The association between built environment and e-bike travel was estimated by the OLS model (Table 3). The adjusted R^2 of OLS model is 0.428, which indicated that our model could explain 42.8% of the variation in e-bike trips in all grids. The VIF of the explanatory factor was <4, so there was no multicollinearity problem. The results showed that the four explanatory variables, i.e., eye-level greenery, building floor area, road density, and public service POI significantly promoted the e-bike trips, while the open sky index and NDVI significantly decreased e-bike trips. The relationships between land-use mix, commercial POI, distance to bus stop and e-bike trips were insignificant. However, the results did not indicate that these variables were not associated with e-bike trips, as the OLS model only calculates the overall effect of the study area.

Regression results of GWR model

The results of Moran's I revealed that there was significant spatial autocorrelation of e-bike usage, and the spatial heterogeneity of drive factors could not be revealed by OLS model. Therefore, we used the GWR model to further explore the association between built environment and e-bike usage. We applied MGWR software (version 2.2.1) for GWR model estimation (Table 4). The results demonstrated that the AICc of the GWR model was 1,559.603, which was about 12.1% smaller than the AICc of the OLS model. In addition, the adjusted R^2 of the GWR model improved from 0.428 to 0.646, indicating that the GWR model had a better explanation of e-bike variation. Therefore, it could be illustrated that the fitting results of the GWR model were better than those of the OLS model.

The positive parameter estimates denoted the independent variable had positive impact on e-bike travel, and vice versa. The statistical results of GWR model were presented in Table 4, the coefficients of all explanatory variables had a wide range interval, which implied that the impact of built environment factors on e-bike travel was diverse in different spatial units. The mean values of the coefficients of the land-use mix and commercial POI variables in the GWR model (−0.032 and −0.056) differed significantly from their coefficient values in the OLS model (0.009 and 0.054), suggesting that the two factors had a stronger positive driving influence on e-bike usage in certain units. In addition, the open sky index had the largest standard deviation (STD = 0.362), which implied a large spatial variation in explaining the degree of association between the open sky index and e-bike trips. Moreover, majority units of road density and public service POI had positive

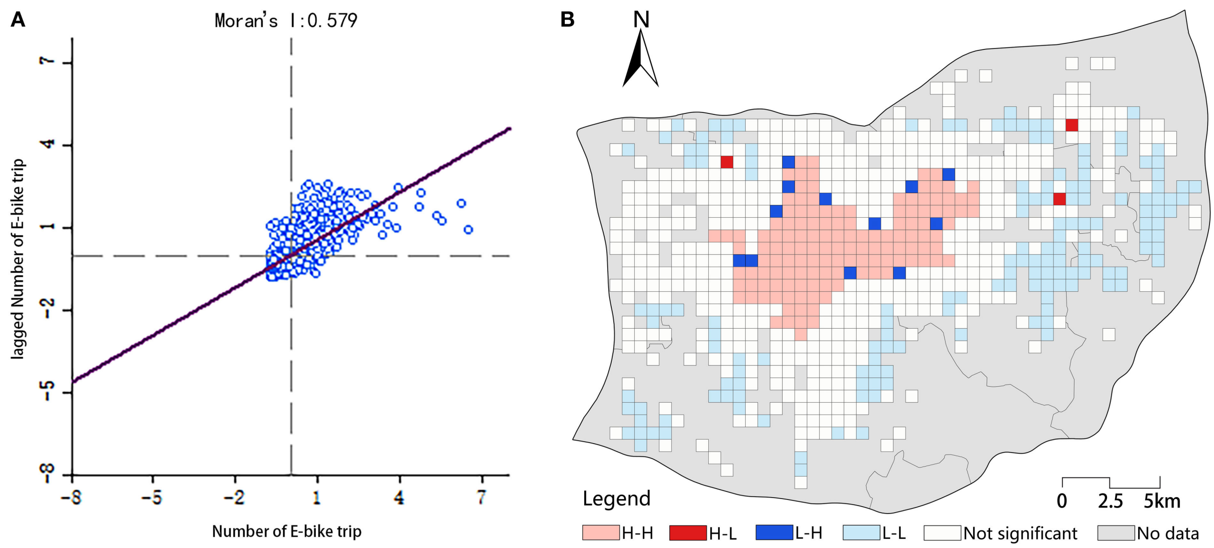

FIGURE 4
Spatial distribution pattern. **(A)** Moran scatterplot. **(B)** Local Moran's I clusters of e-bike trips.

local estimation parameters (1st Quartile>0); while the open sky index and NDVI had a higher number of negative local estimation parameters (3rd Quartile<0).

The above statistical data analysis formulated a preliminary knowledge of the results of GWR model. ArcGIS was used to map the variable coefficient data of GWR model to realize the spatial visualization of the local coefficient values, which is convenient for us to deeply study the factors affecting e-bike travel from a spatial perspective. The spatial distribution of the local coefficients of 9 variables was presented in Figure 5, and the following conclusions can be drawn.

As shown in Figures 5B,I, open sky index and NDVI variables had significantly negative effects on e-bike usage in all grids. The positive values of the open sky index coefficient were aggregated in the southwestern part of the study area, where there were rolling hills and undulating terrain. In contrast to the open sky index, the positive values of NDVI coefficient were not densely distributed but fragmented in the eastern part of the study area. The lowest values of both coefficients were concentrated in the middle of the study area where belonged to the old city of Jinan with high building density and a large number of tourist attractions.

As shown in Figure 5G, the public service POI variable had globally a significant positive effect on e-bike trips. The coefficients of public service POI variable demonstrated a vertical band distribution, with an obvious demarcation line between positive and negative values. The positive coefficients in the central-eastern and western indicated that the public service POI variable laid a positive influence on e-bike usage in these regions; the negative coefficients of public service POI were concentrated in the eastern periphery of the study area, which was a developing area in Jinan, with an incomplete public service support facility.

As shown in Figures 5A,C,H, partially identical patterns in the coefficient distributions of the three variables of eye-level greenery, building floor area, and distance to bus stop were present. It was found that all three variables had both positive and negative effects on e-bike usage, and the proportions of

TABLE 3 Results of ordinary least squares (OLS) model of built environment and e-bike (fishnet = 600 × 600 m, N = 770).

Variable	Coef.	*p*	Std. error	VIF
Micro-scale built environment				
Eye-level greenery	0.106	0.001**	0.031	1.264
Open sky index	−0.137	0.000***	0.030	1.189
Macro-scale built environment				
Building floor area	0.148	0.000***	0.038	1.955
Land-use mix	0.009	0.711	0.033	1.424
Road density	0.133	0.000***	0.034	1.542
Commercial POI	0.054	0.229	0.045	2.707
Public service POI	0.329	0.000***	0.045	2.731
Distance to bus stop	0.027	0.399	0.032	1.396
NDVI	−0.149	0.000***	0.036	1.786
Adjusted R^2	0.428			
Residual sum of squares	435.517			
Log-likelihood	−873.188			
AICc	1,768.724			

The numbers in parentheses represent p-values. ** and *** give the significance at the 5% and 1% levels respectively.

TABLE 4 Results of geographically weighted regression (GWR) model of built environment and e-bike (fishnet = 600 × 600 m, N = 770).

Variables	Min	1st quartile	Mean	3rd quartile	Max	STD
Micro-scale built environment						
Vegetation	−1.088	−0.016	0.049	0.177	0.410	0.216
Sky	−2.070	−0.230	−0.204	−0.005	0.170	0.362
Macro-scale built environment						
Building floor area	−1.045	−0.003	0.089	0.235	0.547	0.271
Land-use mix	−1.195	−0.075	−0.032	0.066	0.481	0.196
Road density	−0.175	0.049	0.112	0.162	0.423	0.103
Commercial POI	−0.404	−0.157	−0.056	0.059	0.230	0.139
Public service POI	−0.131	0.111	0.271	0.405	0.905	0.250
Distance to bus stop	−1.034	−0.034	0.027	0.099	0.770	0.203
NDVI	−1.553	−0.328	−0.212	−0.030	0.074	0.270
Adjusted R^2	0.646					
Residual sum of squares	226.044					
Log-likelihood	−620.704					
AICc	1,559.603					

units with positive and negative values were similar. In addition, the distribution of coefficients for all three variables were found to be concentric circles, expanding outward from the core area of maximum negative value in the middle with the coefficients progressively larger. The distribution of the positive units of the three variables differs. In the northwestern and northeastern part, eye-level greenery positively contributed to e-bike usage, while in the southeastern part, e-bike usage was positive associated with building floor area. The maximum positive value of distance to bus stop variable met the eastern side of the negative core and the distribution was demonstrated in east-west direction which was stripe-like.

The coefficients of land-use mix, road density and commercial POI were distributed differently as shown in Figures 5D–F. The coefficients of land-use mix were distributed in a binomial pattern, and the coefficients of the core area had the lowest negative values, and the positive values were distributed in the central and eastern part of the study area. In the central part, negative coefficients of road density were distributed from west to east, and the distribution pattern was same as the direction and location of the most important traffic artery in Jinan (Jingshi Road). The positive-coefficient units of commercial POI overlapped with several important commercial areas of Jinan, indicating that commercial facilities had a strong attraction and could promote e-bikes usage to some extent.

E-bike travel aggregation characteristics

In Sections Spatial distribution pattern of e-bike travel volume and Regression results of GWR model, we investigated the local spatial effects of e-bike trips and the spatial distribution of the coefficients of each built environment variable by estimating local Moran's I and GWR model, respectively. We found a clear spatial aggregation of e-bike trips. To further investigate the connection between this phenomenon and the built environment, we calculated the mean coefficient values of each explanatory variable of the four types of spatial units (i.e., H-H, H-L, L-H, L-L) from Figure 3B to explore the built environment characteristics corresponding to four spatial types (63).

Figure 6 depicted the results. The positive and negative of the ordinate mean coefficient represented the influence of built environment factors on e-bike travel; the positive value represented the promotion effect, and the negative value represented the prohibitive effect. The average coefficient value of the built environment factor indicated the influence degree of this factor on e-bike travel. The larger absolute value denoted the greater influence degree. The closer the absolute value to 0 indicated faint influence of this factor on e-bike travel. H-H cluster and L-H cluster had similar numerical distribution pattern, and the same pattern was found between L-L and H-L clusters. In addition, H-H and L-H clusters formed the units with large e-bike trips, while L-L cluster and H-L cluster represented the units with few e-bike trips. In the areas with large e-bike trips, the average coefficients of public service POI, open sky and NDVI had the largest absolute values, which indicated that these three factors had the strongest impact on e-bike trips, while other factors had relatively weak impact on e-bike trips. In the areas with few e-bike travel volume, the average absolute values of the coefficients of all types of built environment factors were close, and there was no significant difference among the coefficient values of all variables.

This section might serve as a reference for urban planners in decision making. For example, when creating an e-bike friendly area, priority can be given to build improved public services,

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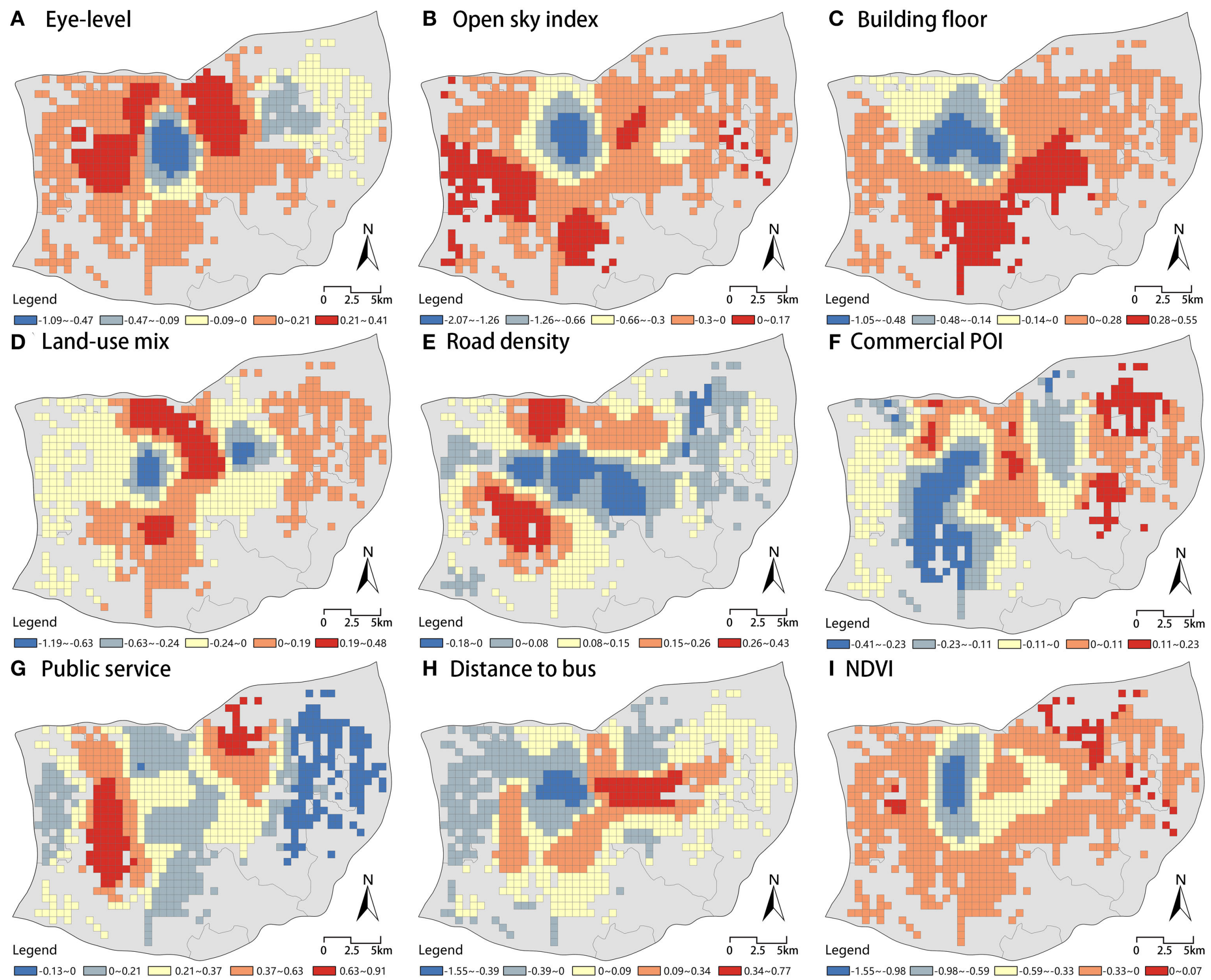

FIGURE 5
Spatial pattern of coefficients in different models. **(A)** Eye-level greenery. **(B)** Open sky index. **(C)** Building floor area. **(D)** Land-use mix. **(E)** Road density. **(F)** Commercial POI. **(G)** Public service POI. **(H)** Distance to bus stop. **(I)** NDVI.

reduce sky visibility to achieve the goal of promoting e-bikes usage. A profound understanding of the built environment influence can help the government to improve money efficiency and lay a solid foundation for building a cycling-friendly city.

Discussion

Major findings

As a new mode of active travel, e-bikes are widely accepted and used worldwide and are even considered to be able to replace motor vehicles in China (20). The healthful and low-carbon advantages of e-bikes are in line with the common consensus on low-carbon and healthy cities. Understanding the association between the urban built environment elements and e-bike travel is critical for urban planners. Although there are plentiful academic studies on the correlation between the urban built environment and various modes of transportation, few study focuses on the built environment effects on e-bike travel, especially from a global and local level. Moreover, previous empirical studies on built environment usually selected macro-level factors, ignoring the micro-level factors which involve residents' perception. This study addresses the abovementioned gap by unveiling the spatial relationship between built environment and e-bike travel of Jinan, and our study yields two major findings.

First, the relationship varies between different built environment variables and e-bike travel. The results of the OLS model indicate that road density is positively associated with e-bike usage. A well-connected street network increases the destination accessibility, thus encouraging e-bike usage. Pronounced diversity and proximity to bus stops reduce trip distance and offer a variety of possible transportation options for the residents (26, 69). In addition, various categories of

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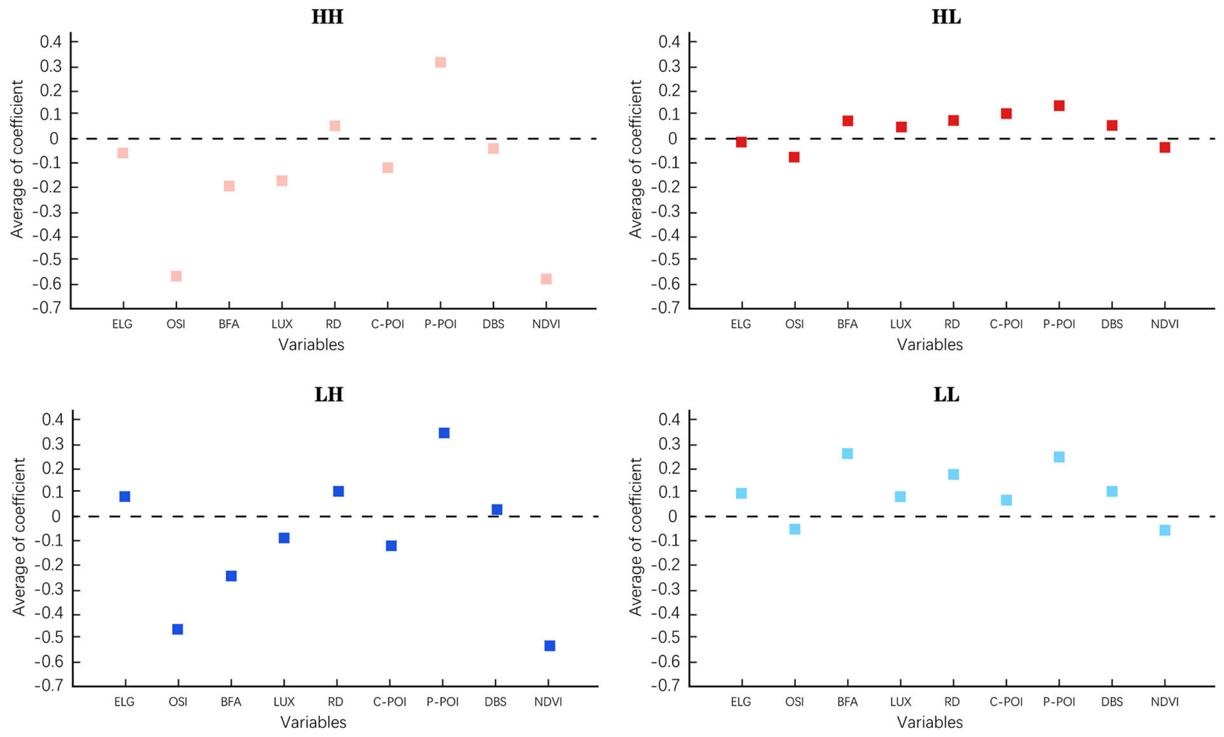

FIGURE 6
Average of built environment coefficient (ELG, Eye-level greenery; OSI, Open sky index; BFA, Building floor area; LUX, Land-use mix; RD, Road density; C-POI, Commercial POI; P-POI, Public service POI; DBS, Distance to bus stop).

destination accessibility have various correlations to e-bike trips. Public service POI has a significant positive relationship with e-bike trips, while commercial POI yields a negative relationship. Our finding is opposite of previous walking-related empirical studies, which prove public service POI has a significant negative impact on pedestrian volume and commercial POI has a positive impact (58, 70). The possible explanation is that the parking facilities for e-bikes are not well configured in most of the commercial establishments in Jinan. In addition, commercial areas attract a large number of people and are prone to block traffic, thus inhibiting e-bike trips. At the micro level, open sky has some inhibitory effect on e-bike usage. The eye-level greenery shows a positive correlation with e-bike usage while the NDVI variable shows a negative correlation with it. The results indicate a mismatch between the human street greenery perception and the bird's view greenery obtained through remote sensing satellites, which is consistent with previous study (61).

Second, there is significant spatial heterogeneity in the relationship between various built environment factors and e-bike usage. The distribution diagram of the GWR model coefficient values (Figure 5) indicates that the coefficients of most variables, except for public service POI, show a negative clustering at the center of the study area. We believe one reason for this phenomenon is that the planning of the old urban area is mainly centered on the preservation of historic sites, streets, and buildings, which has resulted in insufficient space to allocate e-bike related support facilities, including charging posts, parking areas and carriageways. Moreover, there is narrow spatial scale of residential areas in old downtown, thus e-bike travel can easily conflict with other modes of transportation (71, 72). The other reason to explain the finding is that large commercial complexes and scenic spots are not suitable for e-bike travel (73). Unlike small and medium-sized commercial facilities, large commercial facilities are more friendly for walking and motorized access because of the dense crowds and complex traffic conditions, while the high speed of e-bikes poses a greater safety risk in these areas. In addition, insufficiency in e-bike parking facilities in large commercial complexes and scenic spots act as a drag for e-bike riding (32). The old downtown of Jinan has a well-developed public transportation network which motivates residents to carry out their daily travel activities by walking and public transportation rather than using e-bikes (74).

Planning implications

Jinan, as well as many other Chinese cities, is expanding in the rapid-urbanization context, which is a challenge for promoting e-bike commuting. This study indicates that when planning and building new urban areas, planners can achieve the purpose of regulating e-bike flows through the flexible settings of local built environment. In addition, interventions in the built environment can also alleviate traffic congestion in old urban areas to some extent. For example, in the areas with intensive e-bike travel congestion, increasing the sky openness by controlling the height of buildings and the number of trees can reduce the e-bike usages. On the contrast, in the areas without intensive travel congestion, increasing the greenery and constructing public service facilities along the roads can attract more e-bikes pass through these areas. Moreover, e-bike facility policies must also be integrated with vehicle traffic management policies, for example, setting speed limits, subsidizing the use of low-pollution vehicles, and constructing related supporting facilities. E-bike facility policies are also closely related to social equity and environmental justice. Chinese cities urgently need to develop long-term policies aimed at building cycling-friendly cities before they are permanently dominated by motorized forms of travel.

This study provides an effective decision support framework for policymakers to identify the most influential built environment factors associated with e-bike travel so as to build a healthy and low-carbon city (75). Based on this framework, tailored policy and planning interventions may enable residents to have a better e-bike travel experience in their local urban environment. In summary, planners and policymakers should take into fully account the positive or negative effects of different built environment elements on the e-bike usage and provide tailored planning strategy when carrying out specific e-bike related planning.

Limitations

Despite of the theoretical and practical implications for future urban planning and public policy formulation, limitations of our study should also be acknowledged. First, OLS and GWR models are linear regression models, which involve only linear interpolation and have some limitations (37). Therefore, the relationship between urban built environment and e-bike usage should be further explored by model improvement. Second, the spatial scale effect and modifiable areal unit problem (MAUP) is the most important issues in urban planning and geography (76). Due to the difference in travel distance per unit time for choosing different travel modes, the effect of choosing different grid sizes as the basic unit of study may be sensitive to the results (53). In future research, the scale effect of built environment on e-bike usage could be further explored by transforming the grid size in the spatial dimension. Third, due to the limitations of data and technology, this paper only considered eye-level greenery and open sky as representatives of micro-level built environment variables. Future research hopes to further explore the relationship between more micro built environment elements and e-bike usage. Finally, this study did not consider the longitudinal variation of e-bike usage, future studies may work on revealing the effects of built environment on e-bike travel in different time periods.

Conclusion

This study is the first to reveal the relationship between the built environment and e-bike travel in Jinan. Specifically, we designed a framework of built environment variables at both macro and micro levels using multiple sources of data to better quantify the built environment and we applied the OLS and GWR models to compare the coefficients of each variable globally and locally. The characteristics of built environment corresponding to different aggregation pattern of e-bike trips are analyzed using the GWR model and local Moran's I. The results of our study indicate key factors that need to be considered in the planning stage to reduce congestion pressure on urban traffic. For example, public services facilities and reasonable road network density can encourage e-bike traveling, while open sky and NDVI have an inverse impact on e-bike use. However, the impacts may vary across city level and further research is needed to identify the specific impacts across different areas. With more evidence, it would be easier to generalize findings from one region to others and inform built environment planning in China and other developing countries.

Data availability statement

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

Ethics statement

Ethical review and approval were not required for the study on human participants in accordance with the local legislation and institutional requirements. Written informed consent for participation was not required for this study in accordance with the national legislation and the institutional requirements.

Author contributions

YY: data collection, data curation, methodology, and writing-original draft. YJ: conceptualization, methodology, and writing-original draft. NQ: conceptualization, visualization, and writing-review and editing. HG: data collection and writing-review and editing. XH: supervision, methodology, and writing-review and editing. YG: supervision and writing-review and editing. All authors contributed to the article and approved the submitted version.

Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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Housing-related challenges during COVID-19 pandemic among urban poor in low- and middle-income countries: A systematic review and gap analysis

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The abysmal health of the urban poor or slum dwellers was attributed to structural inequities such as inadequate housing, water, and sanitation. This review aimed to assess housing-related opportunities and challenges during the COVID-19 pandemic among urban poor in low-and middle-income countries. For study identification, a comprehensive search was performed in 11 databases that yielded 22 potential studies. The inadequate housing infrastructure makes the lives of the urban poor more precarious during COVID-19. Typically, the houses lacked lighting, ventilation, and overcrowding. This review reflected that it is crucial to reimagine housing policy for the urban poor with an emphasis on pandemic/epidemic guidelines.

KEYWORDS

housing, urban poor, opportunities, challenges, COVID-19, LMIC

Introduction

Socioeconomic factors, such as the location of the residence and the housing infrastructure, as well as health-related behaviors, are among the most significant determinants of human health (1, 2). According to the World Health Organization (WHO), improved housing with access to water and sanitation, as well as affordable preventive and curative health care at the doorstep, can empower marginalized groups and improve the entire community's health (1). The term "housing" refers to a safe living space that facilitates daily activities. United Nations-Habitat estimates that ~40 percent of the world's population will require adequate housing by 2030. While everyone is at risk from hazardous housing, those with low incomes and members of vulnerable groups greatly impacted by structural inequities are more likely to reside in inadequate or insecure housing or be denied a home altogether (3). Unmet housing needs have resulted in informal settlers or unplanned settlements like slums, especially among the urban poor (4).

The United Nation-Habitat defined a slum household as a group of individuals living under the same roof in an urban area that often lacks one or more of the following: durable housing, sufficient living space, security of tenure, sanitation, and infrastructure, and access to improved water sources. The slums result from rapid urbanization with a rise in urban population. Hence, local governments confronted with rapid urbanization cannot address the varying requirements for urban infrastructure to address the needs of the urban poor (5).

Low- and middle-income countries (LMICs), as defined by World Bank are those with gross national income (GNI) per capita less than 12,375 USD (6). With economic distress and rapid urbanization, there are multitude of challenges faced by the residents of LMICs. The poorest people, particularly those who live in slums and are homeless, usually have worse health status than their compatriots in rural areas, despite the fact that wealthier urban dwellers can benefit from the "urban advantage" (7).

The influence of COVID-19 on housing, taking into account the complex impacts of physical distancing and isolation, especially among slum inhabitants was challenging. As a result of the droplet and aerosol transmissions, which both can spread COVID-19, overcrowding has been linked to the spread of infections. There was a 50 percent higher risk of COVID-19 incidence (IRR 1.50, 95 percent CI: 1.38–1.62) and a 42 percent higher risk of COVID-19 mortality (MRR 1.42, 95 percent CI: 1.25–1.61) for every 5 percent increase in the percentage of households with suboptimal housing conditions (8).

The deplorable health of the poor or slum dwellers is attributable to inadequate and overcrowded housing conditions triggered by structural inequities. They are also susceptible to several additional housing-related threats, including hazardous electrical connections, toxic building materials, kitchenettes without ventilation, and hazardous infrastructures, such as inadequate sidewalks (3). In addition, the situation worsened during the COVID-19 pandemic. With limited resources, it is difficult for them to implement physical distance and isolation measures. Thus, in purview of the aforementioned mentioned housing related-problems among urban poor, it mandates to conduct research on how the unprecedented events like COVID-19 worsened the situation. Consequently, this review aimed to evaluate and assess housing-related opportunities and challenges during the COVID-19 pandemic among urban poor residing in low- and middle-income countries (LMICs).

Methods

Protocol and search strategies

The study protocol of this review is registered in PROSPERO (CRD42022300387). We conducted a comprehensive search to identify studies from the databases–PubMed (MEDLINE), Embase, Web of Science, WHO Global Index Medicus, Epistemonikos, ProQuest, EBSCO, Cochrane, MedRxiv and BioRxiv, 3ie, and Google Scholar for the relevant articles published from November 2019 till August 2021.

Inclusion exclusion criteria

The studies with slum-dwellers or homeless populations from urban areas of the LMICs as participants were included. Studies with housing-related interventions in COVID-19 the context were included. As we did not look for the effectiveness of the interventions, thus we did not consider any comparator in the included study. The housing-related studies in the context of COVID-19 were included. Any primary research viz. Randomized Controlled Trials and Non-Randomized Studies of Interventions, such as cohort studies, case-control studies, controlled before-and-after studies, and interrupted-time-series studies, were included. The study selection was not restricted to the language of the studies. However, we did not include any secondary data analysis, reviews, commentaries, editorials, and primary studies in the non-COVID-19 context.

Study selection

Two reviewers screened the studies based on the titles and abstracts. Furthermore, full texts of the potential studies were retrieved and reviewed to check their eligibility for selection. We resolved any disagreements during study selection with discussion and mutual consensus with the other reviewers. The study selection was done independently and in duplicate.

Quality assessment of the included studies

The quality assessment of the included articles was assessed independently and in duplicate by reviewers based on the criteria mentioned in MMAT (Mixed Methods Appraisal Tool) (9). The disagreements were resolved through discussion and mutual consensus with the other authors. The quality assessment was conducted independently and in duplicate. Methodologically, 9 of 22 studies were in concordance with the MMAT criteria for quality appraisal. The remaining included studies (13 of 22) were of compromised quality, as they deviated and did not fulfill the required criteria of the MMAT tool.

Data extraction and synthesis

Two reviewers extracted data in a Microsoft Excel sheet template comprising study characteristics (author, year, country, study design, sample size, study setting, data collection methods), and results (outcome measures, conclusion, recommendations. We resolved the disagreements at any stage *via* discussions with the authors. Furthermore, the author (KCS) reviewed all the studies, open-coded the information, and prepared a codebook—a thematic framework that emerged from the data for selective coding in MAXQDA Analytics Pro 2020 (VERBI GmbH, Berlin). The author SD extracted all the information in MAXQDA using the selective coding approach. Finally, the authors (SD, KCS) synthesized and prepared the results using thematic framework analysis.

Results

We identified 6,490 studies, including 1,482 duplicates. Based on the title and abstract, 5,008 studies were screened, resulting in 134 potential studies for full-text review. Out of 134, 22 studies met inclusion criteria and were finally included in the review. The PRISMA flow diagram is provided to illustrate the entire study selection process in Figure 1.

Characteristics of included studies

Of the 22 included studies, nine were qualitative, eight were quantitative, and five were mixed-method studies. Most of the

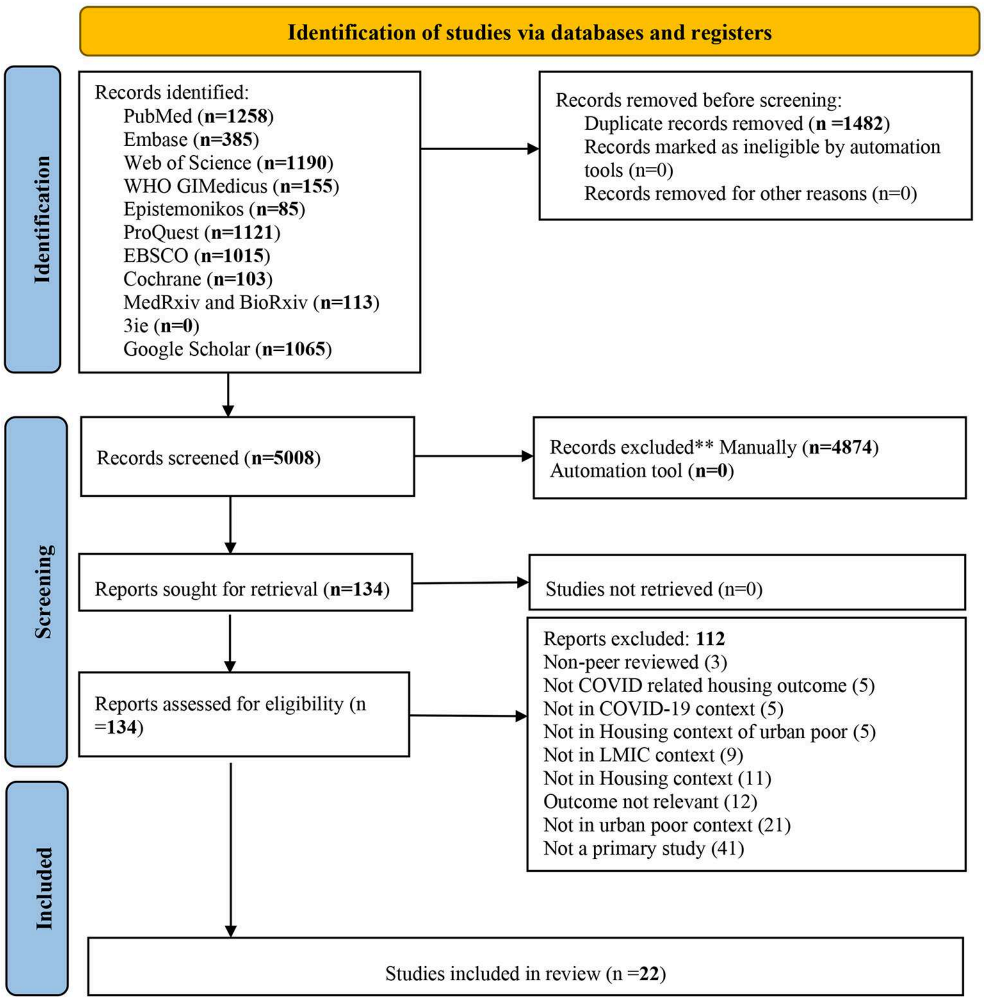

FIGURE 1
PRISMA flow diagram (10).

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included studies were from India ($n = 8$) followed by Bangladesh ($n = 6$), Nigeria ($n = 3$), South Africa ($n = 2$), Vietnam ($n = 1$), Turkey ($n = 1$), and Mixed ($N = 1$). The urban poor in the included studies comprised refugees, slum dwellers, migrant workers, and the urban homeless (Table 1).

Three main themes emerged: (1) Housing infrastructure and existing facilities, (2) Challenges related to housing conditions during COVID-19 pandemics, and (3) Coping mechanisms, social support, and expectations.

Theme 1: Housing infrastructure and existing facilities

Usual population density of the households and community

The poor urban environment's unplanned housing and spatial organization make it unconducive to a healthy lifestyle. In general, it was reported that the dark and unventilated houses with leaky roofs and damped walls increased the vulnerability of the residents. The non-paved narrow lanes measuring about 1 to 1.25 meters with large gatherings contribute to life-threatening congestion while exposing residents to airborne virus transmission. These congested lanes contribute to insufficient indoor lighting and ventilation. As far as crowding is concerned, 4–5 individuals dwell in houses with dimensions ranging from 9.29 to 13.243 meters square. They are bound to improvise a wall in their small rooms to create a living and bedroom. It is challenging for the slum residents to maintain their temporary dwellings as they face adversity due to heavy rain and flooding. The housing units lacked connectivity to basic sanitation infrastructure (11–14, 17, 28). In refugee camps, houses were orthogonal and normal in 10 square feet. These houses were made of concrete and tin with slender and unpaved pathways provided with free electricity and water (15). Most housing units failed to meet the minimum housing lobby standard of 6 feet, as they were even smaller than 4 feet (20).

The study revealed that the houses were constructed in rows with rooms ranging from 80 to 100 square feet. These tiny houses were permanent, with shared bathrooms and metered water taps set at a distance. Twenty families were forced to share a single bathroom and three toilets, which was a clear indication of the facility's high loads. The housing alleys were crowded with diverse populations (24). In slums, an average of 3.2 people resided in a single room, but in non-slums, 2.9 people resided in a single room. In slums, 1.7 rooms were shared by 4.7 people. The majority of urban slum dwellings lacked separate kitchens. Cooking and sleeping in the same room made maintaining physical distance difficult (27). Most slum residents who lack housing amenities reside on sidewalks, putting their health and way of life at risk (30, 32). According to the data, a little shelter was filled by 10 to 11 people, which equates to 1.6 to 2.9 square meters per person, which is below the Humanitarian Charter's suggested standard of 4.5 square meters per person (11–13, 23).

Lack of living space and internal WASH facilities in household

Along with the lack of living spaces, the urban slum residents encountered other problems: they didn't have access to safe and sufficient water facilities for hygiene practices in their households. Most of these cohorts relied on ordinary communal tap water, borewells, or water tankers for their water needs (14). The slum residents had to share toilets and water sources to carry out their daily chores. It is evident from the findings that crowding is significantly high in households sharing both bathing and toilet facilities (median=2.9 m^2/person, 95% CI, 2.63–2.93) (23). Typically, eight to 10 individuals share a tiny 150 sq. ft. shack without natural light or ventilation and no access to safe drinking water, sanitation, or other basic amenities. They did not have separate toilet facilities in their homes and had to rely on dirty, unhealthy, and risky communal lavatories. Moreover, it was more challenging for maintaining hygiene among women and girls. They were even bound to urinate and defecate in the open. They lacked a kitchen in their households. They even had to leave their homes to fetch water from communal taps or tube wells, thus risking infection. Restricted and timed water supplies make it impractical to practice hand hygiene (28).

Theme 2: Challenges related to housing conditions during COVID-19 pandemics

Major challenges during COVID-19

There were many challenges faced by the urban poor due to poor housing conditions. Temporary refugee camps in the lowlands make them more vulnerable to seasonal flooding and calamities like COVID-19. Poor infrastructure and crowding make it challenging to practice physical distancing or follow quarantine measures (11–13, 22). As a respondent stated:

> *"We cannot maintain physical distance within and outside our shelter. Due to the roofing materials, tarp, insufficient sun fans, and natural ventilation, our room becomes extremely warm during this scorching summer. Due to the overcrowding and the risk of contracting Coronavirus, we were unable to remain in a room for an extended period." (11)*

Migrant communities reported struggling to make their living and pay housing rents, which were further aggravated, by food insecurity and stringent lockdown during the COVID-19 infection (19). Lack of apparent government policy concerning

TABLE 1 Characteristics of included studies.

References	Country	Urban Poor	Population (*N*)	Study type	Data collection method	Data Analysis	Result
Akter et al. (11)	Bangladesh	Refugee	66	Qualitative	In-depth interviews	Thematic analysis	Insufficient built infrastructure and unhygienic living conditions, including improper WASH management, increase their risk of COVID-19.
Akter et al. (12)	Bangladesh	Slum dwellers	42	Qualitative	In-depth interviews	Thematic analysis	Infrastructural, and health-related issues had affected slum dwellers' COVID-time vulnerabilities.
Anand et al. (13)	Vietnam	Migrant workers	31.4 million	Quantitative	Secondary data (PLFS, NSSO)	Not reported	The majority (51%) of the slum population reside in a single room while 45% of single rooms were shared by 3–4 members. Thus, the slum population was densely packed making it difficult to comply with the social distancing norms.
Auerbach et al. (14)	India	Slum	321	Quantitative	Telephonic survey	Descriptive statistics	The housing in slums has dense living conditions making social distancing impractical to some extent. They lacked taps in their homes and rely on communal taps or water tankers.
Bercegol et al. (15)	India	Slum	Not reported	Qualitative	Telephonic In-depth interviews	Not reported	The housing in the refugee camps is orthonormal planned with narrow alleys and without pavement.
Budak et al. (16)	Turkey	Refugees	414	Quantitative	Questionnaire	Descriptive statistics	Tents are more sensitive against pandemics while the ones who stay in pre-fabricated houses, tents, and detached houses have lower levels of combating pandemics.
Bueno et al. (17)	Nigeria	Informal settlement	510	Quantitative	Interviews	Inverse probability reweighing	Basic sanitary infrastructure is lacking
Bui et al. (18)	Nigeria	Urban slum	445	Quantitative	Self-administered questionnaire	Cumulative risk assessment	About two third of the migrant workers lived in a small houses (<36 m^2) with their families.
Cloete et al. (19)	South Africa	Sex workers and homeless	60	Qualitative	Informant interview, Focus Group Discussion	Thematic analysis	Closely-packed houses and shacks in informal settlements make physical distancing impractical. The spatial organization of the slum settlements makes it unconducive to maintain social distancing.
Ebekozien et al. (20)	Nigeria	Informal settlement	40	Qualitative	In-depth interviews	Thematic analysis	The majority of informal settlements spread COVID-19 as the dwellings were densely packed with a dimension lesser than 4 feet against the minimum standard of 6 feet with inadequate basic amenities, making individual or group quarantine difficult.
Enwerekowe et al. (21)	Bangladesh	Urban slum	Not reported	Mixed-method	Structured and non-structured interview	Photograph and narratives	Overcrowding, multi-generational homestead composition, extreme poverty, and unchecked mixed-usage of residential spaces as major challenges to effective social distancing (and self-isolation).
Gibson et al. (22)	Bangladesh	Informal settlement	Not reported	Quantitative	GIS Data analysis	Descriptive statistics	The dwellings are denser in fashion making it impractical to practice social and physical distancing while staying at home or outside in the selected settlements.
Hasan et al. (23)	Bangladesh	Urban slum	588	Quantitative	Survey	Exploratory and secondary analysis of World Bank data	Most households were single-room dwellings (80.4%). Median crowding ranged from 0.55 m^2 per person up to 67.7 m^2 per person. A significant positive relationship between crowding and the use of shared facilities.

(Continued)

TABLE 1 (Continued)

References	Country	Urban Poor	Population (*N*)	Study type	Data collection method	Data Analysis	Result
Mohan et al. (24)	India	Slum	113	Mixed-method	Interviews	Descriptive statistical analysis	Pre-existing vulnerabilities (lack of safe drinking water, decent housing, and sanitation) of the workers have amplified and become more visible during the recent COVID-19 pandemic.
Napier-Raman et al. (25)	India	Slum	122	Mixed-method	The rapid survey, in-depth semi-structured interview.	Descriptive and Thematic analysis.	Housing insecurity was a crucial effect of the lockdown, with no clear government policy on rent waiving affecting many families.
Nyashanu et al. (26)	South Africa	Informal settlement	30	Qualitative	In-depth interviews	Interpretive phenomenological analysis	Overburdened infrastructure in the informal settlement, lack of savings- loss of income and shortage of food, anxiety depression made it difficult to practice social distancing.
Patel (27)	India	Slums	Not applicable	Mixed-method	Media reports analysis	Quantitative analyses	When rooms are shared by multiple family members (overcrowding) and used for multiple purposes, extremely challenging to follow home quarantine.
Sahu and Dobe (28)	India	Slum	Not applicable	Qualitative	Document analysis	Document analysis	Overcrowding without provision for safe drinking water, sanitation, or other basic services, make the life of the urban poor challenging.
Saldanha (29)	India	Slum	1	Qualitative	Narrative	Self-reported	Crowding and lack of running water made it difficult to practice social distancing and hygiene among residents.
Spiritus-Beerden et al. (30)	Global	Refugees and migrants	20,742	Quantitative	online survey	Descriptive and exploratory factor analysis	The mental health of refugees and migrants during the COVID-19 pandemic was significantly impacted particularly by insecure housing situations and residence status
Wasdani et al. (31)	India	Slum	6	Qualitative	Case study	Self-reported	The slum's close quarters and communal areas served as ideal breeding grounds for a virus that spread through close physical contact.
Williams et al. (32)	Bangladesh	Urban poor	525	Mixed-method	Telephonic interview	Descriptive statistics	Overcrowding made it difficult to practice preventive measures.

rent waiver, many families faced housing insecurity due to the lockdown (25). The anger and outrage among the informal settlements were marked by the Government's impractical policy toward COVID-19 containment (20). As quoted by the respondents

> *"They [Government] are talking about social distancing and regular handwashing, please ask them if there is a water supply for regular handwashing. Many of the houses in this neighborhood have challenges with toilets, water supply, and adequate housing to the best of my knowledge. So, how can I comply with the physical distancing of about six feet apart when my next neighbor is directly opposite my room with a lobby of about three to four feet wide and shared facilities such as toilet, kitchen, bathroom, etc.?" (20)*

Abiding by the physical distancing norms was a major challenge among the poor urban cohort as they had to deal with overcrowding and homestay orders (20, 21). Due to overcrowding, many inhabitants were compelled to seek refuge under trees and in makeshift outdoor seating places (21). The housing and basic amenities were not optimal, and the rent-seeking mechanism was unjustified. Women had no safe location to meet and socialize, and children had no space to play due to crowded areas, thus deteriorating their health and living with time (24). COVID-19 left many homeless slum dwellers to move into makeshift shelters as the administration forcibly moved them from their usual sleeping spaces (32).

Increase in usual population density, challenges in physical distancing, and overcrowding associated with infection

The overcrowding worsened during COVID-19 as the slum infrastructures were not conducive to maintaining physical distancing and abiding by the quarantine norms due to lockdown enforcement (11, 12). The houses were not optimally apart in slums; they depended on a common water source. Overcrowding was not just confined to homes; it was even seen in minibuses or taxis, making physical distancing among informal settlers impossible (19). The rented house was also overcrowded during COVID-19 due to lockdown and movement restrictions imposition, making it challenging to practice physical distancing, resulting in fear and anxiety of catching an infection (21, 22, 26). Furthermore, women in slums fared worse than their male and female non-slum counterparts in terms of access to secure housing for isolation and physical distance. Most slum women work, but it is usually low-paying, transitory, and exploitative, making them more likely to perform poorly. Many domestic workers could not provide services remotely, resulting in a loss of income that allowed them to feed their families. The concern over the impracticality of taking containment measures among the slum residents was quite evident from the respondents' statements.

> *"I cannot imagine how residents would practice social distancing and hygiene, given crowding and the lack of running water." (29)*
>
> *"Sadly, the tight quarters and the communal spaces of the slums are natural conduits for a virus that relies on physical closeness to spread." (31)*

Challenges concerning isolation–social conflict and stigma

Any crisis comes with loads of challenges. The cramped housing spaces (both indoor and outdoor) make it difficult for refugees to adhere to COVID-19 restrictions as prescribed. The same was evident from the stated statement by a female respondent.

> *"We cannot maintain social distancing in our shelter and outside as well. Our room becomes very hot during this hot summer due to the roofing materials, tarpaulin, insufficient solar fans, and natural ventilation. Therefore, we cannot stay in a room for long, and can't stay outside also because of overcrowded people and the risk of Coronavirus." (11)*

The slum's spatial layout and infrastructural instability made it difficult to maintain social distance. Around 16–30 households share one toilet/bath, while 25–30 families share a tube well. Similarly, about 20 people who had access to water with compromised water quality shared a tap. The lanes in the urban poor residential area were so compact that they found it very difficult to move. The dense living conditions are the biggest challenge in maintaining physical distancing norms (11, 12, 14, 19). A resident stated

> *"The lanes are so narrow that we can barely cross each other; we rub shoulders...We need to travel outside to use common toilets...It is hard to maintain quarantine as we don't have sufficient space and lack (attached) toilets ..." (12)*

The poor urban residents felt stigmatized for contracting the infection due to their overcrowded living conditions. Apart from making it impractical to practice physical distancing, they were under threat of getting a disease as a shack measuring 6 to 15 meters square was shared by around 10 individuals (26). The poor and compacted housing infrastructure significantly affected the anxiety level and exacerbated levels of gender-based violence (16).

Theme 3: Coping mechanism, social support, and expectations

Mal-adaptive practices

Due to the enforcement of stringent lockdowns, physical distancing was hindered as the residents with staggering work in the poor urban regions were compelled to stay at home; consequently, overcrowding worsened more. Insufficient spacing and overcrowding lead residents to take refuge under trees or opt for makeshift seating spaces outdoors (21). Deterioration in health conditions was reported among the residents with the insecure residence. Furthermore, people residing in perilous environments like asylum, streets, or insecure areas were experiencing daily stressors, discrimination along with degrading in their mental health (30).

Social support and community members' expectations

The crises dealt with community engagement and involvement. The rural childcare center, educational institution, community center, and train coaches were transformed into isolation centers to ensure physical distancing (15). Migrant workers were supported with personal protective equipment, food, and housing by the company (18). Investing in decent, affordable, and resilient housing needs was to be prioritized as it could deliver healthcare and prosperity to the individuals.

Discussion

The findings demonstrated that the inadequate housing infrastructure makes the lives of the urban poor more precarious during unprecedented events such as COVID-19. Typically, the houses lacked enough lighting and ventilation. The overcrowding was visible, as the houses and camps in urban poor areas had disproportionate dimensions and clogged streets. The quality of the homes was so low that they could barely withstand harsh conditions such as rain and flooding.

Throughout COVID-19, housing with inadequate WASH infrastructure in urban poor settlements posed a difficulty. Typically, this population lacked personal bathrooms and water taps, requiring them to rely on unreliable communal or shared water supplies and community toilets. During pandemics, this deficiency makes it more challenging to adhere to infection control standards such as physical separation, hand hygiene, and isolation. In a few instances, planned housing with amenities for the urban poor was reported; however, the facilities were sadly shared. According to the results, a handful of the urban poor did not have the luxury of four walls and a roof and was forced to sleep on the streets. The results also indicate that overcrowding worsened due to the lockdown, as the restricted movement made it difficult to adhere to physical distance restrictions. With the increase in population, the stigma of catching the infection increased inside and beyond the home. This increased domestic violence, a problem regardless of gender, as working family heads were forced to remain at home (33–35). Frequently, women in urban slums experience violence (36). Their lives are endangered by maladaptive behaviors like sheltering on or beneath trees.

According to the facts, there was very little social or communal support. However, a temporary effort was made by converting train coaches or institutions into isolation centers. The community's expectations for basic facilities from the government were not realized. Housing insecurity is widespread in LMICs, particularly in urban slums where many urban residents live. According to the data, housing-related problems increased among urban poor inhabitants during unanticipated pandemics. The inclusion of just studies from LMICs limits the generalizability of the findings. As the inequalities and discrepancies among the urban poor regarding access to housing and essential utilities become apparent amid this horrific pandemic, it serves as a wake-up call for concerned authorities worldwide.

There is an urgent need to scale up the implementation of initiatives such as Prime Minister Housing Scheme and JAGA mission of India, Housing microfinance and Participatory Slum Upgrading Program (PSUP) of African countries, Argentina's Slum Housing Upgrade Program across all LMICs. These housing schemes provided accommodation for the urban poor or slum dwellers living in cramped conditions with inadequate infrastructure, hygiene, and drinkable water, thereby improving their quality of life and health (37–42). These are based on *in-situ* slum redevelopment concept that uses slum-occupied land to incentivize the creation of formal settlements for slum residents by private actors. Researchers and policymakers must comprehend and address the housing needs of this vulnerable population. There is little evidence of the impact of housing infrastructure on the overall health of the urban poor. In the context of LMICs, understanding the problem of slum growth and urban housing shortage is crucial. As slums grow as a result of systemic failure, their transformation necessitates a combination of political will, committed leadership, and empowered communities to enable urban changes that are consistent and inclusive.

The incidence and effects of COVID-19 can vary substantially across space and time, with urban populations initially being severely affected. Effective support for poor and vulnerable households will require substantial additional financial resources. In addition, the older adults, children, disabled, and women are prone to have the worst effects. The COVID-19 pandemic is wreaking havoc on women's health and social and economic well-being worldwide. As the pandemic expands to LMICs, the response must address the underlying injustices that put women and girls at greater risk in slums. Women also bear a disproportionate share of the load at home due to school and childcare facility cutbacks, as well as long-standing gender disparities in unpaid labor. During times of crisis and quarantine, women suffer heightened risks of employment and income loss and increased dangers of violence, exploitation, abuse, or harassment. Policy solutions must be quick and take into account the concerns of women (43, 44). Fundamentally, all policy responses to the crisis must incorporate a gender lens and consider women's distinct demands, responsibilities, and viewpoints.

It is crucial to reimagine housing policies for the urban poor, particularly in LMICs, emphasizing pandemic and epidemic management protocol. The COVID-19 Pandemic highlights and exacerbates existing structural inequities and endangers the lives of the urban poorest segments of the population. The pandemic criteria did not align with existing housing, water, and sanitation facilities. The urban slum encountered many obstacles, but in light of the gravity of the situation, they overcame them with patience and diligence. Urban planning and policies should also ensure that the urban poor's housing infrastructure complies with basic housing and health criteria. Urban areas demand a healthy and sustainable housing strategy for the urban poor. Along with other essential utilities, the urban poor should be granted housing rights on humanitarian grounds. A time-bound plan is necessary to support the envisioned urbanization program.

Author contributions

KS, SD, and GD developed the protocol. SD and MS completed the search, screened the articles for inclusion, extracted the data, and completed the risk of bias assessments. KS, PM, SD, and GD extracted the data and synthesized the findings, interpreted the results, and drafted the manuscript. SP and MB interpreted the results. All authors critically revised the manuscript. All authors approved the final version.

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The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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A bibliometric analysis of the study of urban green spaces and health behaviors

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Urban green space can supply a range of ecosystem services and general health benefits for people. This paper reviewed and analyzed 607 papers related to urban green space and health behaviors from 2002 to 2021 in the Web of Science core collection by using Citespace 6.1.R2 software. The scientifically bibliometric analysis and visual analysis were conducted to analyze the basic characteristics, literature co-citation analysis, research hotspots, and frontier trends. The findings show that 11 co-citation clusters indicate the research intellectual base. Also, 19 main keywords with a high frequency and 20 main keywords with a high centrality were extracted. Burst detection analysis reveals three research frontier trends: the correlation between urban green space and health behavior; the driving and impact factors; and the study of environmental justice and social equity. This paper aims to systematically review the progress and basic situation of urban green spaces and health behaviors research around the world, which helps to gain a comprehensive understanding of this field, as well as provide value and references for subsequent research.

KEYWORDS

Citespace, knowledge mapping, bibliometric analysis, urban green spaces, health behaviors

Introduction

Globally, there is no such universal definition of urban green space. Its definition varies according to context or geographic range. Generally, urban green space (UGS) includes parks, gardens, street greenery, wetlands, community green spaces, natural woodland, etc., which is recognized as the optimized mechanism for human living environments and life quality (1, 2). UGS can deliver varieties of ecosystem services and general health benefits for people, especially for women and the old (3, 4), by encouraging various physical activity behaviors and nature contact (5–8).

World Health Organization (9) (WHO) defined "health" as "a state of complete physical, mental and social wellbeing, not merely the absence of disease or infirmity". Currently, the increasing frequency of global public health events, such as COVID-19 (confirmed 504.4 million by April 20, 2022), and the huge burden of disease, such as there were 13.1% age-standardized prevalence of obesity among adults in 2016 (10), has gained more international attention and academic concern. A number of studies have explored and explained the relationship between UGS and human health behavior (HB), concerning physical and mental health. Most studies proved that UGS has a positive influence on HB. For example, a previous WHO report states that UGS can positively affect physical activity and mental health (11). More specifically, greater use and coverage of UGS in residential communities can improve behavioral development, reduce rate of Attention of Deficit Hyperactivity Disorder in children (12), help restorative psychological effects (13), and reduce the feelings of loneliness (14). Also, streetscape greenery positively affects old adults' walking propensity and travel ability (15–17). Urban wildscapes are positively associated with adults' perceived restoration, stress, and mental health (18). Besides, the complex UGS system (i.e., the horizontal, vertical greenery, and proximity of green levels) could reduce residents' obesity (19).

Yet, existing reviews mainly focus on the factors that affect the relationship between UGS and HB, such as the exposure to UGS air pollution and health (20), certain ecosystem services and health (21), UGS and walking (22, 23). The literature on integrating research of UGS and HB in the review article group remains limited. A scientifically bibliometric analysis of the general UGS and HB research is required. In this paper, the publications related to UGS and HB from 2002 to 2021 were analyzed by using Citespace 6.1.R2 software, while contributing to the ongoing discussion. The remainder of this paper is organized as follows. Section Materials and methods presents the methodology of this study. Section Results provides a coherent knowledge base regarding the basic characteristics (distribution of years, journals, disciplines, areas, countries, and institutions), literature co-citation analysis, research hotspots, and frontier trends combined with the visual knowledge maps. In conclusion, implications and limitations, and future development prospects are discussed in section Discussion. The main findings in this paper were concluded in section Conclusion. This study aims to systematically review the progress and basic situation of UGS and HB research around the world, in order to provide a scientific reference for the related research.

Materials and methods

Data collection

A preliminary search in the Web of Science Core Collection (WoSCC) database was conducted to select the keywords. Then, the retrieval type was: (TS = "urban green space" AND "health behavior") OR (TS = "urban park" AND "health behavior") OR (TS = "urban green infrastructure" AND "health behavior") OR (TS = "urban green" AND "health behavior"), only concerning the original research article and review. Timespan (almost 20 years): 2002-01-01—2021-12-31 (since there is no product in 2001), language = English. Search time was July 19, 2022. Finally, 607 publications were obtained, including 553 articles and 54 review articles, according to relevance and then removed the duplications.

Methods

Citespace (Citation Space) is a software that combines scientometric analysis and visual analysis, which can present the structure, rules, and distribution of scientific knowledge. Also known as the "Mapping Knowledge Domains, MKD" (24, 25). Six hundred and seven references were imported into Citespace 6.1.R2, and then were further analyzed regarding the publication output and journal distribution, the development of disciplines and research areas, distribution by countries and institutions, co-citation analysis, research hotspots, and frontiers analysis, by setting and modulating the relevant parameters (see Figure 1). Figure 1 shows that the process of research methodology in this paper.

Results

Profile of publication

Publication output and journal distribution

As can be seen from Figure 2, literature publication generally shows a growing trend from 2002 to 2021, consisting of two periods: a slow growth period and a rapid growth period. First, from 2002 to 2013, it showed a slow growth trend, during which there were three times of decline (2006–2007; 2010–2011; and 2012–2013). During this period, only 83 articles were published, accounting for 13.67%. But in the period of rapid growth (from 2014 to 2021), there were 524 publications, increasing by as much as 8-fold compared to the first period. This may be related to people's increasingly strong pursuit of health awareness and outcomes.

Regarding the study of UGS and HB, the papers were mainly published in journals concerning public, environmental & occupational health, environmental research, and urban studies. Table 1 shows the main productive source publications. *International Journal of Environmental Research and Public Health*, *Urban Forestry Urban Greening*, and *Landscape and Urban Planning* are the top three productive journals. Among these, *Science of the Total Environment* has the highest impact factor (10.753). Articles were published in these ten journals that accounted for about 32% of the total.

Development of disciplines and research areas

Although the amount of literature obtained from the retrieval results is small, the studies involve 93 disciplines in total. There are six categories with articles over 40: Public Environmental Occupational Health (194), Environmental Sciences (148), Environmental Studies (116), Urban

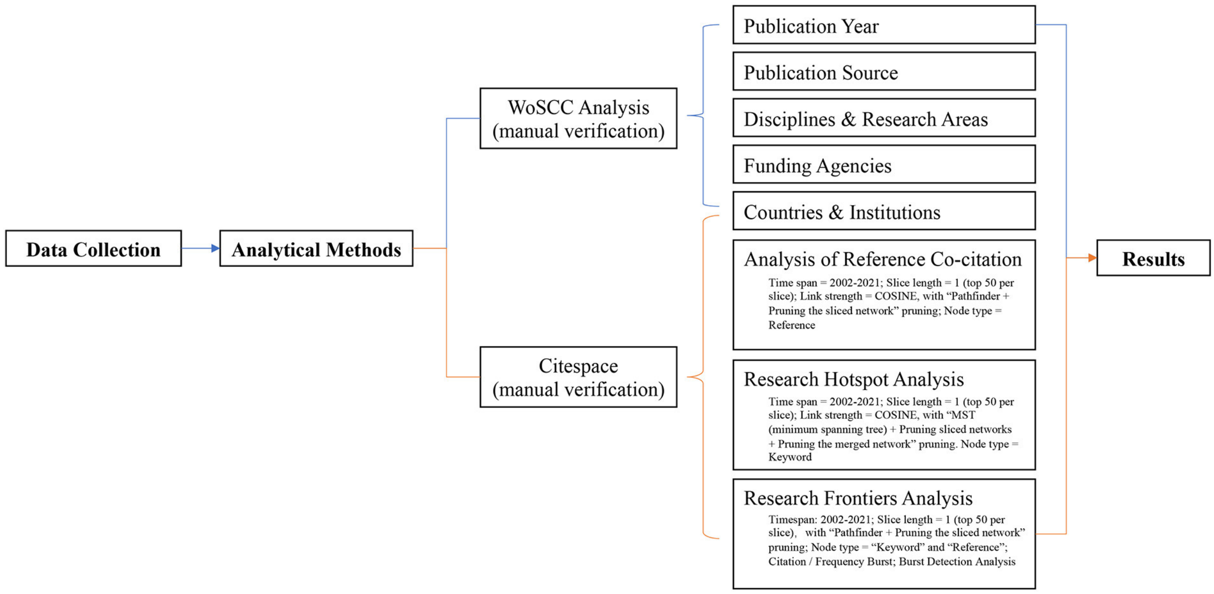

FIGURE 1
Flow chart of analytical methods.

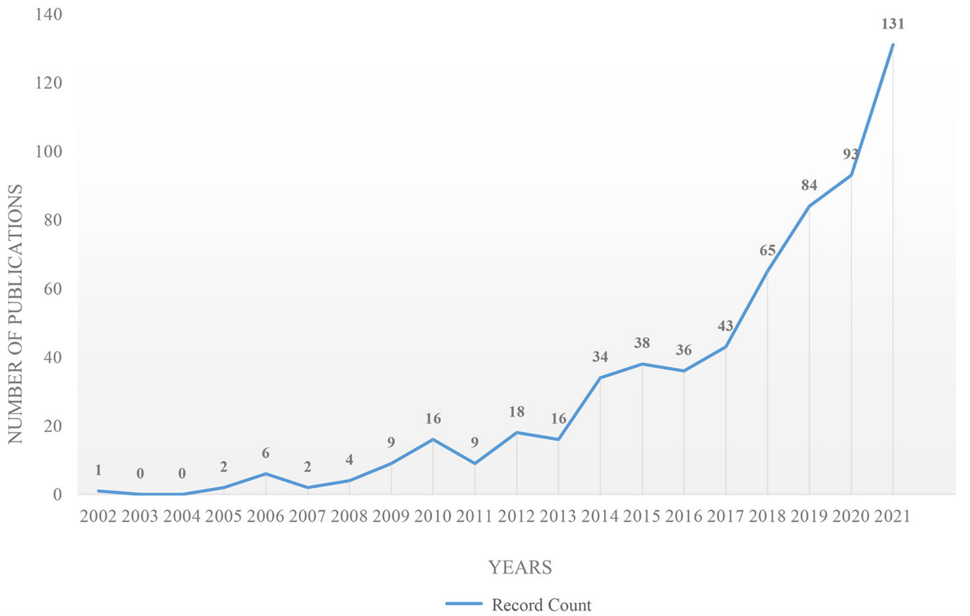

FIGURE 2
Literature distribution by years concerning the study of urban green space and health behaviors. Graphical representation based on WOS Core Collection search on July 19th, 2022.

Studies (82), Green Sustainable Science Technology (43), and Geography (40), respectively. Moreover, the research field involves 73 research areas, of which, the area of Environmental Sciences Ecology accounts for the highest occupation (247 articles).

Distribution by countries and institutions

The publications are from 74 countries and regions in the world. Table 2 presents the top ten most productive countries. Although the United States had the highest number of publications (193), it ranked fifth (0.18) in terms of

TABLE 1 Top 10 productive source publications.

Source titles	Impact factor (JCR 2021)	Record count	% Of 607 publications
International Journal of Environmental Research and Public Health	4.614	51	8.402
Urban Forestry Urban Greening	5.766	35	5.766
Landscape and Urban Planning	8.119	21	3.460
Sustainability	3.889	18	2.965
Health & Place	4.931	16	2.636
International Journal of Behavioral Nutrition and Physical Activity	8.915	15	2.471
Journal of Physical Activity & Health	3	12	1.977
PLoS ONE	3.752	12	1.977
Science of the Total Environment	10.753	12	1.977
BMC Public Health	4.135	11	1.812

JCR, journal citation reports.

TABLE 2 The top ten productive countries or regions.

Countries/regions	Record count	% Of 607	Centrality
USA	193	31.796	0.18
Peoples R China	98	16.145	0.18
England	91	14.992	0.22
Australia	66	10.873	0.37
Canada	38	6.260	0.04
Netherlands	35	5.766	0.21
Germany	34	5.601	0.04
Spain	33	5.437	0.14
Scotland	26	4.283	0.02
Italy	18	2.965	0.34

betweenness centrality value, as the same as China (0.18). Australia ranked fourth regarding the record count (66). Its betweenness centrality value was the highest (0.37), indicating that Australia is in the most critical position in the cooperative network. Italy (0.34), England (0.22) and the Netherlands (0.21) followed. Also, from Figure 3, we can see that European countries form the most important network of cooperative relationships. In addition, China is the only Asian country in the top 10 countries/regions. "the National Natural Science Foundation Of China" ranked fourth among the top scientific research funding institutions. This may be related to the fact that the Communist Party officially put forward the "consciousness of advocating a community with a shared future for mankind" at its 18th National Congress in 2012. The mainstreaming of this consciousness has led scholars to pay more attention to human health.

A cooperation network of institutions produced 120 nodes (Figure 4), indicating the authors are from 120 research institutions. The top three productive institutions are the University of Hong Kong (14), the University of Exeter (14), and the University of Melbourne (11). The top 50 are dominated by the United States (15), Europe (13), Asia (9), Australia (6), Canada (3), New Zealand (3), and Brazil (1). It can be seen that the related studies are almost concentrated in European countries, North America, Australia, and Asia. A few in Latin America. The results are evenly distributed in space. Figure 4 also shows that a relatively close cooperative network has been formed among various academic institutions.

Analysis of reference co-citation

A and B are the co-cited relationship when papers A and B appear together in the reference list of a third cited paper (25). Similar studies can be aggregated by literature co-citation analysis to form major research areas, which shape the citation network that can trace the development context forward and explore the research frontier backward, as well as form the knowledge base of the specific research field. In all, 607 publications were analyzed in Citespace. Eleven clusters were extracted by using the clustering algorithm. They were labeled by the first term from the LLR (log-likelihood ratio, p-level) algorithm, numbered from #0 to #10 (Table 3). In Table 3, the silhouette value of each cluster is >0.7, indicating that the clustering reliability is very high. It is worth mentioning that the larger the silhouette value, the higher the similarity of the cluster members. Among the 11 clusters, the average year of nine clusters was 2015 or later, indicating that most of the clusters (related research) are relatively new. The mean year of publication in Cluster #6 and Cluster #9 was 2020, named "COVID-19" and "utilizing big data", which is related to COVID-19 pandemic in 2019, and the increasing use of internet big data. Moreover, 11 clusters actually reflect the intellectual basis of the UGS and HB research. The largest top three clusters

FIGURE 3
Countries of origin of articles.

are "human health", "park use", and "residents' perception", showing that the main research base is under the human health, park use, and residents' perception research fields.

The co-citation analysis map was achieved (Figure 5). In Figure 5, different colors represent different clusters. Nodes represent different publications, and lines represent network relationships between the publications. Figure 5 shows the complex integration among 11 clusters, indicating that they are not independent studies under 11 research fields, but also cross-over studies.

Besides, the top ten highly-cited publications in the sample range are listed in Table 4. The paper "Nature and Health" published by Hartig et al. (13) is significant since it has the highest citation frequency (66). Besides, regarding the frequency higher than 20, there are four articles in Cluster #1, two each in Cluster #3 and Cluster #4, and one each in Cluster #0 and Cluster #2.

Cluster #0: Human health

Cluster #0 is the largest cluster (86 members), appearing dark green in Figure 5. Cluster #0 was formed from 2008 to 2019, and the average year of publication is 2017, which means this is a new cluster. It quickly became the largest cluster in a very short period of time. This cluster focused on human health, highlighting the key role of the urban green environment in human welfare.

There are four articles that have a citation frequency higher than 10 in this cluster. Moreover, a paper by James et al. (29), "A Review of the Health Benefits of Greenness" had the highest citation count in Cluster #0 (34). It found strong evidence for a positive correlation between greenness and physical activity. Besides, the article "Advantages of public green spaces in enhancing population health" by Sugiyama et al. (35) was the most active paper, since it cited 26 papers from Cluster #0. This paper focuses on the important relationship between public

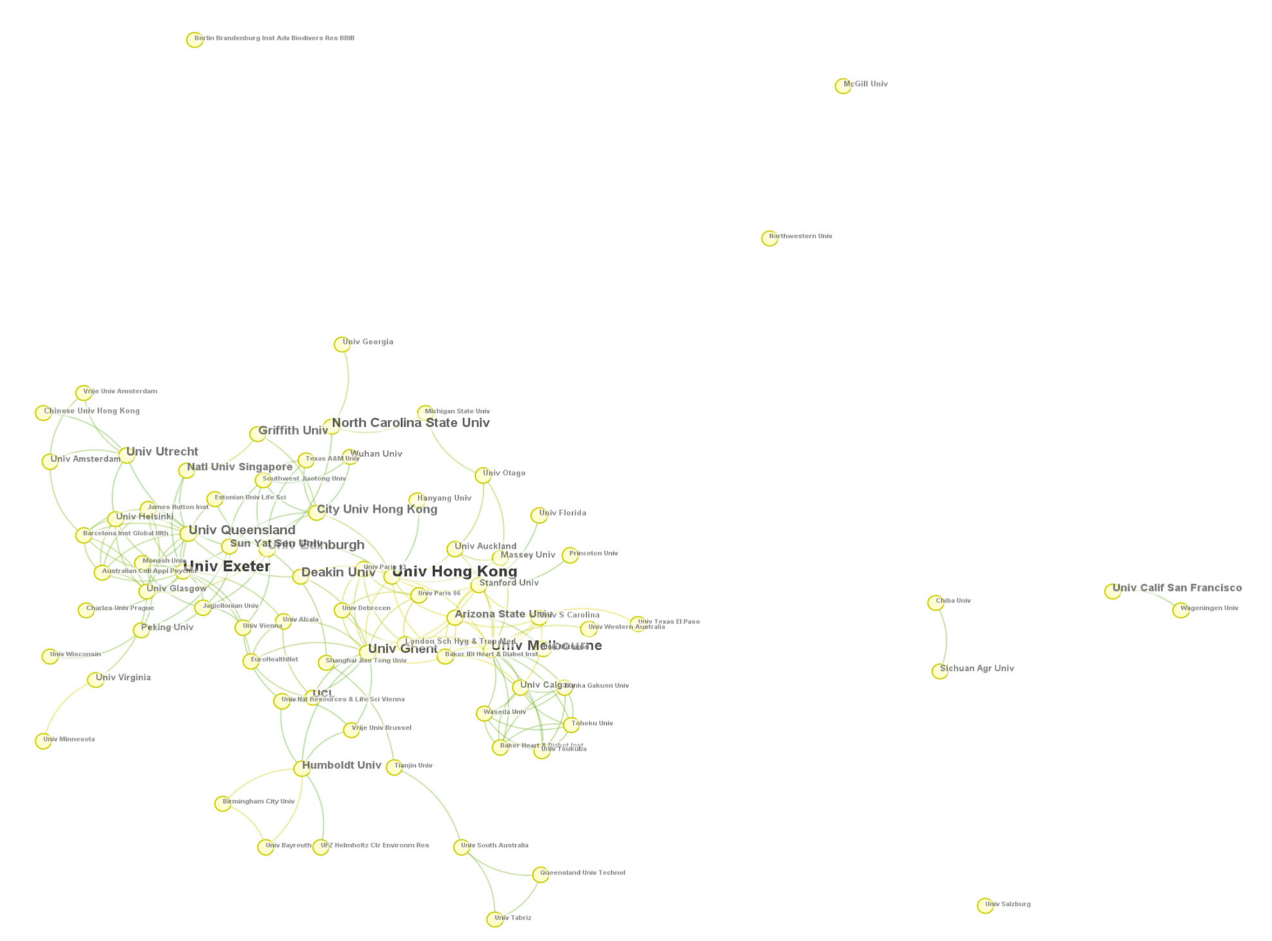

FIGURE 4
Institutions of origin of articles.

green spaces and health benefits, as well as three advantages of using public green spaces as a health promotion measure.

Cluster #1: Park use

Cluster #1 was labeled as "park use" with 78 members. The publication years of this cluster are from 2006 to 2019 (Mean year = 2015). The citation counts of eleven papers exceed 10. This cluster mainly focuses on the studies on how the general or the specific characteristics of parks could affect their usage for residents.

The article by Wolch et al. (5), has the highest citation count, also the third most cited article among 607 papers. It emphasizes the key role of urban green space in public health. It also explained the paradoxical nature of urban green space strategies, whereby creating new green spaces to make neighborhoods healthier (e.g., environmental justice issues), is accompanied by an increase in housing costs.

Furthermore, Sugiyama et al. (35) is still the most active literature that cited 17 papers in Cluster #1. And then the paper "The associations between park environments and park use in southern US communities" by Banda et al. (36), cited 15 papers in Cluster #1.

Research hotspots analysis

Keywords co-occurrence analysis refers to the co-occurrence relationship between two terms when they appear jointly in one paper. The higher the frequency of co-occurrence, the stronger the relationship between the two keywords. Through the co-occurrence analysis of keywords, hot topics in a given field can be analyzed. Then, a co-occurrence analysis map of keywords was obtained (Figure 6). There are 216 nodes (i.e., 216 critical keywords), and 105 links (density = 0.0045).

In Figure 6, the circle node represents the frequency. The higher the frequency, the larger the circle. The purple nodes in the outer ring indicate the highest betweenness centrality. The largest circle node is "physical activity", with a count of 229, as well as the highest betweenness centrality value of 1.29.

TABLE 3 Summary of 11 clusters.

ID	Size	Silhouette	Mean (year)	Top terms (log-likelihood ratio)
#0	86	0.75	2017	**Human health** (66.83, 1.0E-4); New Zealand adolescent (63.1, 1.0E-4); objective neighborhood environment (63.1, 1.0E-4)
#1	78	0.785	2015	**Park use** (92.9, 1.0E-4); urban design (79.16, 1.0E-4); park environment (71.12, 1.0E-4)
#2	74	0.92	2011	**Residents' perception** (118.29, 1.0E-4); walkable community (118.29, 1.0E-4); adjacent park (113.72, 1.0E-4)
#3	66	0.881	2016	**Physical activity** (84.24, 1.0E-4); ecological justice perspective (62.07, 1.0E-4); broad view (62.07, 1.0E-4)
#4	55	0.884	2017	**Urban greenness** (96.55, 1.0E-4); walking behavior (91.07, 1.0E-4); urban green space (58.61, 1.0E-4)
#5	46	0.903	2019	**Edible forest garden** (79, 1.0E-4); salutogenic affordance (79, 1.0E-4); multiple benefit (79, 1.0E-4)
#6	37	0.923	2020	**COVID-19 pandemic** (341.23, 1.0E-4); vulnerable communities (79.55, 1.0E-4); outdoor recreation (74.49, 1.0E-4)
#7	29	0.895	2017	**Green open space development model** (55.04, 1.0E-4); dense urban setting (55.04, 1.0E-4); green space behavior (47.88, 1.0E-4)
#8	27	0.944	2014	**Urban neighborhood** (62.29, 1.0E-4); socioeconomic gradient (58.45, 1.0E-4); neighborhood park (58.45, 1.0E-4)
#9	23	0.999	2020	**Utilizing big data** (70.43, 1.0E-4); city center (44.62, 1.0E-4); smart cities (44.62, 1.0E-4)
#10	15	0.938	2011	**Residential neighborhood** (54.99, 1.0E-4); spatial contagion (54.99, 1.0E-4); influencing participation (45.11, 1.0E-4)

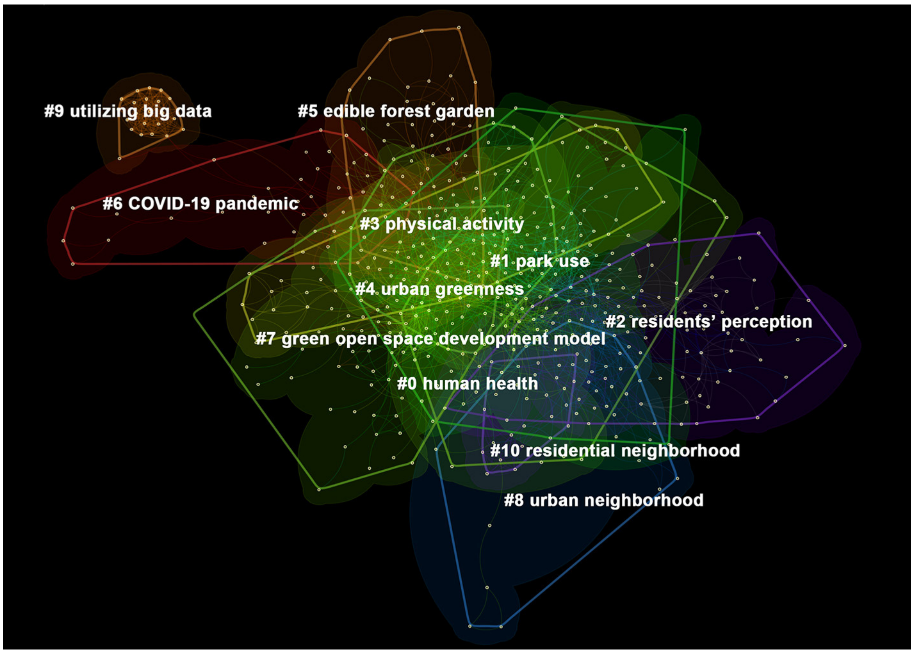

FIGURE 5
Knowledge map of co-cited reference analysis.

It also was the first important keyword appearing in 2005. Moreover, in Table 5, 19 keywords were extracted, since they had a frequency >40, showing that research on such areas has become increasingly popular. Twenty keywords were extracted and ranked by betweenness centrality, indicating that studies on such fields have been a research focus. According to Table 5 and Figure 6, we can see that the keywords mainly involve three research objects: (1) Different scales of UGS, like urban parks, neighborhood parks, recreational facilities, and so on; (2) Different health behaviors and outcomes, such as walking, sedentary behavior, obesity, and mental health; (3) The impact factors, e.g., accessibility, impact, risk.

TABLE 4 Top ten highly-cited references.

Frequency	Cluster	Title	References
66	#3	Nature and Health	Hartig et al. (13)
45	#1	Urban green space, public health, and environmental justice: the challenge of making cities "just green enough"	Wolch et al. (5)
30	#4	Exploring pathways linking greenspace to health: theoretical and methodological guidance	Markevych et al. (26)
28	#1	The health benefits of urban green spaces: a review of the evidence	Lee and Maheswaran (27)
26	#3	More green space is linked to less stress in deprived communities: evidence from salivary cortisol patterns	Ward et al. (28)
24	#0	A Review of the Health Benefits of Greenness	James et al. (29)
23	#1	The impact of interventions to promote physical activity in urban green space: a systematic review and recommendations for future research	Hunter et al. (30)
21	#2	Effect of exposure to natural environment on health inequalities: an observational population study	Mitchell and Popham (31)
20	#1	Opportunity or Orientation? Who Uses Urban Parks and Why	Lin et al. (32)
20	#4	Streetscape greenery and health: stress, social cohesion and physical activity as mediators	De Vries et al. (33)

TABLE 5 Main keywords ranked by the frequency and the betweenness centrality value.

Count	Year	Keyword	Centrality	Year	Keyword
229	2005	Physical activity	1.29	2005	Physical activity
119	2007	Health	1.07	2009	Park
116	2010	Green space	1.05	2010	Public health
112	2008	Built environment	0.98	2011	Urban sprawl
100	2010	Behavior	0.94	2011	Impact
87	2008	Environment	0.94	2006	Risk
72	2009	Walking	0.84	2015	Accessibility
72	2010	Public health	0.82	2007	Health
70	2008	Association	0.82	2008	Area
59	2012	Urban green space	0.8	2009	Sedentary behavior
52	2009	Park	0.8	2009	Recreational facility
51	2010	Mental health	0.77	2009	Walking
51	2009	Obesity	0.72	2015	Park use
51	2011	Impact	0.63	2014	Neighborhood
50	2008	Perception	0.53	2012	Urban green space
50	2016	Benefit	0.5	2008	Built environment
47	2010	Urban	0.33	2009	Obesity
46	2014	Neighborhood	0.3	2008	Environment
44	2012	City	0.26	2016	Ecosystem service
			0.21	2016	Natural environment

Research frontiers analysis

Burst detection can capture nodes with great frequency changes in a certain period of time. Such mutation information can reflect the rise of a research theme, which is often used to do cutting-edge analysis. A map of burst detection of emerging terms and references was achieved (Figure 7). There are 504 nodes and 3,364 links (density = 0.0265). Light yellow nodes represent the reference, and dark yellow nodes represent the terms, in proportion to the degree of betweenness centrality. So, the term "built environment" and the paper by Mitchell and Popham (31) have the highest centrality value.

A total of 9 keywords were extracted (Table 6). As mentioned above, "physical activity" is the first key term that is confirmed again here. Moreover, "built environment" has the strongest strength of citation bursts (8.7), and its influence lasted from 2008 to 2013. However, no important keywords with strong citation burst were added after 2018. Furthermore, the top

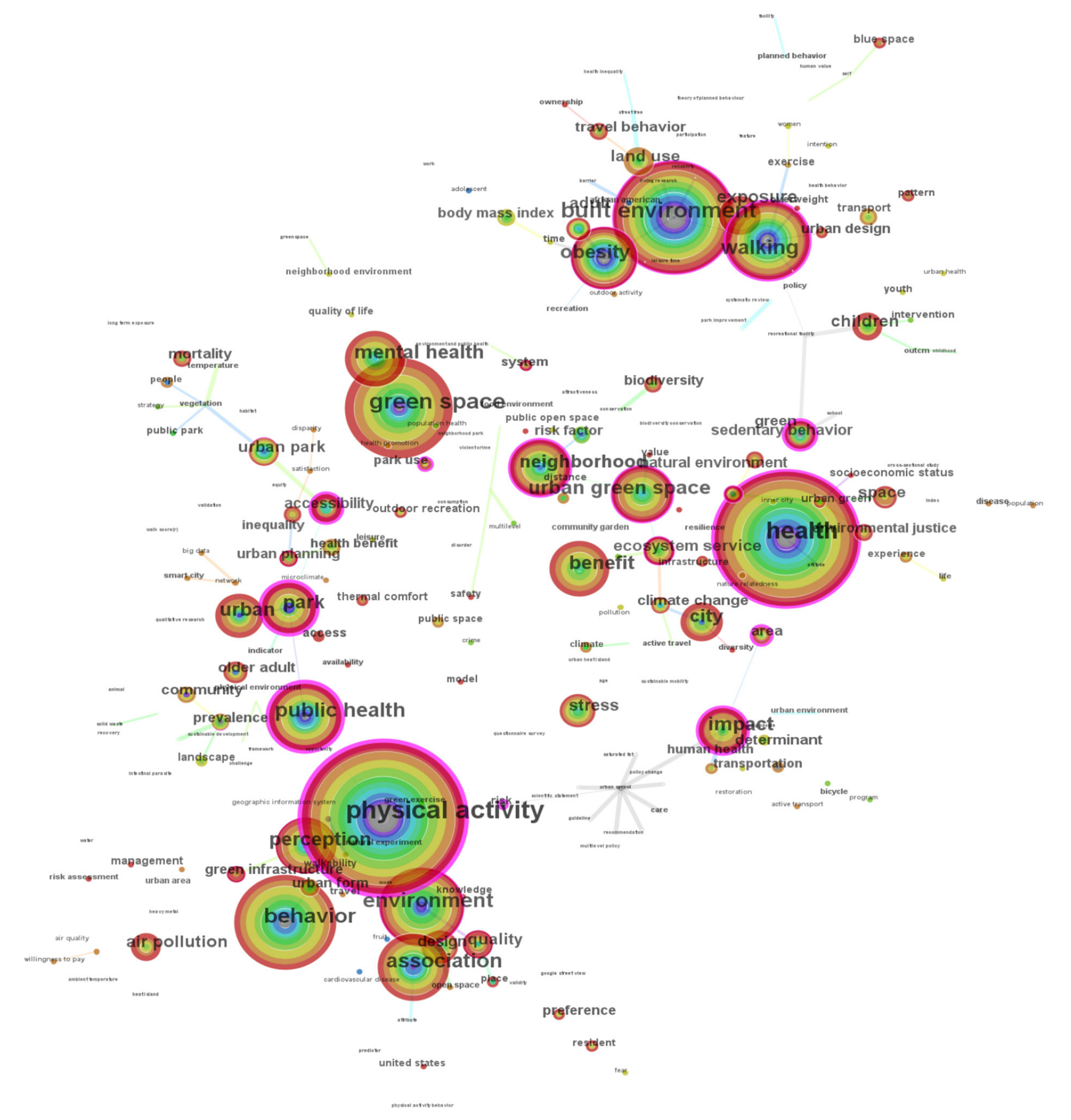

FIGURE 6
Keywords co-occurrence network.

nine keywords with the strongest citation burst also reflect the research frontiers related to UGS and HB, including driving factors (e.g., built environment, risk factors, public parks, intervention); and the dimensions of health (e.g., physical activity, walking, obesity).

Moreover, Table 7 shows the top 15 references with the strongest citation bursts in the WoSCC database from 2002 to 2021. Among them, the strength of the citation bursts started from 2008 to 2021. From 2019 to 2021, there are three papers with high strength in the citation bursts: Wolch et al. (5); Frumkin et al. (37); and Baran et al. (38), indicating that they are nearly 3 years of cutting-edge research.

The top 15 articles further reveal the research frontiers, integrating with the other publications with strong citation

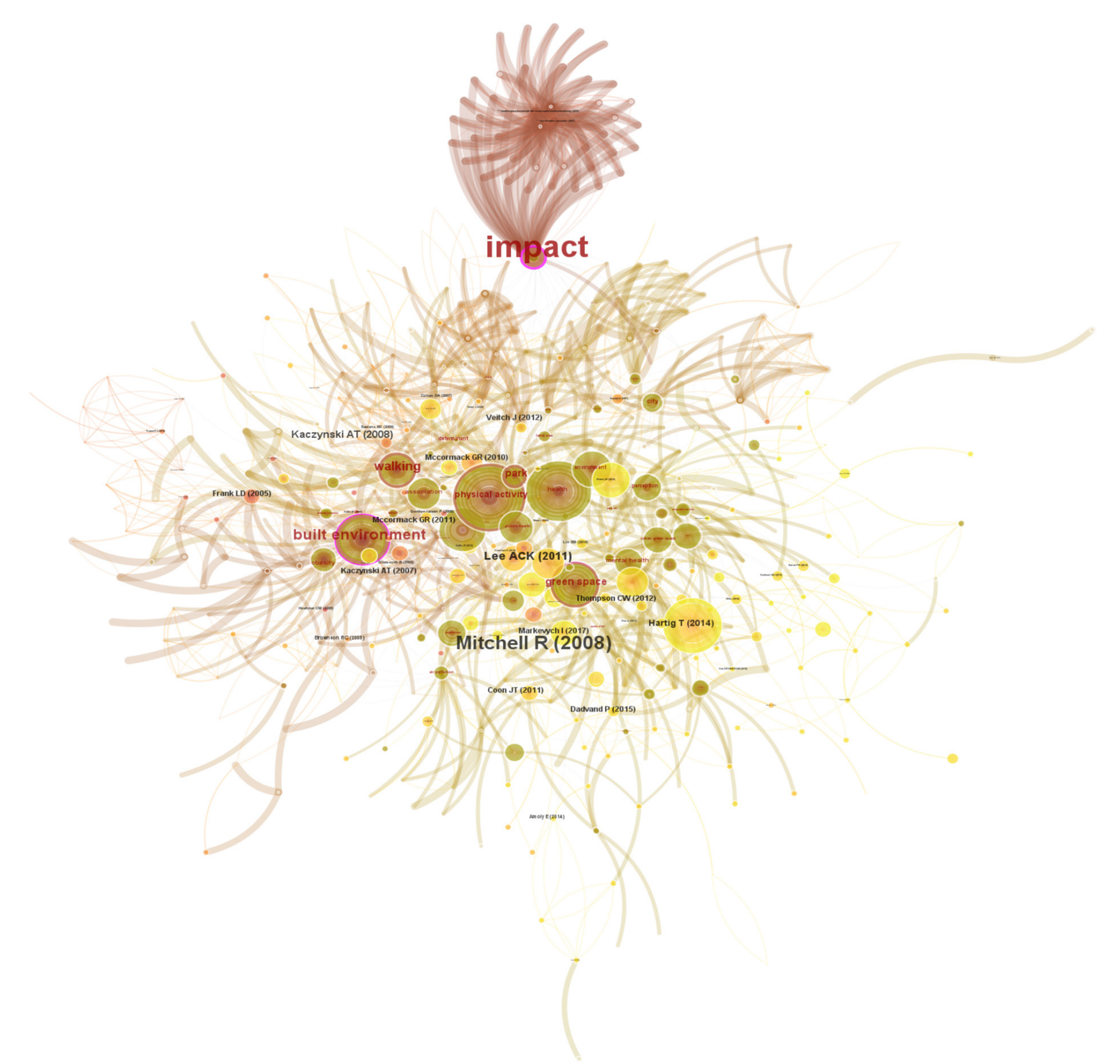

FIGURE 7
Map of burst detection of emerging terms and references.

bursts. Hence, there are three research frontiers regarding the study of UGS and HB in the nearly two decades: (1) the relationship between UGS and HB; (2) the influence factors; (3) environmental justice and social equity.

Discussion

Implications and limitations

The findings show that the number of publications increased from 2002 to 2021. And it has increased significantly since 2014, which is closely related to the global organizations supporting national efforts with much-sophisticated assistance. For instance, *Global Action Plan* was published in 2014 (34), and the 17 United Nations Sustainable Development Goals (SDG) were adopted in 2015. More specifically, SDG 3 "good health and well-being" advocates for all countries to guarantee and improve people's health. Also, SDG 11.7 aims to achieve the following: "By 2030, provide universal access to safe, inclusive and accessible, green and public spaces, in particular for women and children, older persons and persons with disabilities" (48). Furthermore, the most important jump happens from 2019 to 2021, which is a period facing a global public health crisis COVID-19, that

TABLE 6 Top 9 keywords with the strongest citation bursts from 2002 to 2021.

Keywords	Strength	Begin	End	2002–2021
Built environment	8.7	2008	2013	
Physical activity	5.23	2005	2008	
Health	4.98	2007	2012	
Walking	4.94	2009	2016	
Obesity	4.94	2009	2014	
Risk	4.34	2006	2011	
Risk factor	4.28	2014	2018	
Intervention	3.4	2017	2018	
Public park	3.24	2014	2017	

The blue line represents the time measure (2002–2021), which is made up of 19 blue line segments; The red line shows the time period of the citation bursts (from begin to end).

TABLE 7 Top 15 references with the strongest citation bursts in WoSCC database from 2002 to 2021.

References	Title	Strength	Begin	End	2002–2021
Frank et al. (39)	Linking objectively measured physical activity with objectively measured urban form: findings from SMARTRAQ	9.13	2009	2013	
Mitchell and Popham (31)	Effect of exposure to natural environment on health inequalities: an observational population study	8.41	2009	2016	
Giles-Corti et al. (40)	Increasing walking: how important is distance to, attractiveness, and size of public open space?	6.42	2010	2013	
Maas et al. (41)	Green space, urbanity, and health: how strong is the relation?	6.35	2010	2014	
McCormack et al. (42)	Characteristics of urban parks associated with park use and physical activity: a review of qualitative research	5.97	2014	2017	
Saelens and Handy (23)	Built environment correlates of walking: a review	5.58	2011	2015	
Wolch et al. (5)	Urban green space, public health, and environmental justice: the challenge of making cities "just green enough"	5.26	2019	2021	
Gordon-Larsen et al. (43)	Inequality in the built environment underlies key health disparities in physical activity and obesity	5.09	2008	2014	
Kaczynski and Henderson (44)	Environmental correlates of physical activity: a review of evidence about parks and recreation	4.75	2010	2014	
Kaczynsk et al. (45)	Association of park size, distance, and features with physical activity in neighborhood parks	4.54	2010	2016	
Frumkin et al. (37)	Nature Contact and Human Health: a Research Agenda	4.51	2019	2021	
Tzoulas et al. (46)	Promoting ecosystem and human health in urban areas using Green Infrastructure: a literature review	4.35	2012	2015	
Cohen et al. (47)	Contribution of public parks to physical activity	4.29	2010	2015	
Owen et al. (22)	Understanding environmental influences on walking: review and research agenda	4.17	2010	2012	
Baran et al. (38)	Park use among youth and adults: examination of individual, social, and urban form factors	4.1	2019	2021	

The light blue line shows the time measure; The dark blue line means the year of publication, up to 2021; The red line shows the time period of the citation bursts (from begin to end).

may indicate a motivation for academia to focus on health behaviors research.

Besides, most published journals belong to the medical category (e.g., "public, environmental & occupational health", "medicine", "general & internal") and the environmental sciences and ecology category (e.g., "environmental sciences", "urban studies"). Herewith, the natural sciences are dominant in the research of UGS and HB. There are few studies related to social science. A discipline that intersects the natural and social sciences is involved, such as psychology. So, in future research, some sociocultural aspects of UGS, such as aesthetics and historical culture, should be considered for their impact on human health behavior.

Eleven clusters extracted in this paper provide a knowledge base for the research areas of UGS and HB. Through in-depth analysis, some articles are highly cited (Table 4), which is also confirmed by the burst detection analysis (Figure 7). Hence, as a knowledge base, the highly cited articles in the clusters still have enough influence on the current research.

From the keyword co-occurrence analysis in Section Research hotspots analysis, three research objects demonstrate that the keywords mainly focus on the UGS types and scales, HB types and outcomes, and the influencing factors. Yet, there are few keywords related to different human groups (e.g., age, gender, socioeconomic status, race), landscape and ecological characteristics (e.g., aesthetic value, cultural services, biodiversity), and social issues (e.g., landscape equity and justice).

Although considerable research supports that UGS has a positive influence on health, the theoretical and conceptual frameworks for how UGS provides benefits to human health and wellbeing are limited (49). Besides, at present, urban green space design for human health is mostly concentrated in the field of medical and rehabilitation design, which ignores the continuity and correlation of different UGS. Many findings could provide references for urban spatial planning, landscape design, and decision-making (49, 50). Hence, the co-work of landscape architects, urban planners, and designers is essential to devote themselves and their professional knowledge and experience to the maximized and optimized planning and design of UGS concerning the health benefits, combined with scientific studies.

Yet, this paper has some limitations. First, this study only collected publications in the WoSCC database, rather than using multiple databases to collect a larger sample of studies. Also, we only select English articles for analysis. Therefore, some non-English papers will be ignored. Second, due to space limitations, some literature clusters and nodes need to be further analyzed in detail.

Future research trend

First, Plenty of studies have been conducted to explain the relationship between green space and human wellbeing. From the perspective of positive correlation, green space is beneficial to improving people's health and wellbeing (46, 47), both in physical health and mental health. For instance, the percentage of green space in a resident's living environment is positively correlated with their perceived health (41). Besides, Sugiyama et al. (51) evidenced that perceived community greenness was more strongly associated with mental health than physical health, by using a sample of 1,895 adults with physical and mental health scores in the Adelaide of Australia. Although many studies proved that nature contact and UGS may offer a range of human health benefits (13, 37, 44), there is still much evidence that remains unknown. Conversely, green space also leads to negative outcomes, such as the potential pathogenic effects of UGS. Hence, the relationship between UGS and HB is complex and interactive, which is one of the future research trends.

Second, there is comparatively little evidence proving that specific health benefits are associated with certain features of UGS, though in the huge body of literature in this research area. Understanding the impact factors of UGS on human health behaviors is a research priority and frontier, concerning both qualitative and quantitative methods. Different physical health effects and psychological benefits are linked to different characteristics of UGS, which is significant (39, 42, 52, 53). There are two typical kinds of features regarding UGS. One is the particular characteristics and attributes of UGS, referring to size, area, aesthetic characteristics, landscape quality, functional infrastructure, etc. Specifically, the certain functional infrastructure (i.e., trees, lawns, flowerbeds, and play and outdoor fitness equipment) and aesthetic factors of UGS can promote adolescents' health exercise (54, 55). Also, residents prefer to use parks with distinctive designs (45). Another one is the features related to the external environment, such as distribution, distance, and accessibility of UGS. More specifically, the accessibility and distance of UGS can affect human behavior, such as the levels of walking (40). Most studies proved that both have a positive and significant relationship with HB (22). Hence, well-planned, well-designed, and better features of UGS may lead to increased usage and physical activity (56).

Last but not least, due to the many benefits of green space to human health, when green space becomes a special or even a scarce resource, it will inevitably involve environmental and social inequity. For instance, Gordon-Larsen et al. (43) believe that inequality in the availability of UGS for lower socioeconomic status groups may lead to overweight. Recently, some studies focus on the fair access and use of UGS concerning health behaviors and outcomes, especially for different age groups (youth, adults, and old adults) (15, 38, 57), different gender groups (18, 58), people of different race/ethnicity (e.g., white, black, and Hispanic) and income groups (59). For socially disadvantaged groups, whether UGS is provided fairly or not is a vital issue in the field of social and environmental justice (60). Most scholars point out that it is necessary to rationally plan the spatial distribution of UGS, and solve the problem of inequity by supplementing enough UGS and shortening the accessible distance. However, this is a contradictory issue that creating new UGS also increases housing costs and property values (5).

Conclusion

The results show the growing number of published articles from 2002 to 2021, with the number of published papers increasing from 1 in 2002 to 131 in 2021. The publication source with the highest circulation is the *International Journal of Environmental Research and Public Health*. Most important articles were published in journals dealing with the environment, and public health studies. The UGS and HB studies cover a total of 93 disciplines and 73 research directions. Public Environmental & Occupational Health and Environmental Sciences are the two most important disciplines. Research is more concentrated in the natural sciences. The United States had the highest number of publications, and Australia had the highest betweenness centrality value. The most productive institutions are the University of Hong Kong and the University of Exeter. A total of 11 clusters were extracted by literature co-citation analysis. The largest cluster was "human health". The keyword co-occurrence analysis obtained 19 words with the highest co-occurrence frequency and 20 words with the highest betweenness centrality value. Plus, "physical activity" is the most important keyword. Furthermore, the keywords mainly involve three research objects (different scales of UGS; different health behaviors and outcomes; the impact factors). In the end, there are three research frontier trends: (1) the relationship between UGS and HB; (2) the influence factors; (3) the study of environmental justice and social equity.

Data availability statement

The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding author/s.

Author contributions

SZ conceived and designed the study, conducted the systematic review and analyzed the data, and as well as wrote the manuscript. ZC contributed significantly to analysis and manuscript preparation. YO visualized the data and made the tables. SZ and XL reviewed and refined the paper. All authors contributed to the article and approved the submitted version.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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Indoor thermal comfort in a rural dwelling in southwest China

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Recently, indoor thermal comfort has received more scholarly attention than ever due to the COVID-19 pandemic and global warming. However, most studies on indoor thermal comfort in China concentrated on urban buildings in the east and north. The indoor thermal comfort of rural dwellers in southwest China is insufficiently investigated. Hence, this study assesses residents' indoor thermal comfort in a rural dwelling in Linshui, obtains the thermal neutral temperature of the rural area, and analyzes the thermal adaptation behavior of rural dwellers. The results reveal that the thermal neutral temperature of rural dwellers is 29.33°C (operative temperature), higher than that presented in previous studies based on the same climate region. Indoor thermal conditions in rural dwellings are relatively harsh, but various thermal adaptation behavior of rural dwellers significantly improve their ability to withstand the harsh conditions. When people live in an environment with a (relatively) constant climate parameter (e.g., humidity), their perception of that parameter seems compromised. Most rural dwellers are unwilling to use cooling equipment with high energy consumption. Therefore, more passive cooling measures are recommended in the design and renovation of rural dwellings.

KEYWORDS

thermal sensation vote, thermal adaptive behavior, questionnaire survey, operative temperature, rural area, hot-summer and cold-winter region

Introduction

In the context of global warming, extreme heat events have been frequently observed. Some studies demonstrate that extreme heat events pose a serious threat to human health, with excessive temperatures causing subhealth symptoms (e.g., fatigue, dizziness, tachypnea, and tachycardia) and that they are even life-threatening and fatal in severe cases (1–3). Therefore, creating a comfortable indoor thermal environment is essential to deal with excessive temperatures, reduce energy consumption, and safeguard residents' health (e.g., preventing heat-related illnesses such as heat exhaustion) (4–6).

The majority of people spend over 80% of their time indoors (7), so the quality of the indoor environment, which is essential for their physical and psychological health (8–10), is essential. Moreover, the American Society of Heating, Refrigerating and Air-Conditioning Engineers (ASHRAE) defines thermal comfort as "the condition of mind that expresses satisfaction with the thermal environment." Thus, thermal comfort is normally evaluated subjectively. Furthermore, the importance of whether people feel

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comfortable with the indoor thermal environment has recently been emphasized (11, 12). During the COVID-19 pandemic, people spent more time indoors than ever because of mandatory quarantine, stay-at-home orders, travel restrictions, and community closure (13–15). Therefore, indoor thermal comfort should receive much more scholarly attention in this era.

A goal of sustainable development is to design and build dwellings with a comfortable indoor thermal environment without increasing energy consumption. The thermal environment is influenced by various factors, such as wall materials (16–19), the outdoor environment (20–26), and active equipment (27, 28). Numerous locations have devised new construction and renovation solutions to alter the indoor thermal environment of dwellings by changing the above factors (29–31). However, in the rural areas of developing countries, the application and promotion of these (perhaps expensive) design and construction techniques are limited because of poor architectural design technologies and underdeveloped economic conditions (8), thereby posing severe threats to the indoor comfort and health of rural dwellers. China is a predominantly agricultural country with a large number of rural dwellers. According to data released by the National Bureau of Statistics in February 2022 (http://www.stats.gov.cn/), as of the end of 2021, 498.35 million people, which accounted for 35.3% of the total population, lived in rural areas. Therefore, enhancing indoor thermal comfort in rural dwellings in China should receive great attention. An essential step in improving the quality of life and health of rural dwellers is to understand their indoor thermal comfort.

Most studies on indoor thermal comfort aim to understand residents' satisfaction with the indoor thermal environment and, consequently, to improve the quality of their indoor environment. The results of such studies can help improve residents' health and living environment (32, 33). The goals of such studies are in line with the United Nations' Sustainable Development Goals (SDGs), such as SDG 3 "good health and well-being" and SDG 11 "sustainable cities and communities." As of today, numerous studies have focused on indoor thermal comfort in many locations, such as the USA (34, 35), Europe (36–38), and Australia (39, 40). In the context of China, researchers mainly focused on the northeast (41, 42), western (43, 44), and coastal (5, 45–47) regions. Comparatively, indoor thermal comfort in rural dwellings in southwest China received limited attention, although some studies on urban buildings in this region exist (48). Consequently, this study chooses a rural dwelling in Linshui County, southwest China, as the case to explore the indoor thermal comfort of rural dwellers by using subjective and objective methods (32).

The contributions of this paper can be summarized as below: [1] focusing on an under-studied location (a rural area in southwest China) and diversifying the focus of the existing literature on human thermal comfort; [2] examining rural dwellers' perceptions and preferences of indoor thermal environment parameters and analyzing the changes in their perceptions because of long-term adaptation; [3] determining the thermal neutral temperature of rural areas in a hot-summer and cold-winter (HSCW) region of China; and [4] identifying rural dwellers' thermal adaptation behavior patterns. This study provides a valuable reference for rural dwelling design, contributing to optimizing the indoor thermal environment and enhancing the health of rural dwellers.

Methodology

Climate classification in China

China is the third-largest country in the world. It has a highly diverse and complex climate, leading to the formation of numerous regions with diverse climatic characteristics. China has formulated the Code for Thermal Design of Civil Buildings (GB 50176–2016). The code divides China into five climate regions based on the average temperatures of the coldest and warmest months of a year: severe cold (SC) region, cold (C) region, hot-summer and warm-winter (HSWW) region, HSCW region, and temperate (T) region (see Figure 1).

The rural dwelling assessed in this study is located in an HSCW region, where the average temperatures of the coldest and warmest months are 0–10 and 25–30°C, respectively.

Study area

Linshui is a county in Guang'an, northeast Sichuan, southwest China (Figure 2). It is the county closest to Chongqing in Sichuan Province and is 90 km from the urban district of Chongqing. Its longitude ranges from 106°41′ to 107°18′E, while its latitude ranges from 30°01′ to 30°33′N. Linshui has an area and altitude of 1,909 km^2 and 366 m, respectively. As of December 2020, the population was 1.00 million, with an urbanization rate of 21.31%.

Linshui has a humid subtropical climate with mild winters, abundant rainfalls, and long summers. Figure 3 shows the monthly average, maximum, and minimum air temperatures (T_a) and average relative humidity (*RH*) of Linshui between 1981 and 2010. The highest and lowest temperatures are observed in August and January, respectively. The annual average temperature difference is about 20°C. Summer is hot in Linshui, and July and August are high-temperature seasons. The average *RH* is stable, with around 10% variance between the maximum and minimum.

Field measurements

Objective measurements and subjective questionnaires were conducted during the hottest month (August) to assess indoor thermal comfort in a rural dwelling in Linshui (Figure 4). The

FIGURE 1
Climate region for building thermal design of China. Adapted from the Code for Thermal Design of Civil Buildings, GB 50176–2016.

chosen rural dwelling (30°12′13″N, 107°00′47″E) was built in 2002. It is a two-story house with a total area of 225 m^2. The first and second floors are 3.8 and 3.0 m high, respectively. Multiple (four) sites were chosen for measurement, enabling the comprehensive monitoring of the thermal comfort of residents who spend most of their time in living rooms and bedrooms.

Field measurements were conducted between 21:00 August 3 and 17:15 August 6, 2019. Indoor T_a, RH, black globe temperature (T_g), and air velocity (v) were assessed using the measuring instrument listed in Table 1. The measurement tool is installed at each measurement location. The detector is placed 1.5 m above the ground, collecting the data at an interval of 15 min. The air-conditioner is off in the room during the measured period. All parameters (range, accuracy, and resolution) of the instruments used for the study meet the requirement of the ASHRAE Standard 55–2017 (21).

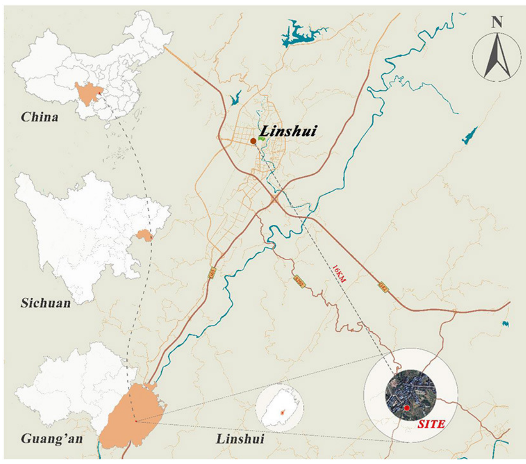

FIGURE 2
The location of Linshui. Elaborated by the authors.

Questionnaire survey

Figure 5 shows the four-part subjective questionnaire. The respondents are rural dwellers living nearby. The number of respondents is smaller than the number of questionnaires because of repeated observations.

Following a face-to-face interview, the interviewer will complete the first part by asking the respondent for basic personal characteristics (i.e., age, sex, height, weight, and length of residence).

The second part records the clothing insulation (unit: clo) and activity (unit: met) status of the respondent.

The third part collects the respondent' subjective responses to five questions on their indoor thermal perception, preference for indoor thermal environment parameters (T_a, RH, and v), and overall thermal comfort. The respondents must evaluate the corresponding options on an ASHRAE 7-point scale and select their answer based on their current thermal sensation when answering question 1. This is known as thermal sensation voting (TSV). Questions 2–4 are preference surveys of indoor thermal environment parameters using 3-point scales to study the respondents' most sensitive environmental parameters. Question 2 is defined as air temperature preference vote (TPV), question 3 is defined as relative humidity preference vote (HPV), and question 4 is defined as air velocity preference vote (VPV). Question 5 is the questionnaire validity test question. It is defined as the overall comfort vote (OCV). The questionnaire is considered to be valid if the results of the TSV and OCV are identical. Table 2 indicates the relationship between the vote results for TSV and OCV.

The fourth part involves gathering information on respondents' summer thermal adaptation behavior to better understand how people in rural areas live.

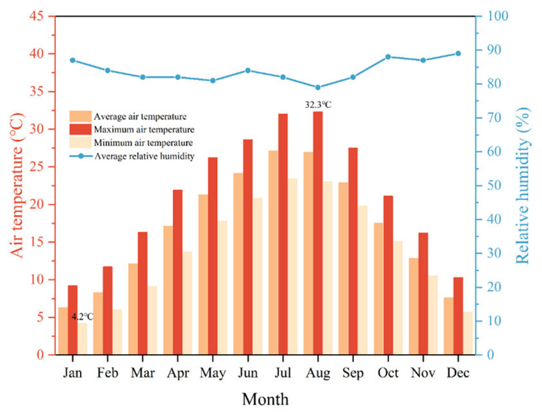

FIGURE 3
Monthly average, maximum, and minimum T_a and RH in Linshui from 1981 to 2010. Elaborated by the authors using the data from the National Meteorological Science Data Center, website: http://data.cma.cn/.

Data analysis

This study selects T_{op} (operative temperature) as an index for evaluating the thermal comfort of rural dwellers. The indoor T_{op} is calculated as follows:

$$T_{op} = A \times T_a + (1 - A) \times T_{mrt}, \quad (1)$$

where T_{mrt} is the mean radiant temperature (unit: °C), and it is calculated using Eq. (2). A can be selected from the following values (Table 3).

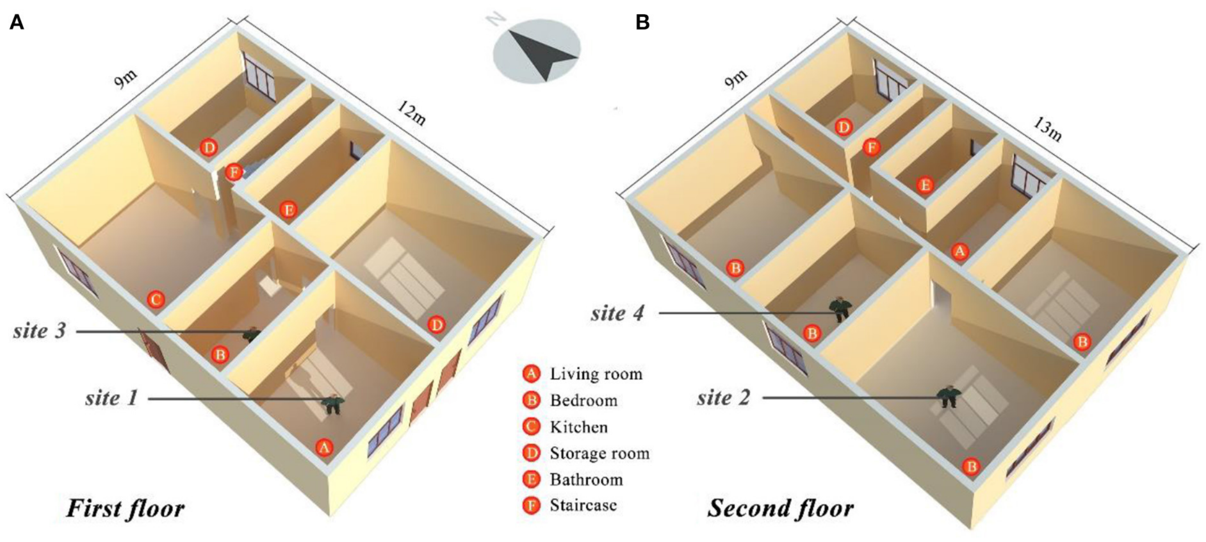

FIGURE 4
The layout of rural dwellings and the location of the measurement sites **(A)** First Floor, **(B)** Second Floor.

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TABLE 1 Specifications of the measuring instrument used in this study.

Instrumentation	Parameters	Range	Accuracy	Resolution	Photos
Testo, 174H-Mini	Air temperature (**T_a**) Relative humidity (***RH***)	−20–70°C 0–100%	±0.5°C ±3%	0.1°C 0.1%	
JT TECH., JRT04	Globe temperature (**T_g**)	−20–125°C	±0.2°C	0.1°C	
TENMARS, TM-404	Air velocity (***v***)	0–25 m/s	±2%	0.01 m/s	

T_{mrt} is calculated using T_a, T_g, and v of the indoor environment. T_g is measured using a black globe thermometer. The formula of T_{mrt} is shown as follows:

$$T_{mrt} = [(T_g + 273)^4 + \frac{1.10 \times 10^8 v^{0.6}}{\varepsilon D^{0.4}}]^{0.25} - 273, \quad (2)$$

where D is globe diameter (=150 mm in this study) and $\boldsymbol{\varepsilon}$ is emissivity (=0.95).

Result

Summary of the objective measurement

As noted above, indoor thermal environment monitoring was conducted in a rural dwelling in Linshui, Sichuan, from August 3 to 6, 2019. T_a, RH, T_g, and v are directly collected by sensors. T_{mrt} and T_{op} are calculated using the above formulas with the input of the collected data. The characteristics of the indoor thermal environment for each site throughout the measured period were summarized in Table 4.

The average T_a for the entire dwelling is 29.24°C. It was a reasonably high value, much higher than the average T_a for the whole county in August (26.9°C) (see Figure 3). In addition, the average T_a of the four sites was very close (the range = 1.57°C). These observations provide some evidence of global warming (49, 50).

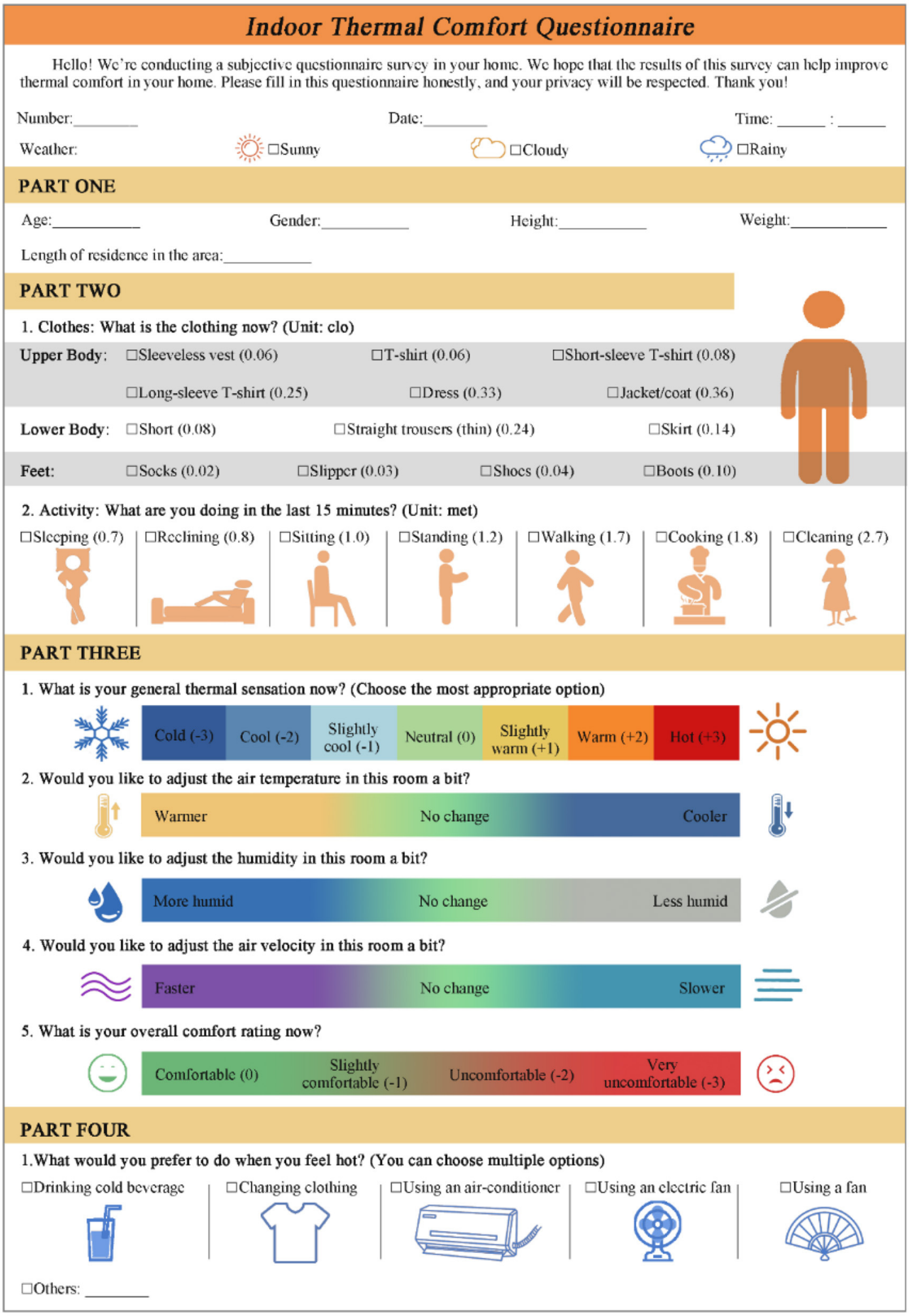
Site 2 had the largest window-to-wall ratio among the four sites. Thus, it received the most solar radiation in the middle of the day, resulting in a rapid increase in temperature. Consequently, site 2 had the highest temperature (38.2°C) of the four sites.

No discernible variation in ***RH*** was noted across the four sites. The average RH of the entire dwelling was 78.76%, which is essentially the same as the average RH of the whole county in August (see Figure 3). Moreover, regarding v, sites 2 and 3 were the largest and smallest among the four sites, respectively. The difference was that site 2 had the maximum window space, directly impacted by the superficial air velocity, while site 3 had no windows and was essentially isolated from the outside environment. Site 2 had the highest T_g, T_{mrt}, and T_{op} average values across the four sites. This observation showed that enormous windows were more vulnerable to solar radiation, which impacted indoor thermal comfort.

Figure 6 shows the T_a and RH data from the four sites. Sites 1 and 2 as well as sites 3 and 4 had highly similar trends. The reason is that the indoor environment conditions at sites 1 and 2 as well as sites 3 and 4 were similar.

From 9:00 to 18:00 on August 5, the temperature of site 2 was significantly higher than that of site 1, but the humidity of site 2 was significantly lower than that of site 1. The reason for this observation is that site 2 had closed windows and doors during this period. In addition, curtains were not used. Hence, the space was exposed to bright sunlight, resulting in a considerable temperature increase. Furthermore, the moisture in the room rapidly evaporated because of the increase in temperature, resulting in a restricted drop in humidity.

The trends of temperature and humidity at sites 3 and 4 were very similar. The temperature in site 4 was usually slightly higher than that in site 3. However, in terms of humidity, site 3 maintained a higher status than site 4. Site 3 had no windows and could not receive solar radiation. Thus, its temperature was lower than that of site 4, but the reverse was true for humidity. This phenomenon demonstrates that rooms with windows obtained a certain amount of solar radiation and affected temperature and humidity fluctuations directly and indoor thermal comfort indirectly. In general, solar radiation is a natural factor affecting the modification of indoor thermal environment characteristics and an indirect factor affecting the human body's thermal comfort.



Indoor Thermal Comfort Questionnaire

Hello! We're conducting a subjective questionnaire survey in your home. We hope that the results of this survey can help improve thermal comfort in your home. Please fill in this questionnaire honestly, and your privacy will be respected. Thank you!

Number:________ Date:________ Time: ______ : ______

Weather: ☐Sunny ☐Cloudy ☐Rainy

PART ONE

Age:___________ Gender:___________ Height:___________ Weight:___________

Length of residence in the area:___________

PART TWO

1. Clothes: What is the clothing now? (Unit: clo)

Upper Body: ☐Sleeveless vest (0.06) ☐T-shirt (0.06) ☐Short-sleeve T-shirt (0.08) ☐Long-sleeve T-shirt (0.25) ☐Dress (0.33) ☐Jacket/coat (0.36)

Lower Body: ☐Short (0.08) ☐Straight trousers (thin) (0.24) ☐Skirt (0.14)

Feet: ☐Socks (0.02) ☐Slipper (0.03) ☐Shoes (0.04) ☐Boots (0.10)

2. Activity: What are you doing in the last 15 minutes? (Unit: met)

☐Sleeping (0.7) | ☐Reclining (0.8) | ☐Sitting (1.0) | ☐Standing (1.2) | ☐Walking (1.7) | ☐Cooking (1.8) | ☐Cleaning (2.7)

PART THREE

1. What is your general thermal sensation now? (Choose the most appropriate option)

Cold (-3) | Cool (-2) | Slightly cool (-1) | Neutral (0) | Slightly warm (+1) | Warm (+2) | Hot (+3)

2. Would you like to adjust the air temperature in this room a bit?

Warmer | No change | Cooler

3. Would you like to adjust the humidity in this room a bit?

More humid | No change | Less humid

4. Would you like to adjust the air velocity in this room a bit?

Faster | No change | Slower

5. What is your overall comfort rating now?

Comfortable (0) | Slightly comfortable (-1) | Uncomfortable (-2) | Very uncomfortable (-3)

PART FOUR

1.What would you prefer to do when you feel hot? (You can choose multiple options)

☐Drinking cold beverage | ☐Changing clothing | ☐Using an air-conditioner | ☐Using an electric fan | ☐Using a fan

☐Others: ________

FIGURE 5
The subjective survey questionnaire used.

TABLE 2 Relationship between the TSV and OCV.

Value of OCV	−3	−2	−1	0
Value of TSV	+3 or −3	+2 or −2	+1 or −1	0
Result of TSV	Hot or cold	Warm or cool	Slight warm or slight cool	Neutral
Result of OCV	Very uncomfortable	Uncomfortable	Slightly comfortable	Comfortable

TABLE 3 Values of *A* that vary with *v*.

v	<0.2 m/s (<40 fpm)	0.2 to 0.6 m/s (40 to 120 fpm)	0.6 to 1.0 m/s (120 to 200 fpm)
A	0.5	0.6	0.7

Summary of the subjective survey

This study collected 216 valid questionnaires. We summarize the respondents' basic personal information, clothing insulation, and activity status (metabolic rate). Females (59.72%) outnumbered males because most males in rural areas chose to migrate to cities to pursue a job, while females chose to raise their children at home. Men (58.3 years) had, on average, an older age than women (42.1 years) because older men had a compromised capability to work in distant cities and chose to stay in rural areas, while many young women stayed in rural areas for childbirth and child-rearing. All respondents have lived in the region for over 10 years. Thus, their thermal comfort is representative. Men's clothing insulation was lighter and thinner than women's, and their clothing insulation was typical of summer indoor dressing in terms of thermal resistance. Regarding activity status, the average metabolic rate for both men and women was 1.1 met, as most people were sitting indoors.

Thermal sensation

The thermal sensation is a crucial psychological indicator of comfort or discomfort. This study aims to assess the various thermal responses of residents. Subjective assessments are necessary to evaluate the indoor thermal comfort of residents (32). The TSV distribution is shown in Figure 7. Most respondents (37.50%) indicated neutral (0) thermal sensation, with 10.19 and 35.19% of respondents voting −1 (slightly cool) and 1 (slightly warm), respectively. Respondents who voted 0, −1, and 1 were often considered comfortable with their current environment. Thus, 82.88% (0, 37.50%; −1, 10.19%; and 1, 35.19%) of the respondents considered themselves comfortable in summer, indicating that rural dwellers of Linshui adapted well to the local summer climate. The overall vote results of the respondents were on the hotter side, which was in line with the basic logic and confirmed that the questionnaire design of this study was reasonable. The analysis results of the data collected by the questionnaire were reasonable.

Figure 8 reveals the results of indoor thermal environment parameter preference voting. The highest percentage of voting was *cooler* (51.85%), and the second-highest percentage was *no change* (41.66%) in terms of the TPV. Comparing the TSV results in Figure 7, we find that the percentage of those who voted −2 (cool) or −1 (slightly cool) was 13.89%, while the percentage of those who voted *warmer* in the TPV was 6.49%. This finding indicates that most respondents favored the cooler side in terms of temperature. Regarding HPV, the percentage of those who voted *no change* was very high, reaching 93.05%. This observation indicated that the residents do not perceive humidity changes significantly. In terms of the VPV, *faster* had the highest percentage of votes, and *no change* had the second-highest percentage of votes. The percentage of people who expected the air velocity to change was 66.67% (faster, 56.94%; slower, 9.73%), which means that most people could perceive the change in the air velocity.

Some phenomena worthy of attention were found from the voting results of indoor thermal environment parameter preference. Rural dwellers in Linshui perceived temperature and air velocity but had little perception of humidity.

Figure 9 shows the percentages of OCV in the studied rural dwelling. Analyzing the OCV can help validate the reasonableness of sensory heat voting fully. The TSV voting result of *neutral* (0) means that the patients feel comfort (0). The TSV voting result of *slightly warm* (1) or *slightly cool* (-1) means that they feel *slightly uncomfortable* (-1). According to the OCV results, 89.35% voted *comfortable* and *slightly comfortable* (comfort, 42.59%; slightly comfortable, 46.76%). The result of the TSV and OCV was very similar (89.35 vs. 82.88%). This finding again indicates that the questionnaire design of this study was adequate and that the collected data was reasonable.

T_{op} is an index for assessing outdoor thermal comfort. However, its applicability in the HSCW region still needs further study. Figure 10 shows that TSV was expressed as the sensitivity of respondents to indoor T_{op}. The scatter plots of T_{op} and TSV were plotted, and their regression equation was shown as follows:

$$TSV = 0.3219 \times T_{op} - 9.4398$$
$$(R^2 = 0.7454, p < 0.001)$$

TABLE 4 Summary of the indoor thermal environment during the measured period.

Site	T_a (°C)			RH (%)	V_a (m/s)	T_g (°C)	T_{mrt} (°C)	T_{op} (°C)
	Avg.	Max.	Min.	Avg.	Avg.	Avg.	Avg.	Avg.
Site 1	28.24	34.50	24.60	82.82	1.21	29.27	30.90	29.77
Site 2	29.68	38.20	25.30	78.26	1.91	31.96	37.79	32.13
Site 3	29.23	30.70	27.40	80.41	0.09	29.95	30.32	29.78
Site 4	29.81	31.70	28.20	73.54	0.81	30.49	31.73	30.46
Total	29.24	-	-	78.76	1.01	30.53	33.19	30.54

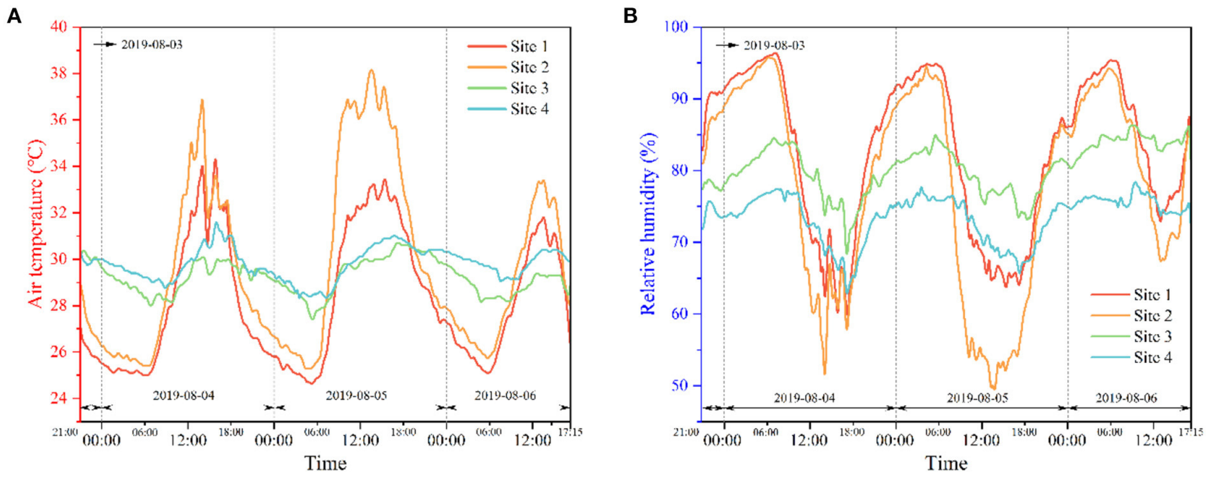


FIGURE 6
Comparison of T_a and RH at four measuring sites during the measured period **(A)** T_a, **(B)** RH.

In summer, the TSV increases with advancing operative temperature. The neutral temperature of the respondents in summer can be calculated by setting the TSV to 0. We found that the neutral temperature was 29.33°C. By calculating the values of TSV equaling −0.5 and 0.5, the neutral temperature range of the respondent in summer can be calculated. We found that the neutral temperature range was 27.77–30.88°C.

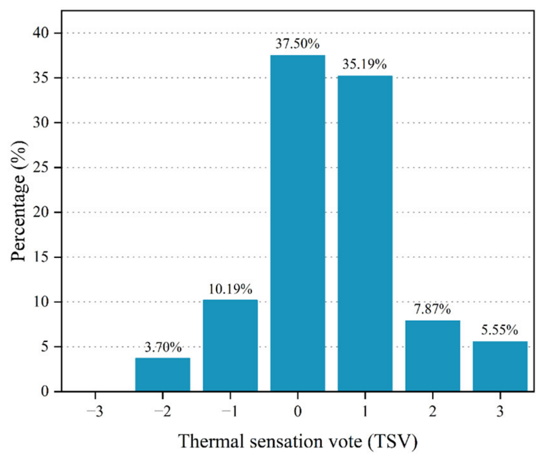


FIGURE 7
Result of thermal sensation vote.

Thermal adaptive behavior

In our questionnaire survey, multiple-choice questions were posed to the respondents. Their adaptive behaviors in the summer included but were not limited to drinking cold beverages, changing clothes, using air-conditioners, using an electric fan, and using a hand-cranked fan.

Figure 11 shows the results obtained from the survey. Most respondents used hand-cranked fans to keep themselves comfortable. Other strategies include using electric fans, changing clothing, and drinking cold beverages, which are cheap and convenient. Much fewer residents used air-conditioners. They switch on it only when the indoor thermal environment is intolerable during the hottest hours rather than using it all day. Most residents agreed that air-conditioners consume a considerable

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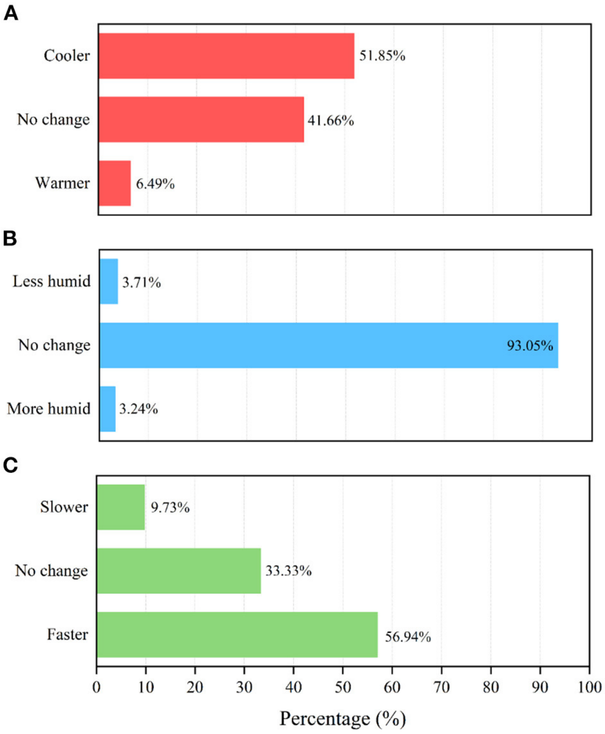

FIGURE 8
Results of indoor thermal environment parameter preference voting. **(A)** TPV, **(B)** HPV, **(C)** VPV.

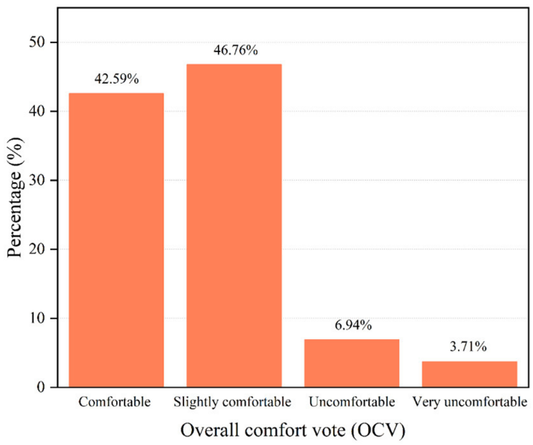

FIGURE 9
Result of the OCV.

sum of energy and are expensive to use. Thus, rural dwellers in Linshui tend to adopt conventional thermal adaptation behaviors rather than cumbersome and costly strategies.

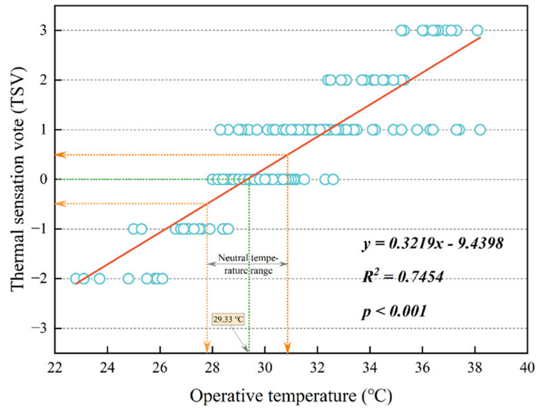

FIGURE 10
Results of the linear regression between TSV and T_{op}.

In contrast with urban residents, who heavily rely on energy-consuming active cooling equipment, rural dwellers prefer traditional cooling strategies (e.g., *using a fan*). Besides the consumption value "frugality," energy poverty (51) and low income (52) make rural dwellers reluctant to pay much for cooling. We hope that mounting studies on rural dwellers' strategy of using air-conditioners for cooling will appear in recent years and that the differences in health effects between using traditional cooling strategies and air-conditioners can be deeply investigated.

Discussion

Comparison of the neutral temperature

We decided to compare the neutral temperature obtained from this study and those presented in studies on indoor thermal comfort based on other regions and building types (see Table 5). The neutral temperatures obtained from the TSV and T_{op} linear regression equations differed by region and building type. The identified neutral temperatures in summer were markedly different from the results of other studies in the same climate region (i.e., HSCW region). Such divergent results may be due to differences in building types. Moreover, studies based on the HSCW region were conducted in urban areas, and their sites for analysis may be in an environment where the air-conditioner operates. However, this study was conducted in rural areas, and the entire dwelling was under natural ventilation during the study period.

Neutral temperatures can be similar in different climate regions, such as 26.19°C in Xi'an (a cold region) (53), 26.44°C in Guangzhou (an HSWW region) (54), and 26.09°C (56) or 26.07°C (58) in Changsha (an HSCW region). This outcome suggests that the thermal comfort of residents in the indoor

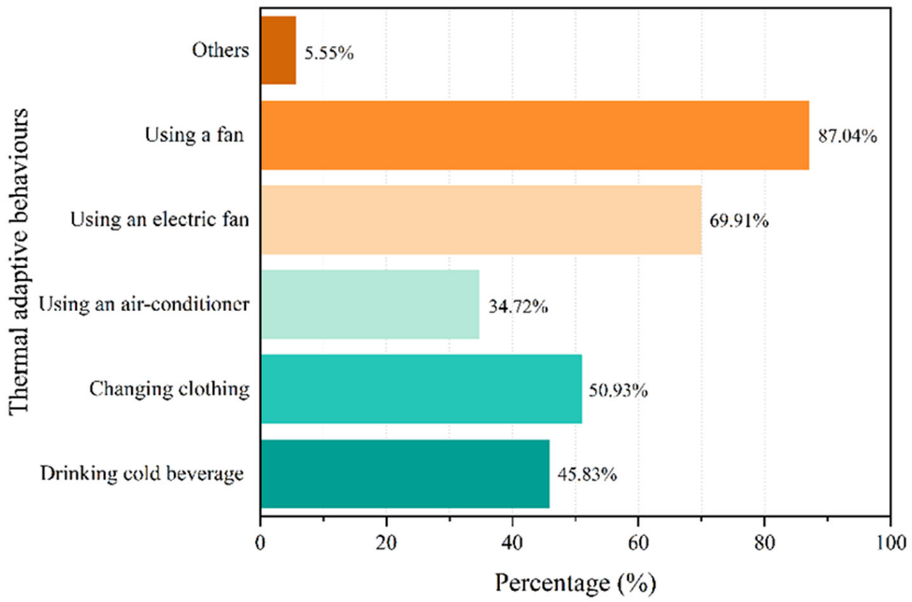

FIGURE 11
Results of thermal adaptive behavior voting.

TABLE 5 Comparison of this study and other studies.

Region	Climate region	Type	Regression equation	Neutral temperature	Reference
Xi'an	C	University building	$TSV = 0.289 \times T_{op} - 7.569$	26.19°C	(53)
Guangzhou	HSWW	University building	$TSV = 0.3596 \times T_{op} - 9.5088$	26.44°C	(54)
Guilin	HSCW	Urban dwelling	$TSV = 0.2576 \times T_{op} - 6.2295$	24.18°C	(55)
Changsha	HSCW	University building	$TSV = 0.33 \times T_{op} - 8.61$	26.09°C	(56)
Shihezi	SC	University building	$TSV = 0.59 \times T_{op} - 16.58$	28.10°C	(57)
Changsha	HSCW	Office building	$TSV = 0.3873 \times T_{op} - 10.0962$	26.07°C	(58)
Linshui	HSCW	Rural dwelling	$TSV = 0.3219 \times T_{op} - 9.4398$	29.33°C	This study

environment was affected by regional differences marginally but by the indoor temperature with the air-conditioner operation considerably. This finding helps determine the appropriate air-conditioner temperature and reach two objectives jointly: (1) the vast majority of people reach a relaxed state, and (2) air-conditioner energy consumption can be minimized (59, 60). This finding also calls for further studies in rural areas. Dwellings in the rural areas of China need to be studied in-depth to discover a broader range of universal laws to enhance the comfort and quality of life of rural dwellers, especially in the post-pandemic era (61, 62).

Limitations

This study used a field research method combining objective measurements of indoor thermal environment parameters and subjective questionnaire surveys. A typical indoor thermal survey was conducted in a rural dwelling in the HSCW region of China, where local thermally neutral temperatures were obtained. Although some interesting results were obtained, this study is by no means beyond reproach. Some research limitations are as follows. First, indoor thermal comfort is strongly influenced by season. This study was conducted only in the summer. Other seasons can be studied to comprehensively understand the changes in indoor thermal comfort throughout the year. Second, this study did not consider the effect of subjective factor differences (thermal resistance of clothing and activity status) on the thermal comfort of rural dwellers. These factors play an important role in shaping the thermal comfort of rural dwellers. Third, the field observation period is short in this study. We agree that it can be substantially expanded. Fourth, the number of respondents was too small to support the thermal comfort analysis of different ages. Last, the generalizability of the results may be questioned and challenged because we selected only one rural dwelling as the case study due to limited experimental conditions, such as the measurement equipment and the number of researchers.

Conclusions

This study conducts indoor thermal environment measurements and subjective questionnaires in a rural dwelling in southwest China. It assesses human thermal comfort using operational temperatures, explores the thermal comfort conditions of rural dwellers in summer, and determines the local neutral temperature for indoor thermal comfort. The main findings of this study are summarized as follows.

1. In dwellings in rural areas, the presence of the window and its size are essential factors that affect the comfort of rural dwellers indoors. In summer, solar radiation through glazing can heat indoor space. Additionally, solar radiation directly affects the temperature and humidity, thereby influencing indoor thermal comfort.

2. Among the various meteorological parameters of the indoor thermal environment, residents in rural areas sensitively perceive the change in temperature and air velocity but have difficulty perceiving the change in humidity (the percentage of "no change" is 93.05%). This finding suggests that when people are exposed to a stable humidity environment (from 70 to 85%) for a long time, their ability to perceive that parameter seems compromised. That is to say, their adaptation to high humidity is evident in this region with the hot and humid summer.

3. Rural dwellers have developed considerable experience adapting to the local climate despite their poor economic conditions. The neutral temperature (29.33°C) in T_{op} is higher than the ASHRAE standard and the standard for urban residents in summer. Due to their long-term thermal adaptation effect, rural dwellers are also less thermally sensitive than urban residents and have an extensive acceptable range of indoor neutral temperatures (27.77–30.88°C).

4. In addition to psychological thermal adaptation, the adaptive behavior adopted by the rural dwellers significantly enhances their ability to tolerate adverse environmental conditions (the percentage of "comfortable" and "slightly comfortable" combined is 89.35%). This study suggests that these rural dwellers have developed unique lifestyles and measures to adapt to the harsh thermal conditions of summer. In addition, even when air-conditioners are installed in conventional homes, the influence of residents' previous cooling experience remains, which significantly increases their satisfaction with their environment. Thermal adaptation behavior alleviates residents' discomfort caused by temperature deviations and expands their comfort zone.

5. At this stage, many rural dwellers are older adults who still adhere to using very few or no energy-consuming cooling devices. They refuse to use the air-conditioner for space cooling even in the presence of high temperatures. This is dangerous because the high temperature may affect the health of older adults and thus lead to heat-related morbidity and even mortality. Therefore, the renovation program of residential buildings in rural areas should be further improved, and more passive cooling measures should be taken to enhance the indoor thermal environment, which can decrease energy consumption and energy bills on the one hand and ensure the health of residents in the extreme hot events on the other hand.

Data availability statement

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

Author contributions

DW: conceptualization, formal analysis, methodology, and writing—original draft. GZ: validation, and writing—review and editing. SL: validation and writing—review and editing. LY: conceptualization, funding acquisition, supervision, and writing—original draft. All authors contributed to the article and approved the submitted version.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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The relationship between school districts and parental commuting behavior: Analysis of gender differences in the Chinese context

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The distribution of school districts would largely influence people's commuting distance, but this association is hardly examined. This study applies the 2015 Xiamen household travel survey to investigate the associations between the school district and parental commuting behavior. The results showed that school districts mainly affect the parents' commuting distance when the interaction effects between gender and commuting distance are considered. Specifically, the school district is positively associated with commuting distances for males, whereas the opposite trend is observed for females. Then, variations exist in the effects of the school district on parental commuting distance between respondents with different levels of education. The school district quality is positively associated with the commuting distance for respondents without college degrees, especially male respondents, whereas no significant association was found for more respondents with college degrees. Male respondents, especially those without college degrees, suffer higher costs and longer commuting distances than their female counterparts. This study highlights that urban planners and policy makers should consider the impact of school districts and rethink the most effective distribution of high-quality primary schools to reduce socio-spatial inequality (e.g., disadvantage of males in commuting).

KEYWORDS
travel behaviors, school district effects, socio-spatial inequality, gender differences, China

Introduction

As an important component of daily life against urbanization, commuting behavior exerts an effect on life satisfaction (Dickerson et al., 2014). In the past few decades, changes in urban, physical, and social spaces have profoundly affected the commuting behavior by changing the commuting time or distance (Li and Zhao, 2022). Due to differences in the time and resources allocated to activities, it is widely recognized that the commuting behavior varies between individuals, cities, and countries. For instance, the average commuting time in the United States is 25 min, as opposed to 38 min in Europe (Rodrigue, 2020). Due to high population density and traffic congestion, Asian cities have an average daily commuting time of 50 min or more (Rodrigue, 2020). According to Li (2021), long-time and/or long-distance commuting can aggravate socio-spatial inequality and produce a range of socio-economic issues. For instance, a lack of resources—which usually indicates lack of money and/or time—will increase the physical stress, affect mental adaption, and generate negative emotions (Liu et al., 2022). Additionally, increased commuting time inevitably reduces the community engagement activities, thereby reducing the social capital (Putnam, 2000). Therefore, how to decrease commuting distance and time has received wide attention from both academic studies and planning/policy practices.

Among the studies, gender differences in the commuting behavior have received a wide attention. It is widely acknowledged that given the household responsibility and social norms, the women's commuting distance is shorter than that of men. Many studies have identified a range of factors affecting the commuting time/distance for males and females. These factors consist of individual and household characteristics. For instance, Crane (2007) revealed that women with a higher level of education have a longer commuting time. Schwanen (2007) found that with the increase in the share of household income, women's housework will decrease to a certain extent, thereby increasing their commuting distance. Nevertheless, other studies showed no significantly positive effect of education or income on female commute. For instance, Fan (2017) confirmed that due to the impact of gender roles, women still need to undertake more housework, even if they earn more money (have a higher level of education) than their husbands.

Although researchers have paid much attention to factors that explain differences in the gender commuting gap, there is a lack of literature that focuses on the association between school districts and parental commuting behavior, especially in the Asian context where school districts prevail. According to Fast (2020), the school district, consisting of a community-based learning area with one or more high-quality primary schools, guarantees access to compulsory education in close proximity. Only when parents buy a house in a particular school district can their children be enrolled in that community school. Therefore, high-quality school districts have become a scarce resource. In the Chinese context, competing for favorable school districts not only increases the household burden through purchasing premium school district housing, but also has a profound influence on parental commuting distance/time (Li and Zhao, 2022). When the school district housing is far from residential neighborhoods, the increase of commuting time will occupy an individuals' leisure time and boost pressure, thus resulting in a series of socio-mental issues.

Despite the argued potential, our understanding of the association between neighborhood-based school districts and commuting behavior remains inadequate. First, some studies have argued that whether neighborhoods have high-quality primary schools may influence people's travel behaviors (He and Giuliano, 2018). This is because households with a high capability to pay price premiums prefer to live near high-quality schools whereas the lower-income families usually choose the opposite option. Parents would have to face differed commute behavior when this option is carried out. Second, previous studies chiefly focused on the effects of school districts on students' school travel behavior, whereas its relation to parents' commuting behavior has been largely neglected (Lin and Chang, 2010; Marzi et al., 2018; Fast, 2020). However, identifying and, more accurately, distinguishing the school district's influence on parental commuting behavior is significant to increasing the status quo through interventions, such as transportation and school district planning.

To fill the gaps, this study uses the 2015 Xiamen household travel survey to investigate the associations between school districts and parental commuting behavior at the individual level. This study makes two-fold contributions. Theoretically, this study is one of the first that empirically explores the effect of school districts—whether to live in high-quality school districts or not—on parental commuting behavior, which can enrich and broaden the current discussions on school districts and parental commuting behavior. Practically, this study can provide references for policymakers and urban planners who are interested in improving the neighborhood-based educational resource layout for facilitating and encouraging sustainable travel behaviors and practices.

In the following sections, Section 2 reviews the gender differences in commuting behavior and the literature on association between neighborhood-based factors (including school districts) and the commuting behavior. Section 3 specifically introduces the data obtained and the methods used by this study. Section 4 presents the research results, followed by discussions on the results in Section 5. Section 6 concludes this study.

Literature review

Gender differences in commuting behavior

Studies have intensively examined commuting behavior and a significant difference in commuting behavior between females and males has been specifically highlighted (Schwanen, 2007; Elias et al., 2015; Ta et al., 2022). Researchers found that males are more mobile and can sustain longer commutes while working women commute much shorter distances (Johnston-Anumonwo, 1992; Clark et al., 2003; Fan, 2017). Studies also indicated that gender differences in the commuting behaviors among two-worker households are more apparent than among one-worker households (Johnston-Anumonwo, 1992).

In the literature, a range of factors have been argued to influence the gender differences in commuting behavior, including social customs, policy conditions, demographic, and socio-economic characteristics such as household size, income, education, car ownership, workplace, and accessibility, and eventhe environment (Rosenbloom and Burns, 1993; Wang and Chai, 2009; Hu et al., 2018; Korzhenevych and Jain, 2018). For instance, with regard to the characteristics of wage, Madden and Chiu (1990) found that the change of job cannot significantly increase women's commuting distance. This is explained by the fact that the spatial difference of wage is small in these jobs. Additionally, the personal or household characteristics may affect the commuting behavior. Mauch and Taylor (1997) discovered that the gender differences in the commuting time are highest among whites and lowest among Hispanics. In this process, the commuting mode played an important role in the commuting time of both men and women. Due to a lack of transit provision and high car ownership among males, males tended to disproportionately make more tours and spend more time traveling by private cars whereas women disproportionately walked. Then, Rosenbloom and Burns (1993) found that due to females' household and childcare roles and responsibilities, their travel patterns differed from those of men. The birth of children may profoundly change the responsibility of women. For example, women may have part-time jobs or a shorter commuting distance. Some scholars argued that there is a need to improve the survey and conduct a holistic understanding of the commuting behavior that take the interplay of activities within the household into account. To do so, Elias et al. (2015) adopted a tour-based approach to examine the commuting behavior in Arab–Israeli communities and found gender to be a significant predictor of commuting.

Furthermore, the role of culture was also stressed on influencing females' commuting behavior (Peters, 2001). For instance, in a society featured with a gender segregation culture, females are often arranged or required to take segregated public transportation or to use segregated doors and seats (Polk, 2004). As a result, their travel behavior would differ considerably from that of males. Some studies revealed that security and safety issues facing female commuters contributed to the gender differences in commuting behavior (Whitzman, 2007). For instance, in a safe environment, females would prefer to choose more public transportation trips (Kabeer, 2004). Note that when culture is deemed as an influencing factor on commuting or travel behavior, we should be cautious of the operationalization problem (Hammel, 1990).

Furthermore, education and income are associated with the employed women's commuting behavior (Lee et al., 2022). With improved equality between men and women, women's education level has been gradually promoted during the past decades and thus has been increasing their income (Tyer-Viola and Cesario, 2010). However, note that the wives' share of the household income is relatively lower than their husbands; therefore, married men can have greater power on the allocation of household resources such as the car (Ta et al., 2022). Consequently, employed women may be more likely to choose non-automobile modes of travel such as bus, subway, or even walk, especially in families with the traditional contracts (Solá, 2016).

The explanation and interpretation regarding the gender differences in commuting behavior can provide important references for the optimization of public service and policies. For instance, the double pressure of both income-earning and household work forces married women to reduce the commuting time and constrict the commuting distance (Turner and Niemeier, 1997). This is named as the household responsibility hypothesis (HRH), which indicates that, affected by the social norms and gender identities, the married women have to undertake the housework such as cooking and cleaning (Gimenez-Nadal and Molina, 2016). Especially, the presence of children may further shorten the commuting distance; women with the children may select part-time jobs near their home (Lee and McDonald, 2003).

School district/school district-housing and parental commuting behaviors

Although some specific factors affecting parental commuting behavior have been explored, little attention has been paid to school districts in relation to commuting behavior. In the Chinese context, a so-called school district means the designated region in which high-quality primary schools are located, making it possible for students to have free admissions to the nearest school (Wen et al., 2017; Peng et al., 2021). Furthermore, the school district (policy) is specifically applied to the 9-year compulsory education which includes primary school (6 years) and middle school (3 years). The rise of school districts results from the Chinese neo-liberalistic education reform since the mid-1980s. Local governments were empowered to administrate compulsory education while private sectors and other market forces were allowed to offer formal basic education (Wen et al., 2017; Xu et al., 2018). It is often argued that the neo-liberalistic education reform has brought a range of benefits to the society such as decreasing the local government's financial load in offering basic education, providing more possibilities for school-aged children, and improving the hard and soft powers of the school (Wen et al., 2017).

However, in reality, school-aged children are often not given an equal quality of education. This is because their enrollment in nearby public school is based on their local *hukou* and the housing property (Xu et al., 2018). As Wen et al. (2017) argued, housing ownership is deterministic to the access to a high-quality primary school. If students own a local *hukou* and their parents own housing property in one school district, they are given the priority to enroll in that high-quality school. Therefore, parents often attempt to buy houses in high-quality school districts. This, however, has created the possibility for parents' rent-seeking behaviors. For instance, the value of basic educational resources is often reflected in the surrounding housing prices and the districts with high-quality schools often have high housing prices. The result is that high-income households can easily afford the housing price whereas low-income families and their children are largely ruled out from the school district-housing market (Li, 2021). Negatively, this aggravates the residential segregation by income and intensifies socio-economic inequalities such as school travel distance/time (Yang et al., 2012; Xu et al., 2018; Fast, 2020).

In terms of the impacts of school districts on travel behavior, studies mainly investigated how school districts influence a student's school travel behavior. For instance, as parents worried much about convenience, security, and the comfort of children's school travel, they would prefer to buy school district housing for shortening the student's school travel (Li, 2021). In another study, Ewing and Cervero (2010) found that the quality of schools such as sizes would affect student travel mode choices.

However, how a school district affects the parental commuting behavior is understudied. As aforementioned, individual-level socio-economic indicators such as differences in gender, education, occupation and income influence parents' capabilities of competing for school district housing, consequently influencing their commuting behavior. With regard to gender, Ta et al. (2019) investigated the travel behavior of females in Beijing and found that, given that women have more household responsibility, they often experience shorter commuting distance. In addition, with the improvement of schooling, commuters can bear longer commuting distance and time. This is because a higher education leads to high-paying jobs, which can compensate the commuting costs (Giménez-Nadal et al., 2022). This influence was observed among commuters with different occupations. For instance, Sermons and Koppelman (2001) found that white-collar commuters in the San Francisco Bay Metropolitan Area had longer commuting time compared with blue-collar commuters, which results from the fact that white-collar commuters would like to escape from the noise downtown, and thus select the farther place of residence. Starting from this, a *hypothesis* is made that school districts influence parental commuting behavior since levels of school districts would have different capitalized residential land values, which influences households' capability to pay the price premiums and their willingness and ability to live near high-quality school district housing. In other words, parents (male and female) with differed educations, occupations, and incomes show different bid capabilities for high-quality school districts and sustain different opportunity costs, thereby having differed commuting behaviors. To test our hypothesis, this article takes Xiamen as the study area, and explores this association.

Methodology

Study area and data source

Xiamen is a city located in the Fujian Province, Southeast China, covering an area of 1,700 km^2 with a population of 5.2 million in 2021. It is one of the most densely populated cities in China. The city has six districts, including Siming, Huli, Haicang, Xiang'an, Jimei, and Tong'an. The municipality was specifically listed in the state economic plan and is directly supervised by the State Council, People's Republic of China. In the past four decades, Xiamen has experienced an intensive urbanization process, leading to a huge change in urban forms and built environments. In terms of the travel behavior, the average commuting distance and time in 2020[1] have reached 22.8 km and 56.75 min, correspondingly.

To examine the relationship between school districts and parental commuting behavior, the socio-economic and travel data were collected from the 2015 Xiamen household travel survey. The dataset consists of socioeconomic data (i.e., age, gender, occupation, car ownership, education level, housing attribute, etc.) and travel behavior data (i.e., origin, destination, trip mode, trip purpose, travel time, etc.). Accounting for 3 % of Xiamen's population, the total number of trips was 219,552 and the commuting data were 49,531. According to the purpose of this research, we further screened the original data. Specifically, for each household, we only retained the household with at least one primary school student and conducted a regression analysis on the commuting distance of these respondents. After filtering the data, a total of 5,419 commuting data were reserved.

Variables and methods

The dependent variable of this study is the logarithm of the commuting distance. Note that the household travel survey did not include the travel distance data but provided departure traffic analysis zones (TAZs) and arrival TAZs. Thereby, we calculated approximate values of parental commuting distance. First, the

1 https://www.numbeo.com/traffic/in/Xiamen

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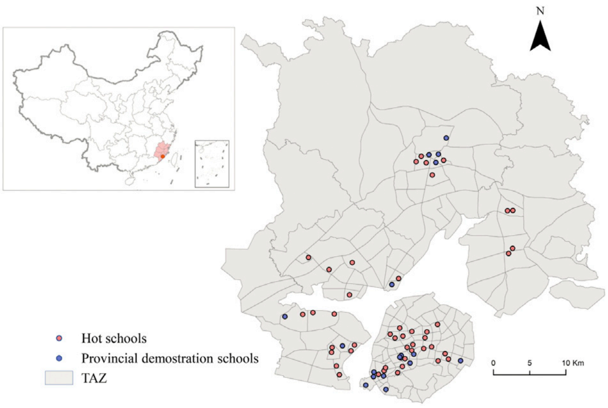

FIGURE 1
The distribution of hot and provincial demonstration schools in Xiamen.

centroid of each TAZ was calculated via using ArcGIS. Then, ArcGIS's Origin–Destination (OD) cost matrix analysis was applied to acquire the commuting distance, spanning from 0.855 to 49.953 km. When the departure TAZ are the same with the arrival TAZ, the OD distance is 0. However, this would be impossible for the OD distance to be assigned a zero value. Thereby, we calculated the average speed of each commuting mode, multiplied by the travel time (provided by the household survey data), to assign a new value to the OD distance (see Supplementary Appendix SA for calculation details).

Furthermore, the school district data were collected from the Website of Bendibao[2]. Two types of high-quality primary schools are included in this study, including hot schools and provincial demonstration schools. Here, a hot school indicates the school that has a high reputation in the quality of education among the local citizens, but the number of admissions of these schools is limited. In other words, there exists a supply–demand mismatch, an imbalance between supply and demand for the number of schools in the market. They often receive high attention and were once treated as model primary schools but now they are called "hot schools". Differed from provincial demonstration schools that are officially confirmed as superior-quality schools, hot schools are often officially announced to the public but are not finally classified as any level of schools. Note that the year of the socio-economic and commuting behavior data was 2015, whereas the school district data consist of all high-quality schools in 2021. Thus, we excluded those schools that were not model schools (schools whose teaching quality was leading) before 2016 and finally obtained 45 hot schools (schools widely sought after by parents and students) and 18 provincial demonstration schools (schools recognized and supported by the provincial government). The distribution of these schools is illustrated in Figure 1. If the district in which one respondent resides has a provincial demonstration school, we assigned this relevant category to him/her. We did the same for the hot schools. Other districts without high-quality schools were assigned the category "ordinary schools".

Furthermore, we divided the education level into two major groups: higher-education groups and lower-education groups, which werebased on whether they received college degrees. The reason for this classification is that we would like to examine how people with different levels of education select their school districts and how the selection would influence their commuting behavior. Then, the workers were classified as blue-collar workers, pink-collar workers, and white-collar workers, comprised 16 %, 31 %, and 53 % of the total sample population, respectively. Gender differences in the parental commuting behavior between these categories were paid special attention.

2 http://xm.bendibao.com/edu/202132/65119.shtm

Descriptive statistics

Table 1 shows the descriptive statistics of the variables. Female and male respondents are at rates of 45.57 % and 54.43 %, respectively. The average travel distance of the respondents is about 6,763 m, and more than half of the respondents (53.51 %) live outside Xiamen Island. Then, white-collar workers, pink-collar workers, and blue-collar workers have rates of 55.72 %, 29.23 %, and 15.05 % and most of the respondents (76.88 %) had local *hukou*. Around 76.47 % of the respondents lived in their own houses, 22.66 % in rent houses, and only few lived in Danwei houses (0.86 %). Concerning school districts, more than half of the respondents chose to live in districts of ordinary schools (57.59 %), and the proportions of living in districts of hot schools and provincial schools were 26.79 % and 15.60 %, respectively.

Approximately 47.19 % of respondents received higher education and of them, 44.73 % were females while 55.27 % were males. It shows that people who received higher education are more likely to have local *hukou* and tend to live in neighborhoods with better access to transportation (higher bus stop and road density), higher population, and job density. Furthermore, respondents with college degrees have longer commuting distance (7,136 m) compared to those respondents without college degrees (6,628 m). Note that 64.33 % of respondents with college degrees live outside the island of Xiamen, which is higher than those without college degrees (44 %). Half of the respondents' own cars and people with college degrees have higher rates of car ownership. In terms of school districts, about half of the respondents with college degrees lived in districts with hot schools and provincial demonstration schools (48.62 %), which is higher than that of

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TABLE 1 Descriptive statistics.

	All sample		Without college degrees		With college degrees	
Variable	**Mean/percentage**	**Std. Dev**	**Mean/percentage**	**Std. Dev**	**Mean/percentage**	**Std. Dev**
Travel Distance	6762.91	6915.67	6030.75	6628.70	7584.83	7136.60
Bus stop density (unit: per sq. km)	6.02	4.61	5.09	4.01	7.06	4.99
Road density (unit: per sq. km)	12.87	6.89	11.55	6.52	14.35	7.01
Population density (unit: 10,000 per sq. km)	1.13	0.79	1.05	0.80	1.22	0.77
Job density (unit: 10,000 per sq. km)	0.57	0.41	0.51	0.39	0.64	0.41
Xiamen Island						
yes	46.49%	0.50	56.15%	0.50	35.67%	0.48
no	53.51%	0.50	43.85%	0.50	64.33%	0.48
Age	37.28	5.54	37.28	6.23	37.28	4.65
Education level						
without college degrees	52.82%	0.50				
with college degrees	45.35%	0.50				
Mater or more	1.84%	0.13				
Profession						
White	55.72%	0.50	35.37%	0.48	78.49%	0.41
Pink	29.23%	0.45	39.47%	0.49	17.78%	0.38
Blue	15.05%	0.36	25.16%	0.43	3.73%	0.19
Hukou						
Locals	76.88%	0.42	65.67%	0.47	89.42%	0.31
Migrants	23.12%	0.42	34.33%	0.47	10.58%	0.31
Home ownership						
Danwei housing	0.86%	0.09	0.73%	0.09	1.01%	0.10
Owner-occupied housing	76.47%	0.42	66.68%	0.47	87.44%	0.33
Rental housing	22.66%	0.42	32.59%	0.47	11.55%	0.32
Car ownership	0.50	0.50	0.45	0.50	0.56	0.50
Household size	3.67	1.07	3.72	1.12	3.62	1.00
School district						
Ordinary	57.59%	0.49	63.13%	0.48	51.38%	0.50
Hot	26.79%	0.44	23.87%	0.43	30.07%	0.46
Provincial	15.60%	0.36	12.96%	0.34	18.55%	0.39
Gender						
Female	45.57%	0.50	46.32%	0.50	44.73%	0.50
Male	54.43%	0.50	53.68%	0.50	55.27%	0.50

the full sample. Among those without college degrees, this proportion was only 36.83 %. This reveals that respondents with college degrees tend to occupy more high-quality schools.

Results

To explore the relationship between a school district and commuting time, we performed an ordinary least squares (OLS) regression analysis (Table 2). The dependent variable is the logarithm of the commuting distance. Model 1 presents a simple model without any interaction effect, whereas Model 2 considers the interaction effects between gender and school districts. Here, the interaction effect indicates the mutual effects of two or more variables on the process outcome. It occurs when the effect of one independent variable relies on another independent variable.

In terms of the built environment, population density has a positive association with the commuting distance. According to Litman (2017), higher urban densities are often related to longer commuting time and greater traffic congestion, which was reconfirmed in this article. Then, the job density is negatively associated with the commuting distance, indicating that the more jobs around the residence, the shorter the commuting distance. This

TABLE 2 Regression of the natural logarithm of commuting distance.

	Model 1		Model 2	
Variables	Coef	Std. Dev	coef	Std. Dev
Bus stop density	−0.002	0.004	−0.002	0.004
Road density	−0.001	0.003	−00.000	0.003
Population density	0.059*	0.034	0.059*	0.034
Job density	−0.237***	0.075	−0.239***	0.075
Xiamen Island	0.100***	0.038	0.101***	0.038
Age	−0.006**	0.003	−0.006**	0.003
Education level (ref: without college)				
college	0.231***	0.032	0.231***	0.032
Master or more	0.256**	0.104	0.252**	0.105
Profession (ref: White)				
Pink	−0.080**	0.033	−0.078**	0.033
Blue	0.076*	0.042	0.079*	0.042
Hukou (ref: migrants)	0.045	0.047	0.046	0.047
Locals				
Home ownership	—	—	—	—
Danwei housing	0.206	0.170	0.206	0.169
Owner-occupied housing	0.165***	0.048	0.166***	0.048
Car ownership	0.273***	0.031	0.273***	0.031
Household size	0.014	0.013	0.014	0.013
School district (ref: Ordinary)				
Hot	−0.013	0.032	−0.025	0.047
Provincial	0.005	0.040	−0.073	0.056
Gender	0.296***	0.030	0.267***	0.037
Male				
School district*Gender	—	—	—	—
Hot*Male	—	—	0.022	0.063
Provincial*Male	—	—	0.148**	0.075
Constant	7.994***	0.117	8.008***	0.117
Observations	5,419	—	5,419	—
R-squared	0.089	—	0.090	—

***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

is understandable that residents would prefer to find jobs nearby (Li et al., 2021). Whether people live on Xiamen Island also affects the commuting distance. As the results show, respondents who live on Xiamen Island experienced a longer commuting distance. One explanation is that in the past decade, a range of manufacturing industries were relocated outside the Xiamen Island, and people who once lived on the Xiamen Island would face longer commuting distance after the relocation. Age is negatively associated with commuting distance. This is understandable that older people would occupy more resources, thus they are more likely to have a chance to live near school districts.

Socio-economic factors as covariates also influence parental commuting distance. The level of education is positively associated with commuting distance, indicating that respondents with college degrees have longer commuting distances (Cassel et al., 2013). The reason may be that some highly skilled and specialized jobs are concentrated in some areas of the city like the central business district (CBD) (Li et al., 2019), while low-income workspaces are more widely distributed, such as convenience stores (Manaugh et al., 2010). Consequently, people tend to be closer to low-paying jobs but far from high-paying skilled jobs (Manaugh et al., 2010). The significant association between the commuting distance and profession also confirms this finding. Given that the wage of a blue-collar work is relatively lower than that of a white-collar work, they have to choose housing with longer commute distance. The pink-collar profession is negatively associated with commuting distance. Another interesting finding is that differing from previous findings (Li et al., 2021), when only families with school-aged children are considered, blue-collar workers travel longer than white-collar workers. One possible reason is that blue-collar workers live in dormitories of their workplaces before they get married. Once they get married and have children of their own, they may relocate to school districts areas for better access to schooling. *Hukou* had no significant effect on travel distance. Compared to those who rent, those who own homes have a longer commuting distance, so as those who have a car (Plaut, 2006; Islam and Saphores, 2022).

Model 2 presents the result with interaction effects between gender and school districts. The positive and negative effects of the control variables, such as built environment and socio-economic attributes on the commuting distance are similar to those in Model 1. In terms of the focus variables, when the gender difference was not considered, the quality of school districts had no effect on the residents' travel distance. After considering the interaction effects between gender and school districts in Model 2, school districts have a significant impact on the commuting distance. As can be seen from Figure 2A, a male's commuting distance is generally longer than that of a female, especially one who lived in districts of provincial demonstration schools. The possible reason for this result is that in order to facilitate women to take care of children, husbands tend to choose to live closer to their wives' work places, resulting in a longer commuting distance for men. Another explanation is that in China, women are often responsible for picking up their children (Zhang (2022); consequently, females would choose to find a job closer to the school district. Table 3 further shows the gender differences in picking up children at different quality schools. With the increase of the level of school quality, the proportion of women picking up is on the rise, while men show the opposite trend. This implies that the higher the quality of the school districts, the higher their wives drop off their children.

Models 3 and Model 4 show the regression results of respondents without college degrees, and Model 4 presents the interaction effects between gender and school districts. Model 5 and Model 6 show the regression results of the respondents with college degrees, and Model 6 considers the interaction

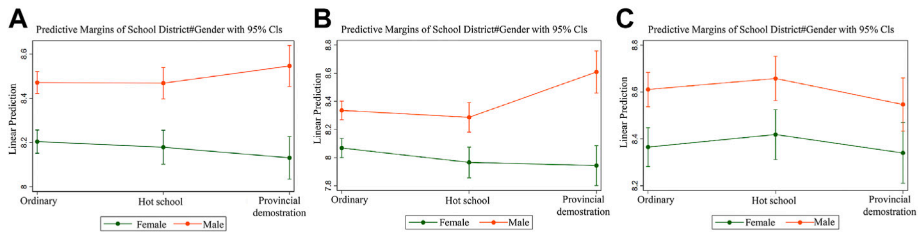

FIGURE 2
(A) Gender difference in the commuting distance of all respondents, **(B)** Gender difference in the commuting distance of respondents without college degrees; **(C)** Gender difference in the commuting distance of respondents with college degrees.

TABLE 3 Gender differences in the percentage of kid drop-offs.

	Female (%)	Male (%)
Ordinary	59.5	40.5
Hot	63.7	36.3
Provincial demonstration	71.0	29.0

effects (Table 4). The results indicate that school districts have a significant impact on respondents without college degrees, especially for the male respondents in this group. For instance, Figure 2B compares the gender difference in the commuting distance. It reveals that in the districts of the provincial demonstration schools, male respondents without college degrees had a much longer commuting distance than those of female respondents. This means that males without college degrees are more likely to sacrifice their commuting time to shorten their wives' commuting distance. Table 5 further shows the gender differences in kid drop-offs by educational level and school quality. Among the groups with college degrees, male and female have a similar rate of kid drop-offs. However, among the groups without college degrees, the proportion of females in kid drop-offs is significantly higher than that of males. This can be explained that the improved education level increases the females' income, which consequently decreases the time they spent on family like kid drop-offs whereas it increases the proportion of males in kid drop-offs.

Except for the influence of school districts, the built environment and socio-economic factors also have a mediating impact on the commuting distance of the respondents. For instance, population and job location density, whether living on Xiamen Island, age, occupation type, housing ownership, and car ownership all affect the commuting distance of respondents without college degrees. This mediating influence is similar to the findings in Table 2. For the group of respondents with college degrees, only car ownership, family size and gender affect their commuting distance, whereas other factors show no significant association. The findings indicate that respondents without college degrees face more restrictions on their commuting behavior besides the school district effect.

Discussions

This research contributes to the existing studies with a focus on the relationship between school districts and parental commuting behavior. Special attention is paid to the gender differences in the impact of the school district on parental commuting behavior. This study is one of the first to investigate the relationship between school districts and parental commuting behaviors in the Chinese context.

First, we provide evidence that school districts have an influence on commuting behavior, but the influence is significant only after considering the interaction effect between gender and commuting distance. We find that school districts are positively associated with commuting distances for men, while showing the opposite trend in the female group. Although the study shows no association between the school district and the commuting distance of the total sample, it verifies that school districts would be vital in influencing the travel behavior between males and females in high-density cities in developing countries. The result confirms the finding by some studies that the male is often subjected to longer commuting distance/time (Kersting et al., 2021), and this feature is more obvious in the Chinese context. As Wen et al. (2017) highlight, males in China would often choose to reside near schools to reduce the school travel of their children, whereas females are often responsible for picking up kids and tend to work more within their communities. The potential influence is that male commuting distance significantly increases but females' commuting distance would be much shorter compared to their male counterparts.

Based on this finding, we highlighted that there is a need to consider how the profits, expenses, and burdens related to commuting are distributed across the population (e.g., females and males) and to identify methods, plans, and policies that can

TABLE 4 Regression of the natural logarithm of the commuting distance for respondents without/with college degrees.

	Without college degrees				With college degrees			
	Model 3		Model 4		Model 5		Model 6	
Variables	coef	Se	coef	se	coef	se	coef	se
Bus stop density	−0.005	0.006	−0.006	0.006	0.001	0.004	0.001	0.004
Road density	0.003	0.004	0.003	0.004	−0.003	0.003	−0.003	0.003
Population density	0.097*	0.053	0.098*	0.053	0.015	0.044	0.015	0.044
Job density	−0.429***	0.113	−0.429***	0.112	−0.073	0.097	−0.073	0.098
Xiamen Island	0.228***	0.054	0.226***	0.054	−0.027	0.052	−0.027	0.052
Age	−0.009***	0.003	−0.009***	0.003	0.002	0.004	0.002	0.004
Profession (ref: White)								
Pink	−0.103**	0.044	−0.093**	0.044	−0.041	0.050	−0.041	0.050
Blue	0.087*	0.050	0.096*	0.050	0.013	0.091	0.012	0.092
Hukou ref: migrants								
Locals	0.097	0.065	0.100	0.064	−0.073	0.069	−0.073	0.069
Home ownership								
Danwei housing	0.389*	0.235	0.386*	0.228	0.002	0.238	0.003	0.238
Owner-occupied housing	0.169**	0.066	0.174***	0.065	0.108	0.071	0.108	0.071
Car ownership	0.290***	0.044	0.288***	0.044	0.262***	0.042	0.261***	0.043
Household size	−0.008	0.017	−0.010	0.017	0.049**	0.021	0.049**	0.021
School district (ref: Ordinary)								
Hot	−0.073	0.046	−0.103	0.065	0.050	0.046	0.053	0.068
Provincial	0.079	0.060	−0.125	0.080	−0.046	0.053	−0.025	0.078
Gender								
Male	0.329***	0.041	0.267***	0.050	0.236***	0.043	0.245***	0.057
School district*Gender								
Hot*Male	—	—	0.054	0.089	—	—	−0.006	0.089
Provincial*Male	—	—	0.399***	0.111	—	—	−0.039	0.101
Constant	8.130***	0.146	8.159***	0.146	8.033***	0.191	8.028***	0.192
Observations	2,866	—	2,866	—	2,553	—	2,553	—
R-squared	0.094	—	0.098	—	0.055	—	0.055	—

Note: ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

TABLE 5 Gender differences in the percentage of picking up children.

	Without college degree		With college degree	
	Female (%)	Male (%)	Female (%)	Male (%)
Ordinary	51.31	48.69	46.15	53.85
Hot	58.29	41.71	55.06	44.94
Provincial_demonstration	63.06	36.94	52.50	47.50

decrease gender commuting gap differences. For instance, constructing more cost-effective and economical transport facilities such as subways and para-transit services would help improve parents' accessibility to jobs and reduce their commuting distance or time. In fact, a recent survey showed that in 2021 there were about 99.4 billion urban public transport passengers in China, and of them, around half used buses or trolleybuses, and around 23.7 billion passengers used the metro (Statista Research Department, 2022). Our study finds that males, especially those blue-collar males, suffered more cost or sustained

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longer commuting time. Thus, promoting the suggestions listed previously could not only enable them to approach more job opportunities, but could also allow them to have higher work duration, subsequently improving their socio-economic condition and position.

Second, the heterogeneous influence of school districts on parental commuting behavior is also evidenced in the groups of respondents with different levels of education. More specifically, we find that the school district is positively associated with the commuting distance of residents without college degrees, especially for the male group. No significant association was found among individuals with college degrees. The finding implies that male respondents, especially those without college degrees, would sustain longer commuting distances. This is according to the finding by Li (2021) that long commutes are the share of both those who are socially advantaged and disadvantaged. The heterogeneity in the influence of school districts on parental commuting behavior with different levels of education actually reflects the long-standing inequality issue concerning affordability of school district housing and accessibility of public services in developing countries like China. As aforementioned, affordable school district housing in China is important for accessing high-quality primary schools and is vital in influencing parental travel behavior and health. Thus, policy makers should rethink existing resource allocation strategies and focus on the most effective distribution of public service resources across city districts.

At present, efforts to tackle high-quality primary school housing are related to random allocation or reorganization of high-quality schools spatially. However, less attention has been paid to target on offering more high-quality primary schools. In particular, there is an extreme lack of government actions on supplying high-quality primary schools to those low- and medium-income households. Therefore, this study recommends refining the public service policy by promoting social fairness concerning the supply and demand for high-quality primary schools. This can be promoted through a balanced spatial allocation of high-quality primary schools. For instance, accessible high-quality primary schools to low- and medium-income households could be included mandatorily in the school district plan. Such measures would allow parents to pay less time on commute and would significantly free up time for other activities such as active travel.

We also acknowledge the limitations. First, the measurement of commuting distance was based on TAZ calculations, thus, values may truly reflect the real commuting behaviors of parents. Further studies could use accelerometers and global positioning system (GPS)-based tracking devices to collect more accurate travel behavior data. Second, we did not consider the commuters' subjective attitude toward the association between school districts and commuting behaviors, thus the relationship could be overestimated or underestimated. Third, this cross-sectional study indicated a correlation between variables, which precluded inferred causality.

Conclusion

The distribution of school districts would largely influence parental commuting distance, but this association is hardly examined. This negligence stimulates this study which examines the associations between a school district and parental commuting behavior. The results show that the school district mainly affects the residents' commuting distance when the interaction effects between gender and commuting distance are considered. Specifically, a school district is positively associated with the commuting distances for males, whereas females show the opposite trend. Then, variations exist in the effects of the school district on the parental commuting distance between respondents with different levels of education. A school district is positively associated with the commuting distance of respondents without college degrees, especially those male respondents, whereas no significant association was found among respondents with college degrees. Compared with females, male respondents, especially those without college degrees, suffer more cost and sustain longer commuting distance. From this, this study highlights that urban planners and policy makers should consider the school district influences and rethink the most effective distribution of high-quality primary schools to reduce socio-spatial inequalities (e.g., disadvantage of males in commute).

Data availability statement

The data analyzed in this study are subject to the following licenses/restrictions: the authors will use the data for another research which is being conducted at this moment. Requests to access these datasets should be directed to huaxiong_jiang@163.com.

Author contributions

HJ: Conceptualization, Supervision, Original draft, and editing; QL: Conceptualization and Writing—review and editing; YL: Conceptualization, Methodology, Supervision, and Writing—review and editing; KG: Results analysis and Writing—review and editing YG: Writing—review and editing.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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Supplementary material

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/fenvs.2022.1019753/full#supplementary-material

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The impact of technological innovation on transport carbon emission efficiency in China: Spillover effect or siphon effect?

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It is currently unknown whether technological innovation will have spillover or siphon effects on transport carbon emission efficiency (TCEE). Therefore, this paper creates a spatial econometric model to explore the spatial effect of technological innovation on TCEE. Taking 30 provinces in China as examples, we find that the TCEE and the technical innovation index have similar evolution characteristics (numerical value grows, the gap widens), and that both have a spatial distribution that decreases from the eastern coast to the western inland. Further research reveals that TCEE has a considerable siphon effects in China. The siphon effect gets stronger the higher the TCEE. Although technology innovation has the potential to improve TCEE in local province, the siphon effect hinders TCEE improvement in surrounding provinces. Furthermore, heterogeneity research reveals that excessive government intervention will inhibit the promotion of technological innovation on TCEE. Greater levels of government intervention in the middle and western regions than in the eastern region have more obvious inhibitory impacts. The results demonstrate that economic growth and transport structure have played a mediating role in the process of technological innovation promoting TCEE. Regional collaboration and less local protectionism can help the government achieve the dual goals of technological innovation development and TCEE promotion.

KEYWORDS

technological innovation, carbon emission efficiency, transport industry, spatial effect, government intervention, mechanism analysis

Introduction

Transportation is a basic and leading industry to support the development of social economy. It is also an important field of energy consumption and carbon dioxide emissions (1). According to International Energy Agency (2), China's carbon emissions accounted for 31% of the global carbon emissions in 2020, while transportation accounted for about 10% of the national carbon emissions, making it the third largest carbon dioxide source after industry and construction (3). Carbon emissions from transport sector will continue to rise in the future as people's living standards rise (4). China is facing enormous pressure to reduce emissions.

In order to achieve the emission reduction targets of the transportation industry, the Chinese government has issued a series of policies and laws. In 2019, the State Council issued the Program of Building National Strength in Transportation, which clearly pointed out that it is necessary to promote the transformation of transportation development from pursuing speed and scale to focusing on quality and efficiency, shift attention from independent development to integrated development, and promote innovation instead of relying on traditional elements (5). The report of the Communist Party of China's 19th National Congress pointed out that scientific and technological innovation is not only a critical factor in achieving the carbon emission reduction target and developing a low-carbon economy, but also an inherent requirement for China's high-quality economic development. It has become the main driving force of carbon emission reduction in China, and the improvement of carbon emission efficiency has also forced the government and enterprises to carry out scientific and technological innovation to varying degrees (6).

At present, it is still unclear how technological innovation will affect the transport carbon emission efficiency. Some researchers believe that technological innovation may reduce carbon emission efficiency, because it may require more energy consumption, which will lead to more carbon emissions (7, 8). However, more researchers are coming to the conclusion that technological innovation can improve carbon emission efficiency by developing new techniques to reduce carbon emissions and improving traditional measures of pollutant emission reduction (9–12). Furthermore, according to Karacay (13), capital, labor and other elements of production tend to flow to regions with advanced technology, which may reduce the carbon emission reduction capacity of regions with backward technology. This statement also applies to China. Although China's science and technology has advanced quickly over the past 40 years, there is still a significant imbalance between regions, and the competition is fierce (14). Over-concentration of production factors in sophisticated regions will reduce the overall resource allocation efficiency when resources are constrained. The technological development gap would widen due to insufficient growth drivers and incentives in neighboring provinces, ultimately lowering carbon emission efficiency (15).

In addition, evidence indicates that technological innovation has obvious spatial dependence (16). The advancement of science and technology in one region affects not only local economic activities and carbon emissions, but also the production and living activities of other regions through information transmission and factor flow, so impacting carbon emission efficiency (17, 18). Therefore, spatial effect is a critical consideration when assessing the influence of technical innovation on carbon efficiency. Most studies, however, have overlooked it. Although some scholars have taken into account the spatial effect, most of them have neglected the influence of spatial weights on the spatial correlation of carbon emission efficiency (19). The existing literature mainly adopts a symmetrical weighting scheme based on the adjacency or distance principle, and the mutual influence between the two evaluation units is consistent by default (20, 21). In fact, the transportation network transcends geographical boundaries and distance constraints, enabling people and goods in non-adjacent regions to be transported over long distances, which may lead to the asymmetry of the interaction between the two provinces, and thus lead to inaccurate measurement results.

Based on the above analysis, there is no uniform answer to the impact of technological innovation on TCEE at present, we think it is necessary to find out the spatial relationship between technological innovation and TCEE, which will help to find out the driving mechanism of TCEE and provide a new path for carbon emission reduction. Our research has made contributions to the existing literature. Firstly, the theoretical foundation has a certain frontier. According to the concept of green development and the strategic requirements of a strong transportation country, we have separately constructed the evaluation framework of transportation carbon emission efficiency and science and technology innovation index, and discussed the spatial relationship between them, thus organically integrating the green development of transportation industry, environmental constraints and science and technology innovation. The research results enrich the theoretical framework of carbon emission efficiency of transportation and improve the development theory of transportation emission reduction path.

Secondly, the research perspective innovation. Based on the spatial theory, we use spatial pattern statistics and testing methods to measure the spatio-temporal characteristics and spatial relationship of China's transportation carbon emission efficiency and science and technology innovation index from the macro level. We also use the principles of proximity, distance and reciprocal of economic distance to construct three spatial weight matrices, which prove the rationality of asymmetric spatial weights in judging TCEE spatial relations. This is helpful to clarify the growth mechanism of carbon emission efficiency of transportation, and provides a new idea for speeding up carbon emission reduction of transportation.

Thirdly, the research results are worth popularizing. On the basis of identifying the spatial characteristics of China's transportation carbon emission efficiency, the spatial effect of scientific and technological innovation on transportation carbon emission efficiency, the heterogeneity and transmission mechanism of government intervention are measured by spatial econometric model, and targeted and differentiated strategies for improving transportation carbon emission efficiency are put forward. Our conclusion is helpful to fully understand the spatial effect of scientific and technological innovation on carbon emission efficiency of transportation, and have important practical value in assisting the transportation industry to cope with carbon emission peak and carbon neutrality.

Literature review

The carbon emission efficiency is very important for the building green transportation. Transport sector is one of the major carbon emitters. Improving the carbon emission efficiency of the transport sector is the essential courses to build green transportation and realize carbon neutrality. Technological innovation is an important carrier and breakthrough to drive the transformation of energy structure and improve energy efficiency, which can affect carbon emission efficiency to a large extent. Therefore, we will review relevant literature from two aspects: carbon emission efficiency and the influence of technological innovation on carbon emission efficiency.

Many scholars have conducted relevant research on carbon emission efficiency, with a particular focus on the following aspects: carbon emission efficiency measurement (22, 23), spatial effect (24, 25), and driving factors (26, 27). Single-factor method was first applied to measure carbon emission efficiency due to its simple operation (28–30). Subsequently, some scholars began to use the total-factor evaluation method, such as data envelopment analysis (DEA), to measure the TCEE (31, 32). For example, Cui and Li (33) employed the virtual frontier data envelopment analysis model to evaluate the TCEE in 15 countries and used the Tobit regression model to identify the major contributing factors. Ren et al. (34) established a DEA model with radial opportunity constraints to calculate the TCEE of China. Park et al. (35) used the SBM model to assess the environmental efficiency of the transport industry in the United States from 2004 to 2012, and estimated the carbon emission reduction potential of 50 U.S. states. Omrani et al. (36) rank the operation efficiency of the transport departments in Iran's provinces using the cooperative game and cross-efficiency technique.

In addition, some scholars have discussed the spatial heterogeneity of carbon emission efficiency, but neglected the influence of asymmetric spatial weights (2, 37–39). Previous research has primarily used symmetric spatial weight matrices, such as the adjacency and distance matrices, in which the mutual impact between the two evaluation units is consistent by default (19). However, this does not fully reflect the mutual influence of geographical elements in different evaluation units. For example, due to varying levels of economic development, the impact of province i on j is often different from that of province j on i. Therefore, setting the spatial weight among the evaluation units as an asymmetric weight in the application process can more effectively reflect the spatial heterogeneity of geographical elements (40, 41). Besides, scholars also use exponential decomposition (42, 43), input-output (31, 44) and econometric models (45, 46) to study the driving mechanism of carbon efficiency. Unlike the index decomposition, input-output and the traditional econometric regression model, the spatial econometric model can take account of the spatial factors, and gradually becomes the mainstream method for investigating the elements that influence carbon emission efficiency (47).

At present, there is no unified assessment standard for the index of technological innovation, and academic circles hold different views on the impact of technological innovation on carbon efficiency. Many academics argue that technical innovation can promote the promotion and utilization of new energy and the improvement of energy use efficiency, reducing the total carbon emissions (46, 48), and the research and application of carbon reduction technology can improve carbon efficiency (49, 50). However, Some studies believe that the promotion effect of technology on improving energy efficiency is not enough to offset the expansion effect of carbon emissions in the process of production and living, which is not conducive to the ultimate improvement of carbon emission efficiency (8). For example, Lee and Brahmasrene (51), Salahuddin et al. (52) investigate the impact of technological development on carbon emissions in nine ASEAN countries and all OECD countries, finding that the internet use significantly increases the carbon emissions in these countries. Another viewpoint is that the impact of technological innovation on carbon emission efficiency is uncertain (53). The "double-edged sword" effect of technological innovation not only enhances energy utilization efficiency, but also intensifies the increase of energy consumption and total carbon emissions. The direction of technological innovation's influence on carbon emission efficiency is unknown due to the combined action of the driving and constraining effects (54).

To sum up, there is no uniform answer to the impact of technological innovation on TCEE, which could be owing to differences in research regions, time periods and backgrounds. In addition, most studies in this field ignore the spatial effect. Although some studies do consider the spatial effect, they often assume that regional interactions are constant, ignoring the asymmetric effect caused by regional differences, which leads to biased conclusions. Therefore, our research attempts to solve the following problems: First, what is the development level of the technological innovation and TCEE in China, and is there a spatial relationship between them? Second, would technological innovation have a significant impact on TCEE? If so, which effect is more dominant: spillage or siphon? Third, is there any heterogeneity in the spatial impact of technological innovation on the TCEE? Does government intervention work? Fourth, How does technological innovation affect TCEE, and what is its transmission mechanism?

Materials and methods

Data

Measuring index system of TCEE

We used input-output data from the transport industry from 2003 to 2018 for 30 provincial administrative regions in China (excluding Taiwan, Tibet, Hong Kong, Macau). The socioeconomic data were obtained from the China Statistical Yearbook (55), while the energy data were obtained from the China Energy Statistics Yearbook (56). The specific indicator descriptions are shown in Table 1.

Note, the capital stock of the transport industry was calculated using the perpetual inventory method (57). The data were converted to 2003 base period prices; the added value of the transport industry was also treated. Additionally, according to the conversion coefficient of standard coal, as published in the China Energy Statistics Yearbook, all types of energy were standardized and converted to calculate the energy consumption of the transport industry. Transport carbon emission data is calculated according to Liu et al. (58).

Technological innovation index

At present, there is no unified standard for the calculation of technological innovation index in China. On the basis of previous studies, this paper constructs China's provincial-level comprehensive index of technological innovation from seven aspects: hardware facilities, capital investment, talent training, service intensity, technological achievements, achievement transformation and energy saving level (see Table 2). Please refer to the reference of Ma et al. (31) for the specific calculation process.

Mediator variables

Economic level (*lnpgdp*)

On the one hand, technological innovation has greatly changed people's life and production mode, and effectively promoted economic growth. Undoubtedly, science and technology are the primary productive forces, and technological innovation is the core power of economic development (59). On the other hand, sustained economic development will improve people's quality of life and increase transport demand. In addition, the expansion of cities and population has further stimulated the growth of transport demand, which may increase energy consumption and carbon emissions (58). However, with the change of economic growth mode to green and high-quality growth, people's consumption habits and travel modes have also changed. Public transportation has become a new fashion, and clean energy vehicles are also replacing fossil energy-fueled vehicles. This will help to reduce carbon dioxide emissions, thus affecting the changes of TCEE. Therefore, we believe that technological innovation can affect the TCEE by improving economic operation efficiency, reducing economic costs and changing travel modes. The economic level is expressed as the logarithm of GDP per capita, which is the data were converted to 2003 base period prices.

Transport structure

Technology innovation promotes the optimization and upgrading of transport structure in two aspects. One is the transformation of electrification. Science and technology innovation promotes the widespread application of natural gas buses and new energy vehicles. The other one is the digital upgrade. New Internet technologies is constantly integrated with the intelligent transport field to make more effective use of resources (60). For example, the Electronic Toll Collection (ETC) charging system reduces the braking and restarting of vehicles, which can reduce carbon dioxide emissions by over 50%. In terms of new infrastructure such as high-speed rail, intercity rail transit and charging pile network, the comprehensive application of artificial intelligence (AI), big data, cloud computing and other technologies can improve transport efficiency and reduce resource consumption and carbon emissions. Energy consumption mainly reflects the impact of the transport structure on the TCEE. As a "green" mode of transport, an increased proportion of railway and waterway transport use yields reduced energy consumption, which is conducive to improving the TCEE. Conversely, the higher the proportion of road transport, the lower the TCEE (19). Based on the large proportion of current road transport in China, we used the ratio of road turnover and comprehensive turnover to measure the transport structure.

Control variables

To make the results more accurate, some important control variables are added to the model. It include population size (ln*pop*), industrial structure (*ins*), urbanization level (*urban*), energy structure (*ens*), and transport intensity (*tri*). The following describes all of the variables used in this study.

Population size

The impact of the population size on the TCEE is bidirectional (19). The expansion of the population scale accelerates the spatial flow of people and goods between provinces, resulting in an increase in the transport demand, which in turn leads to an increase in energy consumption and CO2 emissions and a decrease in the TCEE. Furthermore, an increase in the transport demand due to population expansion increases the economic output of the transport industry and improves the TCEE. We used the total population of a province to determine its population size.

Industrial structure

The optimisation of and upgrades to the industrial structure can promote regional economic growth, increase transport demand, and change transport intensity. Furthermore, the evolution of the industrial structure can change the energy consumption structure and transition economic development from relying on fossil fuels, such as coal and petroleum, to

TABLE 1 Transport carbon emission efficiency evaluation index system.

Indicators	Level 1 indicators	Level 2 indicators	Unit
Input	Infrastructure	Total mileage of road, railway, waterway, and pipeline transportation network	10,000 kilometers
	Capital stock	Capital stock in transportation	100 million
	Labor force	Individuals employed in the transportation industry	Individuals
	Energy consumption	Energy consumption in transportation	10,000 tons of standard coal
Output	Expected output	Value added in transportation	100 million
	Unexpected output	CO2 emissions of transportation	10,000 tons

TABLE 2 The index system of technological innovation.

Target layer	First-level index	Second-level index	Indicator type	Weight
Technological innovation index	Hardware facilities	Penetration rate of internet	Positive	0.082
	Capital investment	Proportion of science and education expenditure to government budget expenditure	Positive	0.026
	Talent training	Number of people per 10,000 with university degree or above.	Positive	0.034
	Service intensity	Full-time equivalent of R&D personnel	Positive	0.084
	Technological achievements	Number of patent authorizations	Positive	0.267
	Achievement transformation	Trade in technology markets	Positive	0.345
	Energy saving level	Reciprocal of energy intensity	Positive	0.162

clean energy, which effectively reduces carbon emissions and improves the TCEE (61). In this study, the proportion of the tertiary industry was used to represent the industrial structure.

Urbanization level

Urbanization is a dynamic process, involving population, space, economy and society. On the one hand, the advancement of urbanization can effectively promote population agglomeration and economic growth. On the other hand, urban expansion will bring more traffic demand, and increase carbon emissions of industry and service industries and product consumption. Therefore, the influence of urbanization on TCEE is uncertain. We use the ratio of urban population to the total population to express the urbanization level.

Energy structure

The impact of the energy structure on the TCEE mainly depends on the consumption ratio of diesel oil and gasoline. Owing to its high carbon emissions coefficient and maximum consumption, the higher the ratio of the energy structure, the lower the TCEE (20). Therefore, the energy structure was expressed as the ratio of diesel and gasoline consumption to the total energy consumption of the transport industry.

Transport intensity

Transport intensity can reflect the relationship between transport and economic development, which is usually expressed as the ratio of the transport turnover to the regional GDP. A lower transport intensity usually indicates a higher technical level of transport organization and management (Shao and Wang, 2021); thus, the TCEE is higher. When calculating this index, passenger and freight volumes were converted into a comprehensive conversion turnover according to the conversion coefficient specified by the Chinese statistical system.

The descriptive statistics of the variables are reported in Table 3, and we calculated the variance inflation factor (VIF) of each variable to prevent multicollinearity (Table 3). The results showed that the VIF values were all < 5, indicating that no multicollinearity was present among the variables.

Methods

SBM-DEA model for TCEE calculation

The DEA model is the most popular method for measuring the carbon emissions efficiency (35, 62, 63). Among the various DEA models (e.g., the CCR, BCC, and SBM, among others), the SBM model proposed by Tone (64) considers unexpected output and reveals the influence of slacks on the measured value. Therefore, we selected the SBM model to measure the TCEE. We do not give the particular calculation formula in this work because the SBM model is mature and widely used. Please see Ma et al. (31) for details.

TABLE 3 Descriptive statistics and multicollinearity test of the variables.

Variable	Obs.	Mean	Std. Dev.	Min	Max	VIF
TCEE	540	0.480	0.264	0.091	1	-
S	540	0.126	0.103	0.009	0.728	4.31
ln*pgdp*	540	10.324	0.740	8.218	12.013	4.91
trs	540	0.332	0.186	0.006	0.729	1.32
ln*pop*	540	8.176	0.749	6.280	9.443	1.52
ins	540	0.443	0.095	0.283	0.839	3.65
urban	540	0.532	0.149	0.238	0.942	4.25
ens	540	0.689	0.205	0.081	1.028	2.34
tri	540	0.440	0.388	0.062	3.961	1.30

Spatial Durbin model

The spatial lag model (SLM), spatial error model (SEM), spatial autoregressive (SAR) model, and spatial Durbin model (SDM) are all classic models for characterizing spatial effects (19, 65). Among them, the SLM is mainly used to describe an endogenous interaction effect between the interpreted variables (Y). The SAR model mainly describes an exogenous interaction effect between the explanatory variables (X). The SEM mainly describes an interaction effect between the error items (ε). Finally, the SDM comprehensively considers an endogenous interaction effect among the interpreted variables (Y) and an exogenous interaction between the explanatory variables (X) and related error items (ε). Therefore, we employ SDM to assess the spatial effect of technological innovation on TCEE, as follows:

$$\begin{aligned} Y_{it} &= \alpha_0 + \rho W Y_{it} + \gamma S_{it} + \beta_k \sum_{k=1}^{m} X_{it,k} + \gamma_1 W S_{it} \\ &\quad + \lambda_k W X_{it,k} + \mu_i + \xi_t + \varepsilon_{it}, \end{aligned} \tag{1}$$

where Y_{it} represents the TCEE of province i in year t. Sit is the core explanatory variable (technological innovation index) and γ is its coefficient. W is a spatial weight matrix. ρ, $\gamma 1$ represents the coefficient of the spatial lag term for the Y_{it} and S_{it}, respectively. $X_{it,k}$ is the kth control variable in period t in province i, β_k and λ_k are the regression coefficient and spatial lag coefficient of the kth control variable, respectively. n and m are the number of regions and control variables, respectively. μ_i and ξ_t represent the time and spatial fixed effects, respectively, and ε_{it} is a random error.

However, the introduction of spatial weights transformed the linear structure of the spatial econometric model into a nonlinear structure, potentially resulting in a feedback effect (66). As a result, the regression coefficient obtained by the SDM cannot fully reflect the impact of the S_{it} on Y_{it}. To solve this problem, Lesage and Pace (67) transformed both the SDM into a partial derivative matrix and the regression results into direct, indirect, and total effects, which represent the average influence that the core explanatory variable (S_{it}) has on explained variable (Y_{it}) of local province, other provinces, and all provinces, respectively, calculated as follows:

$$Y = (I - \rho W)^{-1}(\beta S + \theta WS) + E \tag{2}$$

where E contains the error and constant term. The partial derivative matrix of the S to Y, can be written as follows:

$$\begin{aligned} \left[\frac{\partial Y}{\partial x_{1k}} \cdot \frac{\partial Y}{\partial s_{nk}}\right] &= \begin{bmatrix} \frac{\partial y_1}{\partial s_{1k}} & \cdots & \frac{\partial y_1}{\partial s_{nk}} \\ \vdots & \ddots & \vdots \\ \frac{\partial y_n}{\partial s_{1k}} & \cdots & \frac{\partial y_n}{\partial s_{nk}} \end{bmatrix} \\ &= (I - \rho W)^{-1} \begin{bmatrix} \beta_k & \omega_{12}\theta_k & \omega_{1n}\theta_k \\ \omega_{21}\theta_k & \beta_k & \omega_{2n}\theta_k \\ \vdots & \vdots & \vdots \\ \omega_{n1}\theta_k & \omega_{n2}\theta_k & \beta_k \end{bmatrix} \end{aligned} \tag{3}$$

where the average value of the elements on the main diagonal is a direct effect, representing the influence of the S on Y in this province. The average value of elements on the off-diagonal line is indirect effect, representing the influence of the S on Y in other province. The sum of direct and indirect effect is the total effect.

Setting of spatial weights

Reasonable values for the spatial weight matrix is particularly important for determining the spatial relationship of the research objects. Therefore, we established the following three spatial weighting schemes to determine the impact of the spatial weight on the spatial relationship of the TCEE and technological innovation index.

Spatial weighting scheme based on spatial adjacency (W_1) principle

There are two spatial adjacent weight matrices. One is based on a common vertex, i.e., two evaluation units require common points for adjacency. The other is based on common edges, i.e., given that there are common edges between two evaluation units, they can be considered adjacent. In this study, 30 provinces in China were used as evaluation units. As there were no common vertices among the different provinces, the second spatial adjacent weight matrix was selected.

$$W_{ij} = \begin{cases} 1 \text{ (Province } i \text{ and } j \text{ have a common boundary)} \\ 0 \text{ (Otherwise)} \end{cases} \tag{4}$$

Spatial weighting scheme based on spatial distance (W_2) principle

There are three types of spatial distance weight matrices based on the following principles: minimum distance, polygon, and reciprocal distance. The spatial weight matrix based on the minimum distance principle uses a certain distance as the threshold value. If the distance between two provinces is less than the threshold value, they are considered adjacent and assigned a value of 1; otherwise, they are considered non-adjacent and assigned a value of 0 (68). According to the spatial weight matrix based on the polygon principle, the nearest points in space can form a specific polygon with a common boundary as its neighbor, with a value of 1; otherwise, the weight is 0. The spatial weight matrix, which is based on the reciprocal distance principle, states that the correlation between evaluation units is inversely proportional to their distance. The transport network breaks the the limit of distance between provinces. According to the distance attenuation principle, the third space distance weight matrix was selected as follows:

$$W_{ij} = \begin{cases} \frac{1}{d_{ij}} \ (i \neq j) \\ 0 \ (i = j) \end{cases} \tag{5}$$

where d is the distance between the geographical centers of the provinces. This paper uses the longitude and latitude of the provincial capital city center to calculate the provincial distance.

An asymmetric spatial weighting scheme based on economy-distance reciprocal (W_3)

The above two spatial weight matrices are symmetric matrices because the mutual influence between two evaluation units in these matrices is, by default, identical. However, due to the driving factors, such as the economic level, resource endowment, and others, the mutual influence between two regions differs, even with distance. Therefore, when calculating the spatial correlation of the TCEE and technological innovation index, setting the spatial weight as asymmetric may be more realistic. The asymmetric spatial weight matrix with the economy-distance reciprocal was introduced into the spatial correlation measurement.

$$W_{ij} = \begin{cases} \left(\frac{G_i}{G_j}\right)^{1/2} \times \frac{1}{d_{ij}} \ (i \neq j) \\ 0 \ (i = j) \end{cases} \tag{6}$$

where G_i and G_j represent the GDP of provinces i and j, respectively.

Spatial mediating model

Based on the significance test results ($\alpha 1$) of model (1), a spatial mediating model is constructed by using the three-step method of mediating effect and spatial econometric model (69, 70), and the transmission mechanism of technological innovation on the TCEE is discussed.

$$\begin{aligned} M_{it} &= \alpha_0 + \gamma S_{it} + \beta_k \sum_{k=1}^{m} X_{it,k} + \gamma_1 W S_{it} + \lambda_k W X_{it,k} + \mu_i \\ &\quad + \xi_t + \varepsilon_{it} \end{aligned} \tag{7}$$

$$\begin{aligned} Y_{it} &= \alpha_0 + \phi S_{it} + \phi_1 W S_{it} + \nu M_{it} + \nu_1 W M_{it} + \beta_k \sum_{k=1}^{m} X_{it,k} \\ &\quad + \lambda_k W X_{it,k} + \mu_i + \xi_t + \varepsilon_{it} \end{aligned} \tag{8}$$

Where M_{it} represents the mediating variables. If the coefficients γ, ν, ϕ are significant, the mediating variable M_i plays a partial mediation effect. If the coefficients λ, ν are significant and ϕ is not significant, the mediating variable M_i plays a full mediation effect.

Results

The spatio-temporal characteristics of TCEE and technological innovation index

Figure 1 shows the time-varying trends of TCEE and technological innovation index in China. According to Figure 1A, the TCEE has obvious "double peak" distribution at four time nodes. The first peak's efficiency value is around 0.3, while the second peak's efficiency value is 1, indicating that China's transport carbon emission efficiency has obvious polarization during the study period, with most provinces having low efficiency. Specifically, from 2003 to 2010, the peak width of TCEE narrowed and the median moved up slightly, indicating that the TCEE improved. The box-plot become shorter, indicating that the degree of TCEE dispersion is reducing and the regional differences are shrinking. From 2010 to 2020, the peak width of TCEE widened, and the Kernel density curve and median moved up, which indicated that TCEE was on the rise, while the dispersion was enlarged and the polarization was aggravated. The technological innovation index shows a "single peak" distribution, as seen in Figure 1B. With the passage of time, the Kernel density curve moves up, the peak width and the box-plot stretches, indicating that China's technological innovation index presents an upward trend during the research period, but tends to be discrete and the regional differences become larger.

Figure 2 describes the spatial distribution patterns of the TCEE and technological innovation index in China. Figure 2 shows that China's technological innovation index and transport carbon emission efficiency have similar spatial distribution characteristics, namely decreasing from east to west. At the same time, the regions with high technological innovation index are mostly located in the economic circle of Beijing-Tianjin-Hebei (BTH), Yangtze River Delta (YRD) and Pearl

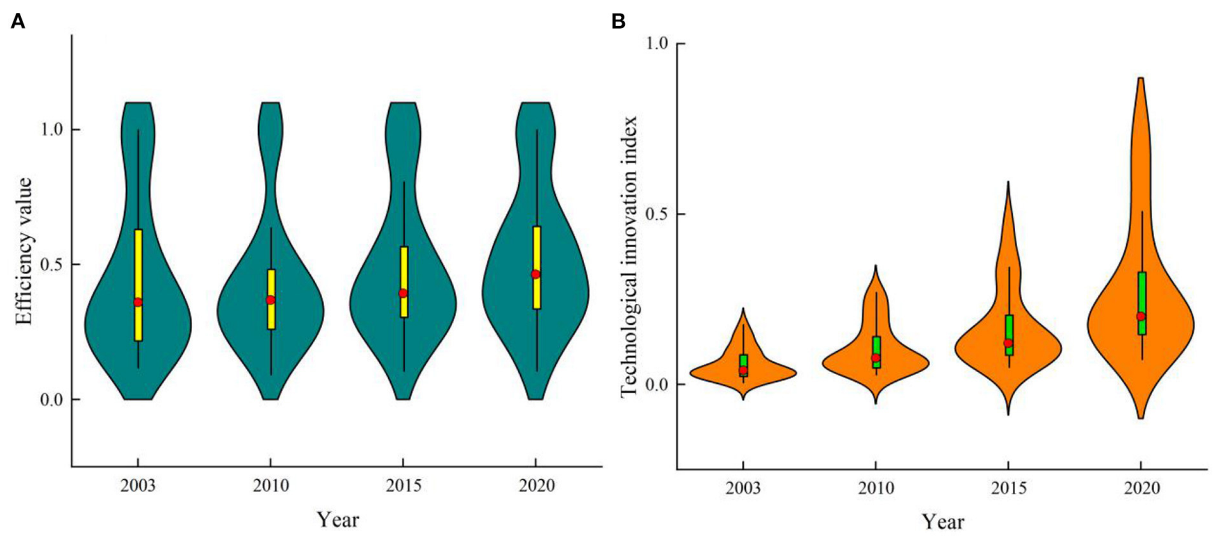

FIGURE 1
Time-varying trend of TCEE and technological innovation index in China. **(A)** Transport carbon emission efficiency. **(B)** Technological innovation index.

River Delta (PRD), which is in line with the actual situation. The regions with higher TCEE include Shandong, Shanghai, Hebei, Tianjin, Jiangsu, Beijing and Fujian provinces, which are highly coincident with those with higher technological innovation index. The explanation for this could be that the eastern provinces of China are generally richer in resources, better in transport infrastructure, more advantageous in policies, and more conducive to the development of science and technology. Simultaneously, science and technology are used to promote production and improve the transport carbon emission efficiency.

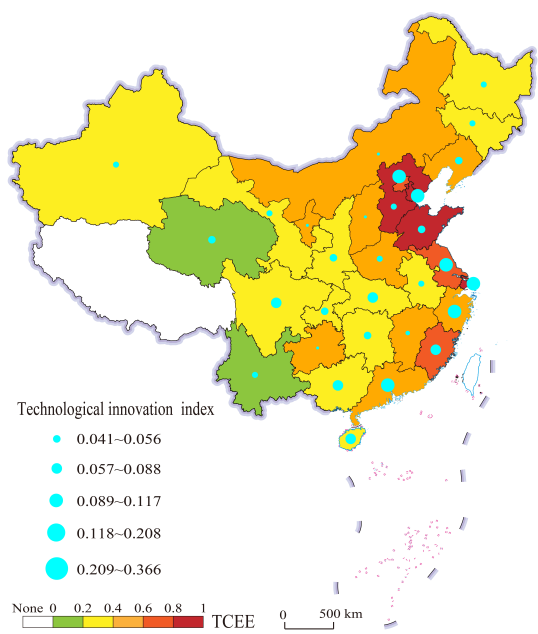

FIGURE 2
Spatial distribution pattern of TCEE and technological innovation index in China.

Spatial correlation test

In order to further analyze the spatial effect of TCEE and technological innovation index, we calculated Moran's I of TCEE and technological innovation index under three spatial weight matrices from 2003 to 2020. Please refer to Table 4 for the results.

Table 4 shows that, under three spatial weight matrices, the global Moran's I of China's TCEE and technological innovation index from 2003 to 2020 are all positive, and all of them passed the 5 % significance test, indicating that the TCEE and technological innovation index have a high positive spatial correlation, namely, a cluster phenomenon. The Moran's I calculated using the W_1 and W_2 spatial weight matrices were larger than that calculated using W_3, showing that the spatial correlation of the symmetric spatial weight calculation was higher. However, the p value obtained using the symmetric spatial weight matrix changed with a change in the random Monte Carlo random test times, leading to partial uncertainty in the evaluation results. The p value obtained using W_3 was derived under the random assumption of spatial non-correlation. Although the Moran's I was not high, the spatial weight matrix had a negligible influence on the z-value test,

TABLE 4 The results of spatial correlation test.

Year	W_1		W_2		W_3	
	Moran's I	z	Moran's I	z	Moran's I	z
2003	0.579***/0.348***	5.099/3.223	0.182***/0.083***	6.212/3.405	0.131***/0.067***	5.155/3.189
2004	0.572***/0.389***	5.029/3.590	0.198***/0.091***	6.654/3.682	0.154***/0.082***	5.874/3.663
2005	0.571***/0.380***	5.014/3.513	0.182***/0.088***	6.197/3.591	0.143***/0.078***	5.510/3.537
2006	0.551***/0.410***	4.890/3.763	0.165***/0.093***	5.754/3.734	0.133***/0.081***	5.239/3.631
2007	0.493***/0.382***	4.442/3.496	0.149***/0.083***	5.305/3.396	0.122***/0.071***	4.889/3.318
2008	0.394***/0.365***	3.645/3.356	0.109***/0.083***	4.217/3.406	0.093***/0.070***	4.025/3.258
2009	0.401***/0.375***	3.727/3.460	0.107***/0.082***	4.159/3.390	0.092***/0.070***	3.981/3.274
2010	0.434***/0.398***	3.988/3.614	0.115***/0.090***	4.371/3.588	0.097***/0.062***	4.145/3.015
2011	0.440***/0.379***	4.025/3.456	0.110***/0.085***	4.217/3.439	0.092***/0.060***	3.966/2.953
2012	0.429***/0.375***	3.926/3.437	0.104***/0.086***	4.059/3.471	0.086***/0.061***	3.788/2.980
2013	0.439***/0.409***	4.073/3.704	0.085***/0.093***	3.547/3.690	0.051***/0.055***	2.705/2.802
2014	0.327***/0.395***	2.985/3.606	0.061***/0.085***	2.719/3.454	0.027**/0.048***	1.925/2.576
2015	0.488***/0.396***	4.341/3.650	0.112***/0.083***	4.206/3.432	0.058***/0.051***	2.871/2.689
2016	0.561***/0.414***	4.923/3.789	0.142***/0.086***	5.030/3.510	0.079***/0.046***	3.516/2.532
2017	0.556***/0.395***	4.854/3.624	0.141***/0.078***	4.982/3.274	0.083***/0.036**	3.650/2.213
2018	0.584***/0.390***	5.117/3.605	0.160***/0.079***	5.551/3.315	0.093***/0.035**	3.975/2.174
2019	0.596***/0.376***	5.229/3.500	0.163***/0.078***	5.661/3.310	0.090***/0.032**	3.882/2.103
2020	0.603***/0.360***	5.283/3.334	0.165***/0.082***	5.691/3.415	0.092***/0.033**	3.943/2.122

TCEE, technological innovation index.
***, **, and * denote the significance at the 1%, 5%, and 10% levels, respectively.

which showed that W_3 could support the overall evaluation of the spatial correlation of the TCEE and technological innovation index. Therefore, we selects W_3 as the spatial weight matrix to perform the spatial Durbin regression analysis.

Figures 3, 4 illustrate the LISA agglomeration maps of TCEE and technological innovation index in China, respectively. As shown in Figures 3, 4, the TCEE and technological innovation index in most provinces are positively correlated with those in the surrounding provinces since most observations belong to H-H and L-L agglomeration for both years. According to Figure 3, in 2003, 9 provinces are classified as H-H agglomeration and 16 provinces are classified as L-L agglomeration. In 2020, 10 provinces belong to H-H agglomeration, and 16 provinces belong to L-L agglomeration, accounting for 83.33 and 86.67% of the total sample, respectively. This further confirms the spatial correlation of TCEE. Spatially, the H-H agglomeration type of TCEE are relatively stable in North China and the Yangtze River Delta, while the L-L agglomeration type are mainly located in the central, western and northeast regions.

The same pattern is applicable to China's technological innovation index. Figure 4 shows the clustering results of technological innovation index. In 2003 and 2020, 5 and 8 provinces are classified as H-H aggregation type, while 14 and 15 provinces are classified as L-L aggregation type. In 2003 and 2020, the two types account for 63.33 and 76.67% of the total sample, respectively. Further, the H-H agglomeration type gradually spread from the YRD and PRD to the BR economic circle, while the L-L agglomeration type tend to spread to the south.

In a word, the spatial distribution and exploratory spatial test reveal that there is a positive spatial correlation of TCEE and technological innovation from 2003 to 2020 in China, rather than a random distribution. In addition, their geographical distribution is relatively stable, showing obvious "path dependence" characteristics. The high-value aggregation area of technological innovation index matches with the high-value aggregation area of TCEE, while the low-value aggregation area of technological innovation index matches with the low-value aggregation area of TCEE. Therefore, it may be extrapolated that technological innovation has promoted the TCEE, and the polarization of TCEE may be intensified due to the siphon effect. In order to prove this hypothesis, spatial econometric analysis is further conducted.

Regression results of technological innovation index on TCEE

Parameter estimation of non-spatial panel model

Table 5 reports the linear estimation results of the technological innovation on TCEE without considering the

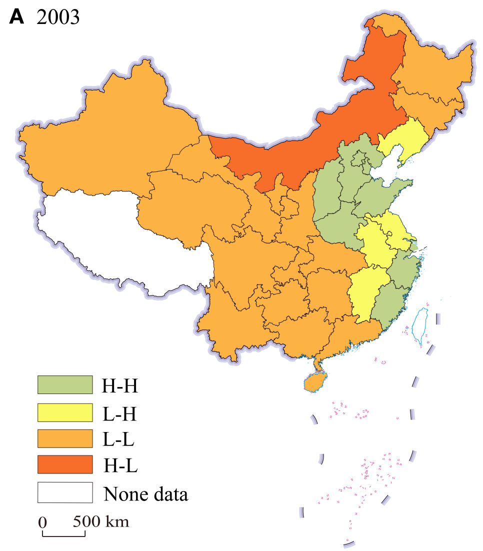

FIGURE 3
LISA agglomeration maps of TCEE. **(A)** 2003; **(B)** 2020.

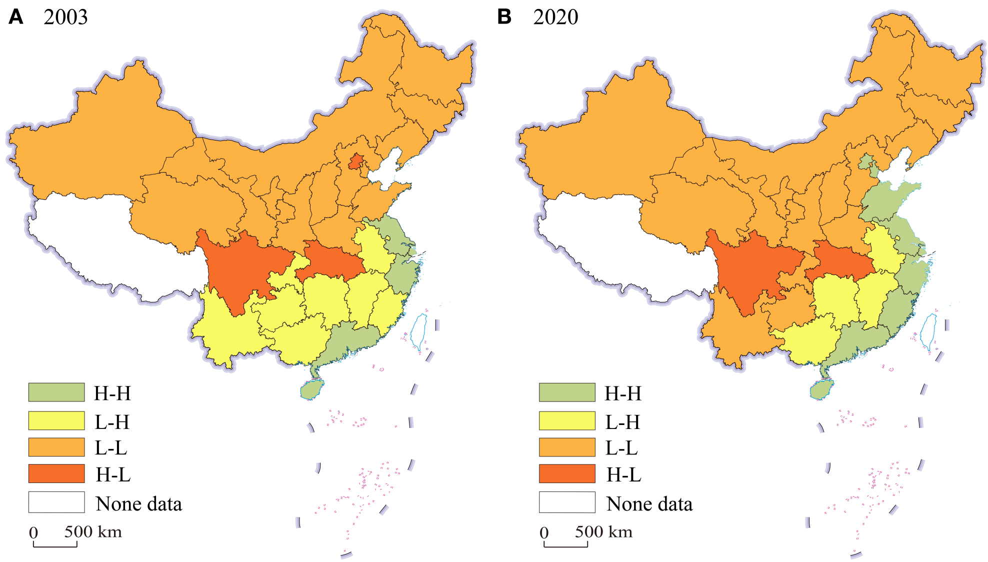

FIGURE 4
LISA agglomeration maps of technological innovation index. **(A)** 2003; **(B)** 2020.

spatial effects. Column (1) is the regression result without adding control variables. The result show that the coefficient of core explanatory variable is 0.401, which is significant at the 1% level, demonstrating that technological innovation can effectively promote the growth of TCEE. To verify the robustness of the results, we added control variables in turn to carry out stepwise regression. According to the regression results of column (2) to (6), all regression coefficients are positive and significant, indicating that technological innovation can effectively improve TCEE in China without considering the spatial effect.

However, if the panel data is spatially dependent, the results of the classical econometric model may be biased, and invalid parameter estimation may be obtained because the spatial interaction between the observed data is ignored (71). As mentioned above, China's TCEE and technological innovation

TABLE 5 Basic estimation results without spatial effects.

Variables	(1)	(2)	(3)	(4)	(5)	(6)
S	0.401***	0.637***	0.587***	0.559***	0.537***	0.585***
	(6.49)	(6.51)	(5.65)	(5.32)	(4.91)	(5.15)
ln*pop*		−0.282***	−0.297***	−0.322***	−0.360***	−0.445***
		(−2.97)	(−3.11)	(−3.34)	(−3.58)	(−3.88)
ins			0.160	0.219*	0.186	0.151
			(1.46)	(1.90)	(1.52)	(1.21)
urban				−0.275	−0.253	−0.277
				(−1.64)	(−1.49)	(−1.63)
ens					0.007	0.020
					(0.13)	(0.38)
tri						−0.029
						(−1.53)
Cons	0.430***	2.843***	2.954***	2.958***	3.113***	3.782***
	(48.33)	(3.74)	(3.87)	(3.88)	(3.98)	(4.22)
Obs.	540	540	540	540	540	540
R^2	0.677	0.697	0.701	0.706	0.716	0.720
Adjust-R^2	0.669	0.683	0.691	0.699	0.706	0.711

***, **, and * denote the significance at the 1%, 5%, and 10% levels, respectively; t statistics are shown between parentheses.

TABLE 6 Lagrangian multiplier (LM) test results.

Weights	Test statistics	No fixed	Time-fixed	Spatial-fixed	Spatio-temporal fixed
W_1	Lag-LM	55.7101***	3.6057*	13.6527***	5.7725**
	Lag-R-LM	12.8401***	9.3337***	17.8668***	4.6167**
	Error-LM	49.5304***	0.8725	39.3853***	3.5660**
	Error-R-LM	6.6604***	6.6004***	43.5994***	1.4101
	R^2	0.6314	0.6502	0.8694	0.9811
W_2	Lag-LM	46.4152***	0.0002	87.7985***	9.3103***
	Lag-R-LM	3.2049*	4.4000**	12.4370***	1.9326
	Error-LM	56.8292***	7.3925***	21.8372***	7.6808***
	Error-R-LM	13.6188***	11.3925***	37.4757***	0.3031
	R^2	0.6319	0.6530	0.8675	0.9816
W_3	Lag-LM	18.9134***	1.6887	73.9362***	16.6302***
	Lag-R-LM	32.6917***	8.1017***	15.9828***	11.2288***
	Error-LM	54.5495***	10.6771***	91.2727***	15.7408***
	Error-R-LM	68.3278***	9.0902***	33.3193***	10.3394***
	R^2	0.6318	0.6539	0.8676	0.9821

***, **, and * denote the significance at the 1%, 5%, and 10% levels, respectively.

index have obvious spatial correlation characteristics. Therefore, we use SDM to further explore the influence of technological innovation on TCEE.

Model screening and testing

Before using SDM for regression, it is necessary to choose the appropriate spatial econometric model and spatial weights. We conducted a Lagrangian multiplier (LM) test (see Table 6). Among the four models, W_1 failed the significance test of spatial autocorrelation error term. Furthermore, W_2 did not pass the significance test of spatial lag explanatory variables and spatial auto-correlation error term. Only the LM test of W_3 passed the significance test at 1 %. Therefore, this verified the spatial effects of the sample data and the robustness of W_3.

TABLE 7 Spatial model test results.

Test statistics	W_1	W_2	W_3
Lag-Ward	18.0367**	37.0135***	39.3284***
Lag-LR	17.3539**	35.7360***	37.4137***
Error-Ward	17.4099**	33.7804***	38.5969***
Error-LR	15.2676*	15.9652**	36.0248***
Hausman	39.9577***	80.9123***	45.1509***

***, **, and * denote the significance at the 1%, 5%, and 10% levels, respectively.

TABLE 8 Regression results of spatial Durbin model.

Variables	Coefficient	*t*	Variables	Coefficient	*t*
S	0.4379***	4.18	*W***S*	−0.0941**	−2.03
ln*pop*	−0.0020	−0.02	*W**ln*pop*	0.1418	0.13
ins	0.1217**	1.97	*W***ins*	−3.5613**	−2.23
urban	−0.4699***	−2.90	*W***urban*	2.7768**	2.09
ens	−0.1018**	−2.09	*W***ens*	−0.1371	−0.36
tri	−0.0101	−0.60	*W***tri*	0.7493***	3.30
ρ	−1.3143***	−6.28	R^2	0.7627	
σ^2	0.0057***	16.49	Log-likelihood	595.1071	

***, **, and * denote the significance at the 1%, 5%, and 10% levels, respectively.

We note that the Lag-LM under the time-fixed effect failed the significance test (1.6887) in the LM test with W_3 as the spatial weight matrix. Therefore, caution should be exercised when choosing this model. In this paper, the Ward test, likelihood ratio (LR) test, and Hausman test were used to select the model and determine whether the SDM would degenerate into an SLM or SEM (see Table 7). The test results showed that the Lag-Ward, Lag-LR, Error-Ward, and Error-LR tests were all significant at the 1 % level, indicating that the SDM should be used. Furthermore, the Hausman test results showed that the model rejected the random effect (45.1509***). The model R^2 was the largest (0.9821) under the spatio-temporal fixed effect, as reported in Table 5. Therefore, the SDM with fixed time and space was selected as the optimisation model for the regression analysis.

Parameter estimates from spatial Durbin model

Table 8 presents the regression results for the SDM. The coefficient, ρ, was −1.3143, which passed the 1 % significance level test, indicating that there was a notable negative spatial spillover effect on the TCEE in China, i.e. siphon effect. The R^2 was 0.7627, which indicates that the regression result of the SDM is good. As mentioned above, whether technological innovation can improve TCEE in the surrounding provinces depends on the trade-off between "spillover effect" and "siphon effect". If the former exceeds the latter, i.e., technological innovation can promote TCEE in the surrounding provinces, the coefficient of W^*S should be positive, and vice versa. Table 8 shows that the W^*S is significantly negative, indicating that technological innovation has reduced the TCEE of the surrounding provinces. Specifically, the "siphon effect" of local attraction of labor, capital and other elements is greater than the "spillover effect" of technological innovation on the flow of green production technology, environmental awareness and advanced systems to the surrounding provinces.

Control variables, the coefficients of industrial structure (*ins*) are significantly positive, indicating that the factor have positive promotion effects on TCEE. Urbanization level (*urban*) and energy structure (*ens*) coefficient are negative, and significant at 1%, and 5% levels, respectively, indicating that they have a negative impact on TCEE. This is consistent with Zhao et al. (19). Transport intensity (*tri*) has a negative impact on the TCEE, Transport intensity reflects the relationship between transport and economic growth. The reduction in transport intensity means a reduction in turnover per unit GDP. Therefore, transport intensity has a negative impact on TCEE through economic growth; that is, the transport intensity decreases and carbon emission efficiency improves. In addition, the lag items of industrial structure, urbanization level, energy structure and transport intensity have a significant impact on TCEE, among which the coefficient of urbanization level and transport intensity are significantly positive, while the industrial and energy structure are significantly negative.

Because of the feedback effect, the regression coefficient of SDM can not fully reflect the influence of core explanatory variables on TCEE. Therefore, the direct, indirect, and total effects are used to reflect the influence of technological innovation on the TCEE (see Table 9). The direct effect of the technological innovation index is positive and the indirect effect is negative, both of them are significant, indicating that technological innovation can improve the local TCEE, but reduce the TCEE of the surrounding provinces through siphon effect. In addition, the total effect of the technological innovation index is significantly positive, indicating that technological innovation can improve TCEE on the whole. Therefore, local governments should strive to break down the regional barriers, speed up the regional flow of technological elements, and transform the siphon effect of technological innovation on TCEE into a spillover effect, so as to improve the TCEE as a whole.

Results robustness test

Robustness test of control variables lag

Robustness testing of results is essential. First of all, we deal with all the control variables with lag one period, which aims at eliminating the interference of the control variables on TCEE (72). The results of robustness test show that the direct

TABLE 9 Direct, indirect and total effects of technological innovation on TCEE.

Variables	Direct effect		Indirect effect		Total effect	
	Coefficient	*t*	Coefficient	*t*	Coefficient	*t*
S	0.5357***	4.99	−0.2695***	−2.86	0.2662*	1.74
ln*pop*	0.0021	0.02	0.0633	0.12	0.0655	0.14
ins	0.0032	0.02	−1.6372**	−2.21	−1.6340**	−2.09
urban	−0.5904***	−3.22	1.5609**	2.53	0.9705*	1.68
ens	−0.1001*	−1.85	−0.0112	−0.06	−0.1113*	−1.66
tri	−0.0393**	−2.30	0.3574***	3.21	0.3181***	2.94

***, **, and * denote the significance at the 1%, 5%, and 10% levels, respectively.

and total effect coefficient of technological innovation index are significantly positive, while the indirect effect coefficient is negative and significant (see Table 10), which indicates that technological innovation can effectively improve TCEE in the province, but it is not conducive to neighboring provinces. The regression results of control variables are basically consistent with Table 9, and the previous conclusion is still valid.

Robustness test of spatial weight matrix

Considering that the estimation coefficients of the spatial econometric model is sensitive to the spatial weight matrix, we use adjacency matrix (W_1) and distance matrix (W_2) to analyze the robustness of the results. The results show that changing the spatial weight matrix has little influence on the estimation results, which once again proves that our conclusion is reliable (see Supplementary Table 1).

Robustness test by adjusting the time bandwidth

We continue to perform robustness testing by adjusting the time bandwidth to eliminate non-common trend issues due to the excessively long time span. After deleting the data before 2005, 2007 and 2010 respectively, the result of the core explanatory variables is basically consistent with the regression results in Table 8 after shortening the time bandwidth (see Supplementary Table 2).

Robustness test of random sampling

Finally, in order to avoid the chance of results, we used the random sampling method to regress the samples (73, 74). Because the spatial econometric regression model requires the panel data to be balanced, this paper randomly deletes the data of 3 years and repeats it several times. Some results can be found in Supplementary Table 3. The result is the regression value of a random sample instead of the average value of several samples. The slight change in the core explanatory variables in the regression results shows that the results in Table 8 are relatively stable, and our conclusion is reliable.

Spatial heterogeneity: The role of government intervention

According to Table 2, the weight of the achievement transformation index is 0.345, which is much larger than the weight of the indicators such as hardware facilities (0.082), capital investment (0.026), talent training (0.034) and service intensity (0.084), indicating that the level of technological innovation depends on the transformation of scientific and technological achievements, rather than factors investment. Therefore, technological innovation is a highly market-oriented factor of production. Considering the different degrees of regional market, the driving forces of transport carbon emission efficiency will be different. In China, government intervention has a significant impact on the level of regional market. Excessive government intervention may damage the regional market and further inhibit the promotion of technological innovation on TCEE. Therefore, we conducted an empirical test based on different levels of local government intervention to analyze this heterogeneous effect.

According to the classification standard of the National Bureau of Statistics, 30 provinces in China are divided into the eastern, central and western regions. The eastern region includes 11 provinces and cities, including Beijing, Tianjin, Hebei, Liaoning, Shandong, Jiangsu, Shanghai, Zhejiang, Fujian, Guangdong and Hainan. Including eight provinces in central China, such as Heilongjiang, Jilin, Shanxi, Anhui, Jiangxi, Henan, Hubei and Hunan. The other 12 provinces belong to the western region, namely, Inner Mongolia, Guangxi, Chongqing, Sichuan, Guizhou, Yunnan, Shaanxi, Gansu, Qinghai, Ningxia and Xinjiang. We use the ratio of transportation expenditure to GDP to measure the level of government intervention (*gov*). The calculation results show that the central (2.344) and western (3.079) regions of China generally have a higher level of government intervention, while it is relatively low in the east (1.048). As mentioned above, the spatial Dubin model with both time and spatial fixed is used to analyze the heterogeneity of government intervention. The results are shown in Supplementary Table 4.

According to Supplementary Table 4, the spatial autoregressive coefficient ρ of TCEE in each region is negative and significant, and its absolute value decreases from east to west, indicating that the siphon effect is stronger in regions with higher TCEE. At the national level, the coefficient of $S^{*}gov$ is significantly negative (−0.1324). This indicates that excessive government intervention will inhibit the promotion of technological innovation on TCEE. As for the eastern region, the

TABLE 10 Robustness test results of control variables lag.

Variables	Direct effect		Indirect effect		Total effect	
	Coefficient	*t*	Coefficient	*t*	Coefficient	*t*
S	0.5320***	4.86	−0.2637***	−2.85	0.2683*	1.74
ln*pop*	0.0400	0.31	−0.3932	−0.74	−0.3532	−0.74
ins	0.0613	0.33	−1.3440*	−1.80	−1.2826*	−1.62
urban	−0.7405***	−3.71	1.9927***	2.89	1.2522**	2.03
ens	−0.0668	−1.14	0.0650	0.33	−0.0018	−0.01
tri	−0.0564***	−3.23	0.4037***	3.48	0.3474***	3.06

***, **, and * denote the significance at the 1%, 5%, and 10% levels, respectively.

coefficient of $S^{*}gov$ is 0.1058, which passes the significance test of 5 %. It shows that technological innovation can significantly promote the TCEE in the eastern region where government intervention is low, but it is not significant in the central region. On the contrary, the coefficient of $S^{*}gov$ in the west is negative (−0.2460), and it has passed the significance test of 1 %, which shows that excessive government intervention has hindered the improvement of TCEE by technological innovation. The above results prove that the impact of technological innovation on TCEE is spatially heterogeneous under government intervention. In addition, the influence of control variables on TCEE also has significant spatial heterogeneity. For example, the increase of population size will inhibit the increase of TCEE in the east, but it has a positive promoting effect on the west. The improvement of energy structure has a significantly higher promotion effect on TCEE in the eastern and central than in the western region.

Mechanism analysis

Technological innovation, economic growth and TCEE

Supplementary Table 5 shows the test results with economic level (ln*pgdp*) as the mediator variable under the three spatial weight matrices. The results of columns (1), (4), and (7) show that technological innovation has significantly promoted the TCEE. Similarly, the results in column (2), (5), and (8) are all significantly positive, indicating that technological innovation can significantly improve the level of economic development. Columns (3), (6) and (9) show that the regression coefficients of technological innovation and economic level under the three spatial weight matrices are 0.528 and 0.364, 0.566 and 0.243, 0.445 and 0.211, respectively, which indicates that technological innovation can improve the TCEE by promoting economic growth. Both coefficients have passed the 1% significance test, indicating that there is a partial mediating effect on economic growth. Specifically, scientific and technological innovation has been deeply integrated into all aspects of social and economic development. While improving production capacity, quality and efficiency, its contribution to the national economy has increased significantly. Besides, economic growth is also related to energy consumption and carbon emissions in transport. Changes of consumption concepts and travel mode directly affect the scale and structure of energy consumption, and then affects the TCEE.

Technological innovation, transport structure and TCEE

Supplementary Table 6 shows the test results of transport structure (*trs*) as the mediator variable under the three spatial weight matrices. The results in columns (1), (4), and (7) are the same as those discussed above. The results in columns (2), (5) and (8) are all significantly negative, indicating that technological innovation can optimize the transport structure and significantly reduce the proportion of road transport. Columns (3), (6) and (9) show that when both technological innovation and transport structure are incorporated into the regression model, the technological innovation coefficients are 0.663, 0.622 and 0.470, and the transport structure coefficients are −0.030, −0.037 and −0.028, respectively, which indicates that technological innovation can improve the TCEE by optimizing the transport structure. Furthermore, the technological innovation coefficient has not passed the significance test, while the transport structure coefficient has passed the 1% significance test, indicating that the transport structure has a complete mediating effect. Specifically, with the development of the scientific and technological revolution, the transport field is becoming more and more green and intelligent. The deep integration of technological innovation and transport mode has accelerated the "road-to-railway" and "road-to-water" transport, and greatly optimized the transport structure. In addition, the optimization of transport structure reduces the consumption of fossil energy (such as, gasoline, diesel) and carbon emissions, which in turn affects the TCEE.

Discussion and conclusions

Discussion

It is a common consensus in various regions to promote carbon emission reduction and improve carbon emission efficiency through technological innovation, and many scholars have confirmed this view. Unfortunately, most researches ignore the spatial effect, which leads to inaccurate measurement results. We use the spatial econometric model to test the spatial effect of technological innovation on transport carbon emission efficiency, and identify the spatial heterogeneity of government intervention and the transmission mechanism of technological innovation on TCEE.

In Section 4.3.3, the regression coefficient of technological innovation to TCEE is significantly positive, indicating that technological innovation can effectively improve TCEE, which reminds us that we should spare no effort to improve the level of technological innovation. However, the results in Table 2 show that the weight of achievement transformation index is 0.345, and the weight of capital investment index is only 0.026, which indicates that the level of technological innovation mainly depends on the degree to which scientific and technological achievements are transformed into productive forces, that is to say, we should pay attention to the transformation of scientific and technological achievements into productive forces instead of blindly increasing scientific and technological investment, which is the key to improving the level of technological innovation.

In addition, that result in Table 8 indicate that transport carbon emission efficiency has a significant siphon effect, and technological innovation will also hinder the improvement of TCEE in the surrounding provinces. Therefore, the government should be alert to the siphon effect. We can attempt to address these issues by enhancing regional cooperation, breaking down regional barriers and encouraging the flow of scientific and technological innovation elements.

In Section 4.5, after joining the government intervention index, the spatial effect of technological innovation on TCEE shows significant spatial difference. Specifically, the regression coefficient in the eastern region is significantly positive, while that in the central and western regions is significantly negative, which indicates that excessive government intervention is not conducive to the improvement of TCEE by technological innovation. The government should streamline administration and delegate power, simplify administrative inspection and approval procedures, improve government efficiency, and minimize excessive administrative oversight of technology innovation.

Anything else, when formulating policies, the government should fully consider the regional differences, such as economy, population, industrial structure and other factors, and formulate targeted and differentiated emission reduction policies. For example, in the northeast and west, where there is a high rate of brain drain and a small population, the government should encourage childbearing, and formulate a preferential settlement policy to attract talents, in order to boost economic growth and reduce carbon emissions. Giving full recognition to the leading roles of developed provinces, such as the BR, YRD, and PRD in western China, promoting the overflow of new technologies, methods, and knowledge, reducing regional differences, and realizing overall improvements to the TCEE are all necessary.

The results in Section 4.4 show that technological innovation can improve TCEE by promoting economic growth and improving transportation structure. Economic growth is related to all aspects of social development. Improving the transportation structure can be achieved through the following two points. On the one hand, the government should vigorously develop clean energy vehicles, such as those using pure electric power, hybrid power and hydrogen energy, to reduce the consumption of fossil fuels such as gasoline and diesel. On the other hand, vigorously promote the transformation from road to water and rail transport, and adopt new transport organization methods such as multimodal transport to promote container transport and reduce transport intensity, in order to optimize the energy and transport structure, and improve TCEE.

Conclusions

The TCEE and technology innovation index have similar spatio-temporal evolution characteristics in China, i.e. the value increases with time while the regional differences continue to expand. Spatially, the high-value provinces of TCEE and technological innovation are all distributed in the eastern region, showing a decreasing distribution from the eastern coast to the western inland.

China's TCEE and the development of technological innovation have a strong positive spatial correlation and high stability, showing an obvious "path dependence" feature. Spatially, the high-value (low-value) agglomeration area of technological innovation index is highly coincident with the high-value (low-value) agglomeration area of TCEE.

The TCEE in China has a significant siphon effect, and the higher the efficiency, the stronger the siphon effect in the region. Technological innovation can effectively improve the TCEE in local province, but it inhibits the improvement of TCEE in the surrounding provinces through siphon effect.

Spatial heterogeneity analysis reveals that excessive government intervention will inhibit the promotion of technological innovation on TCEE. The central and western regions, which have a higher level of government intervention than the eastern region, have more obvious inhibition effects.

Mechanism analysis shows that technological innovation can improve the TCEE by improving economic level and optimizing transport structure. Among them, economic growth has a partial mediating effect, and the transport structure has a full mediating effect.

Data availability statement

The original contributions presented in the study are included in the article/Supplementary material, further inquiries can be directed to the corresponding author.

Author contributions

Methodology: PJ. Software, validation, formal analysis, writing—original draft preparation, and visualization: QM. Writing—review and editing, supervision, and funding acquisition: PJ and HK. All authors have read and agreed to the published version of the manuscript.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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Supplementary material

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Spatial differences in thermal comfort in summer in coastal areas: A study on Dalian, China

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Thermal comfort is an important indicator for evaluating the environment of urban public space, and appropriate thermal comfort can effectively prolong the duration of outdoor activities. In the existing studies, there is a lack of thermal comfort comparison between hot spots and cold spots. In this study, we selected the coastal city of Dalian in China as our study area and conducted field investigations on the thermal comfort of two landmark resorts, namely, a downtown commercial street and coastal leisure park. The study was conducted on typical summer days and consisted of interviewing several residents to understand their thermal comfort requirements. We investigated the thermal expectations of the interviewees through meteorological measurements and questionnaires. The universal thermal climate index (UTCI) was used to determine the thermal benchmarks of the on-site subjects. The results indicated that (1) globe temperature and air temperature were the most important factors that affected thermal comfort, followed by relative humidity and wind speed in summer daytime. (2) Shaded spaces are more comfortable than open spaces, and tree shade is preferred over artificial shade in coastal park. (3) The neutral UTCI (NUTCI) of the respondents were 24.1°C (coastal park) and 26.0°C (commercial street); the neutral UTCI ranges (NUTCIR) were 20.8–27.4°C (coastal park) and 23.3–28.7°C (commercial street). (4) The upper thermal acceptable range limits of the coastal park and commercial street were 30.2 and 32.1°C, respectively, which were substantially higher than the upper NUTCIR limit, indicating that the residents in Dalian were well-adapted to hot weather. The results can provide a good reference for determining ideal design strategies to optimize the thermal environment of urban outdoor recreation spaces in summers and improve the quality of life in coastal cities.

KEYWORDS

coastal city, outdoor thermal comfort, coastal park, commercial street, universal thermal climate index

Highlights

- We conducted field investigations on thermal comfort in two areas in Dalian, China.
- Survey was conducted (>800 respondents) and various indexes were analyzed.
- Respondents felt more comfortable in shaded areas, especially in the shade of trees.
- People in commercial street were more adapted to high temperatures, and people in coastal area preferred cooler environments.
- The residents in Dalian (coastal city) were well-adapted to hot weather.

Introduction

Extreme hot weather and heat waves caused by global warming, along with urban heat islands caused by urbanization, have greatly affected the livability of urban regions (1–4). A comfortable outdoor environment can not only prolong the duration of outdoor activities and reduce the use of air conditioning, thus, reducing building energy consumption (5), but also optimize urban space utilization and enhance outdoor activities, social solidarity (6, 7), public health (8, 9), and tourism (10). Relevant studies conducted in different climate zones have shown that the regional thermal benchmarks of outdoor thermal comfort (OTC) need to be calibrated, due to the possible differences in their thermal history (11), social culture (12, 13), and thermal adaptation of local residents (14), along with other factors. Therefore, determining the outdoor thermal benchmark of a region can help urban planners to design and plan open urban spaces effectively to enhance outdoor thermal comfort and improve urban microclimate (15).

OTC has been extensively studied in continents other than Antarctica (16, 17), focusing on dry and hot (18), severe cold (19), humid and hot (20), and subtropical climate zones (21), and some cities have been investigated repeatedly. Investigating *in-situ* thermal conditions vs. subjective thermal perception has become a routine method for assessing human thermal perception in different climate zones (22–24). However, due to different measurement procedures (location, season, time) and measurement tools, the same city may show different comfort ranges by using the same analysis methods, e.g., the UTCI "no thermal stress" range in Xi'an was defined as 18.0–29.1°C (11) and as 15.8–28.5°C (25), and the PET neutral range in Harbin is defined as 8.5–26.8°C (26) and as 13.0–21.0°C (27). In addition, the OTC of different locations in a city may vary significantly depending on urban morphology or land cover factors (28–31), such as sky view factor (SVF), building height, compactness, street orientation, vegetation, and albedo (32–37). Accordingly, the above issues should be fully considered in OTC surveys and analyses.

Most of the studies investigated one type of urban outdoor environment e.g. squares (38), parks (36), campuses (26, 39), scenic areas (40), streets (27, 41), etc. However, the literature (17) suggests that both hot spots (squares, main streets) and cold spots (parks, water bodies) should be considered when discussing the OTC of a city. Some studies fully compared OTC in different areas of the city, but they are similar in one type, such as the study of Umeå compared city park and university park (42), the study of Melbourne compared three university campuses (43), and the study of Victoria selecting 11 streets with different orientation and geometry (41). There are also some studies that fully considered multiple space types in a city, for example the study (44) that compared human thermal perception outdoors in summer in Singapore and Changsha by selecting 13 and 17 outdoor measurement points, including parks, squares, commercial streets and university campus respectively, but did not compare the OTC of each type of space, however, no comparison was made among the types of space thermal comfort. The study in Tel Aviv (45) selected city parks, city squares and wide streets in low-density neighborhoods for a 4-year variability study and compared them with different climate zones, with the only regret that only one measurement point was available for each space type. Although a large number of studies are currently for inland cities (16), OTC studies in coastal cities have also been conducted extensively, including Shanghai (46), Hong Kong (21), and Nagoya (47) in addition to the above cities, but comparative studies of OTC in open coastal areas and within high-density urban areas are still deficient.

In summer coastal cities, people generally stay outdoors for longer durations, and the most significant spaces for leisure activities are coastal parks and commercial streets near the city center, and there are crucial differences between the spatial characteristics of urban centers and those of the parks near the coastline. Due to limited land resource and high levels of development, commercial streets in urban centers generally portray high-density and high-rise urban form patterns, with lower greening ratio, in contrast to the low density and high greening ratio of coastal parks (48). In addition, the climate conditions in low-density coastal areas and the high-density neighborhood are generally quite different (49), for instance,

Abbreviations: OTC, Outdoor thermal comfort; SVF, Sky view factor; T_g, Globe temperature; T_a, Air temperature; RH, Relative humidity; V_a, Wind speed; UTCI, Universal thermal climate index; T_{mrt}, Mean radiant temperature; ASHRAE, American Society of Heating Refrigerating and Air-conditioning Engineers; TSV, Thermal sensation vote; TPV, Thermal preference vote; TAV, Thermal acceptability vote; PET, Physiological equivalent temperature; TCV, Thermal comfort vote; mTCV, Mean thermal comfort vote; mTSV, Mean thermal sensation vote; NUTCI, Neutral universal thermal climate index; NUTCIR, Neutral universal thermal climate index range; TAR, Thermal acceptable range; LR, Linear regression.

coastal areas may feature higher wind speed and solar radiation, besides, the heat island intensity as well as the temperature in commercial areas is higher (50).

Most studies have confirmed that physical factors centered on microclimate parameters have the greatest influence on human thermal perception, and among the four microclimate variables of air temperature (T_a), wind speed (V_a), relative humidity (RH), and globe temperature (T_g), many studies have confirmed that T_a is the most important parameter for OTC (51, 52), but there are few low-cost methods to reduce the local T_a (53). Therefore, a more effective approach in creating thermally comfortable open urban spaces is to control thermal radiation and wind speed (16). Furthermore, previous studies have confirmed that wind speed and the difference in radiant temperature have equally significant effects on thermal comfort (54). Therefore, it is important to identify the factors that influence the spatial thermal comfort in coastal cities to optimize the designs of urban spaces.

In this study, the universal thermal climate index (UTCI) was used to study the OTC in the coastal city of Dalian in summer. Two of the most famous resort sites in the city, the Xi'an Road (commercial street) and Xinghai Park (coastal park), known to host frequent outdoor social activities in summer, were selected as the study areas. We selected six measurement points for each study site to conduct the meteorological measurements and questionnaire surveys and ensured that the spatial types were rich enough to reflect the effects of spatial differences on human thermal comfort. The objectives of this study were to (1) analyze the main meteorological elements that affect the OTC in coastal cities in summer; (2) compare the thermal comfort expectations of different areas and types of leisure spaces in coastal cities, including thermal sensation, thermal comfort, and thermal preference; and (3) establish outdoor thermal benchmarks (e.g., neutral temperature, neutral temperature range, and thermal acceptable range) for littoral regions and business districts in coastal cities and discuss their spatial differences. The results of the study may provide theoretical evidence that can improve the quality of open spaces in summer coastal cities, enhance urban design strategies, and enable governance at a finer spatial scale.

Materials and methods

Study area

Dalian (121°6′ E, 38°9′ N), a famous coastal tourist city in China, is located on the Liaodong Peninsula and surrounded by the sea on three sides, making it an ideal habitable coastal city that can provide an ideal environment to study the OTC in coastal cities. The climate in Dalian is relatively pleasant in all seasons, with no severe cold in winters and pleasant summers. According to the Köppen climate classification (55), it is located in a temperate monsoon climate (Dwa, D: cold, w: dry winter, a: hot summer), with maritime characteristics. According to meteorological data from 2011 to 2021, the highest monthly mean temperature occurred in August (25.0°C), and the maximum monthly mean temperature occurred in July 34.4°C. The hottest days in summer in Dalian mainly occur from late July to early August. The lowest monthly mean temperature occurred in January (-4.6°C), with a minimum temperature of −14.2°C. The annual average RH was generally between 51 and 80% (56) (Figure 1).

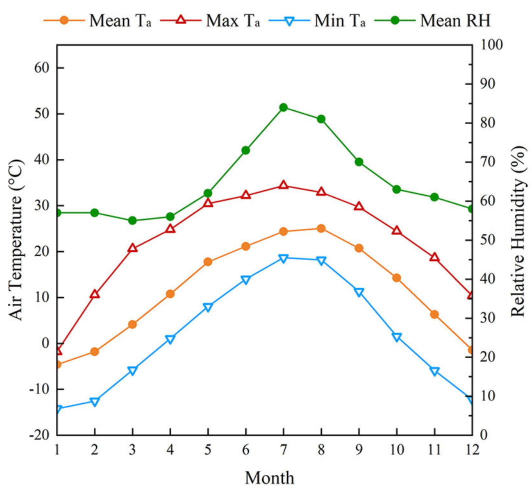


FIGURE 1
Monthly mean, maximum, and minimum air temperature (T_a) and mean relative humidity (RH) in Dalian, China, from 2011 to 2021 (56).

Field tests were conducted in a famous coastal park (Xinghai Park) and commercial street (Xi'an Road) in Dalian, China. As the two space types differed greatly, with Xinghai Park being more open and Xi'an Road having a higher building density, we selected six measurement points each in both the areas (CP1–CP6, CS1–CS6, respectively) and compared the differences in the factors that influenced the thermal comfort in these areas, while considering the openness and radiation orientation of the space and their shaded regions (57) (Figure 2).

The T_a in urban spaces within a radius of 10–150 m from the center were influenced by the surrounding environment (58). Therefore, the composition of the landscape within the range of 10 m was measured from the physical midpoint of the 12 measurement points (CP1–CP6 and CS1–CS6) (40). Fisheye photographs of the measurement points were captured and input into the RayMan software to calculate their corresponding SVF values (Table 1).

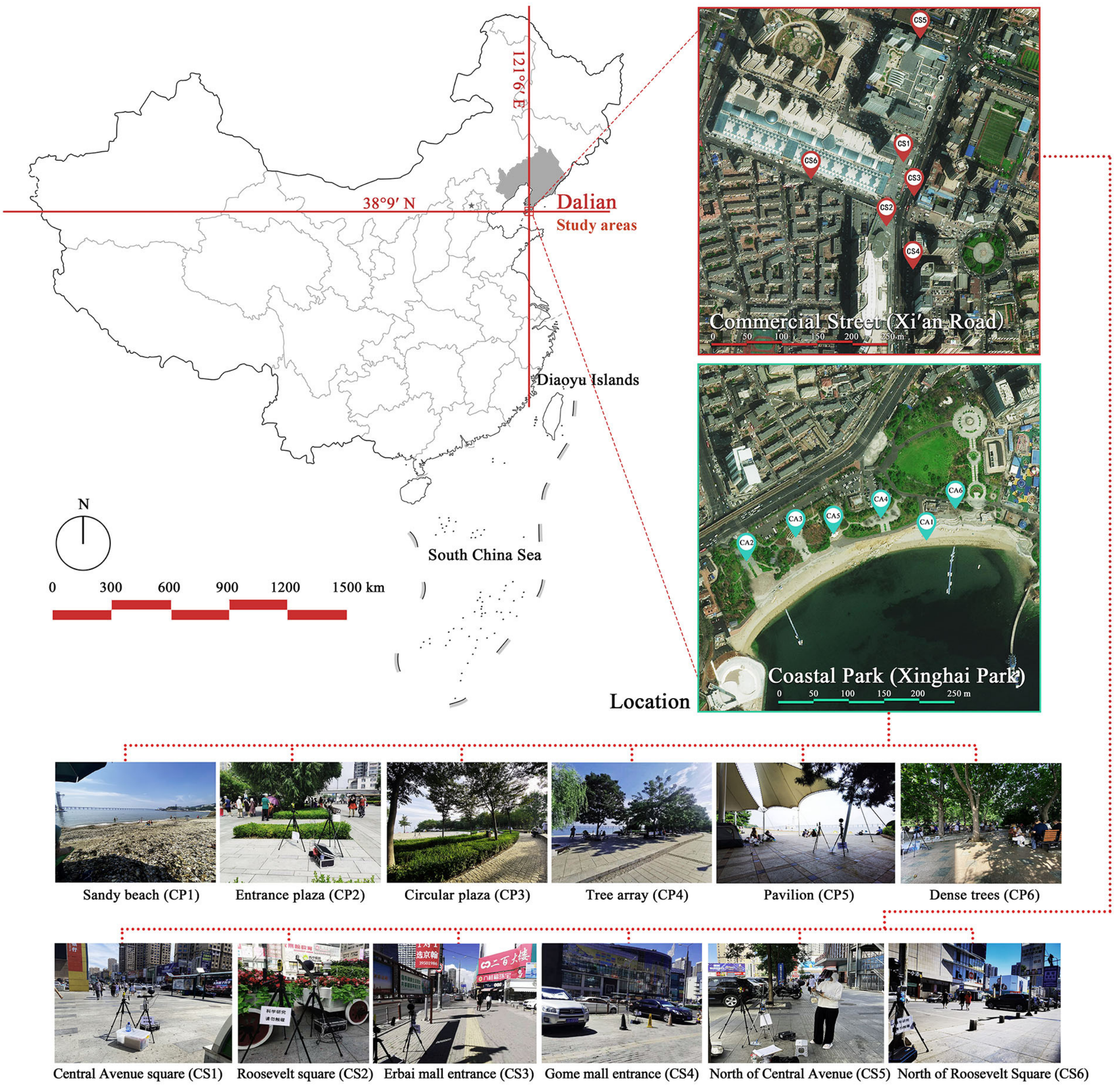


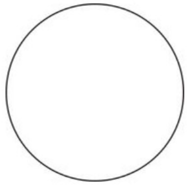
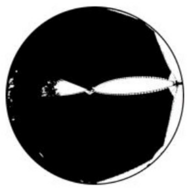
FIGURE 2
Study areas considered in this study and the six measurement points for the Xinghai Park and Xi'an Road (CP1–CP6 and CS1–CS6, respectively).

Physical measurements

In this study, we selected the typical hot weather days in Dalian city in summer to conduct the field tests; the measurement period was from 09:30 to 17:30 h, which was the peak time for outdoor activities. The tests were conducted on July 24, 25, 26, and 28 and August 4 in 2021 (a total of 5 days). The meteorological parameters, namely, T_a, RH, V_a and T_g, were recorded every min. The measuring instruments used for this purpose and the parameters considered in this study are listed in Table 2, all in accordance with the ISO 7,726 standard (59).

According to American Society of Heating Refrigerating and Air-conditioning Engineers (ASHRAE) standard 55 (60) and some field studies (61, 62), there is no significant difference in the measured meteorological parameters above 0.6 m (head level), above 1.1 m (abdomen level) and above 1.7 m (ankle level). So, the sensors were set at 1.5 m above ground level in the formal field survey. We calculated the mean radiant temperature

TABLE 1 Characteristics of measuring points of Xinghai park and Xi'an road.

Coastal park (Xinghai park)			Commercial street (Xi'an road)		
Test location	**Measuring-point environment**	**Fisheye photo**	**Test location**	**Measuring-point environment**	**Fisheye photo**
CP1 (Beach)	Close to the sea and backed by tableland. Full of coarse sand and pebbles.	 SVF = 1	CS1 (Central avenue square)	The plaza in front of the mall is paved with marble. The square was open and unobstructed.	 SVF = 0.718
CP2 (Entrance plaza)	Connects the beach to the city road, with dense vegetation on both sides and flower beds in between, marble groud.	 SVF = 0.793	CS2 (Roosevelt square)	The plaza in front of the mall is paved with marble. The plaza was empty and somewhat sheltered by buildings on the south side.	 SVF = 0.704
CP3 (Circular plaza)	Semi-enclosed, open to the marine area, backed by a circular terrace bench and planted with rows of trees. Marble groud.	 SVF = 0.579	CS3 (Erbai Mall entrance)	The north-south streets are covered with permeable brick, screened by multi-story building to the southeast.	 SVF = 0.789
CP4 (Tree array)	The space is a resting space formed by a combination of large and small tree beds, with granite slate flooring.	 SVF = 0.335	CS4 (Gome Mall entrance)	The north-south streets are covered with permeable brick, screened by high-rise building on east side.	 SVF = 0.644
CP5 (Pavilion)	Seaside tensioned membrane structures for pavilions, marble groud.	 SVF = 0.097	CS5 (North of Central Avenue)	East–west street have marble floors, with commercial buildings on the south side and more trees in the street	 SVF = 0.240

(Continued)

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TABLE 1 (Continued)

Coastal park (Xinghai park)			Commercial street (Xi'an road)		
Test location	Measuring-point environment	Fisheye photo	Test location	Measuring-point environment	Fisheye photo
CP6 (Dense trees)	Dense forest area. Dense woods and buildings creating large shade. Marble groud.	 SVF = 0.008	CS6 (North of Roosevelt Square)	East–west street have marble floors, with multistory building on south side, perimeter parking, and no vegetation.	 SVF = 0.426

TABLE 2 Parameters considered in this study and the instruments used to measure them.

Parameter	Instrument	Range	Accuracy
Air Temperature (T_a)	HOBO, MX2301	−40–0°C	±0.25°C
		0–70°C	±0.2°C
Relative humidity (RH)	HOBO, MX2301	0–10%	±5%
		10–90%	±2.5%
		90–100%	±5%
Air Velocity (V_a)	Kestrel 5,500	0.1–9.99 m/s	+ (0.05 m/s + 5% readout)
		10.0–20.0 m/s	+ (5% readout)
Globe Temperature (T_g)	JTR10 WBGT	5–120°C	± 0.5°C

(T_{mrt}) using the ISO 7,726 standard, as shown in Equation (1) below:

$$T_{mrt} = \left[(T_g + 273)^4 + \frac{1.10 \times 10^8 {V_a}^{0.6}}{\varepsilon D^{0.4}} (T_g - T_a) \right]^{\frac{1}{4}} - 273 \quad (1)$$

where D is the globe diameter ($D = 0.15$ m in this study), and ε is the emissivity ($\varepsilon = 0.95$ for a black globe).

Questionnaire surveys

The questionnaire used for the study was divided into two parts (Appendix A, Figure A1). The first section contained basic information about the interviewee, including gender, age, height, weight, clothing, thermal history, and purpose and intensity of activity. We used the ASHRAE standard 55 (60) to determine the interviewees' thermal resistance of clothing and their metabolic rate. We measured the field meteorological data in conjunction with the questionnaire, to ensure accuracy, the measurements were conducted within 3 m of the position of the measuring instruments.

The second part consisted of thermal sensation information, including votes for the thermal sensation, preference, and acceptability and adaptive behavior of the respondents. One of these votes, the thermal sensation vote (TSV), was quantified using a seven-point scale (−3, cold; −2, cool; −1, slightly cool; zero, neutral; one, slightly warm; two, warm; three, hot), based on the ASHRAE standard. The thermal preference vote (TPV) was measured using a three-point scale (−1, lower/weaker; zero, no change; one, higher/stronger). The thermal acceptability vote (TAV) was measured using a four-point scale (−2, completely unacceptable; −1, unacceptable; one, acceptable; two, completely acceptable).

Thermal comfort index

There is no universal model for studying OTC, and choosing the right model is the key to accurately analyze the OTC of a region (16, 22, 63). Currently, physiological equivalent temperature (64), predicted mean vote (65), UTCI (66), and standard effective temperature (67) are the four most commonly used models.

The application of UTCI in recent OTC assessments has been increasing. The UTCI is defined as the isothermal T_a of a reference condition that can trigger the same dynamic response in a physiological model (66). This index refers to the metric developed by the International Society of Biometeorology based on the concept of equivalent temperature applicable to the major fields of human biometeorology. Furthermore, the index is based on the Fiala's multi-node human physiology and thermal comfort model and simulates the dynamic physiological response by combining a human thermoregulation model with a state-of-the-art clothing model (64). In addition, the UTCI values correspond to heat sensation and stress levels on the UTCI 10 scale (68, 69). Most studies redefined the heat sensation or stress levels for the UTCI according the study site, and many recent studies used the UTCI model and demonstrated that the UTCI thermal index model can be suitable for OTC studies. However, only a few studies have been conducted in the cold regions of China; thus, future studies must consider the applicability of the model in cold regions.

Data analytical methods

Comparative analysis

Comparative analysis is a strategy to determine whether there are comparable differences between two or more different categories. In this study, it was used to analyze the differences in meteorological variables between the points in coastal park and commercial street separately to demonstrate the necessity of each point selected. The meteorological data (T_a, RH, V_a, T_g, T_{mrt}, $UTCI$) were investigated at each of the six measurement points in two study areas.The maximum, minimum, mean and standard deviations (Appendix C) were plotted for meteorological variables of each point during the survey period, but this was not sufficient to show the variability between the measurement points, and due to the very large amount of meteorological data, *post-hoc* multiple testing was required. In this study, Tukey's test was chosen as the *post-hoc* test because the use of this method requires the same sample content for each group. The results are described in section Meteorological parameters and confirm a significant difference between measurement points.

Correlation analysis

Correlation analyses were performed to examine the importance of the influence of four conventional meteorological indicators (T_a, RH, V_a, T_g) on thermal sensation vote (TSV) in coastal park and commercial street. Spearman correlation analysis was performed by SPSS (IBM, USA) and the results can be compared with other studies to determine the degree of influence of meteorological variables on human thermal comfort in different areas.

Regression analysis

Regression analysis can determine the interdependent quantitative relationship between two or more variables. This study used regression analysis to determine the comfort range, and conducted normality tests on the TSV, TCV, Unacceptable vote, and UTCI sample data, and confirmed that they all met the normal distribution and could be analyzed by regression. In the OTC studies, Linear Regression(LR), Probit Analysis (PA), Ordinal Logistic Regression (OLR), Cubic Regression (CR), Quadratic Fitted Curve (QFC) are universal regression equations (17).

The UTCI range of the mTSV (−0.5, 0.5) was the neutral range (70). The LR method based on bind mTSV that varies between ±0.5, is the most commonly used method to determine the Neutral UTCI range (NUTCIR). The Thermal acceptable range (TAR) based on percentage of acceptability varies between 80%, can modify original UTCI scale in the local climatic zone. The E functions were fitted to the regression models of TAR in this study. The CR and QFC methods are not suitable for this study because our survey time is in the hot summer and there is a lack of cold stress surveys. This E functions was also used in a OTC study of summer campus in Guangdong (71).

Results

Descriptive analysis

Respondent attributes

A total of 872 volunteers participated in the study, all of whom were local residents, had lived in the city for at least 1 year, and were well-adapted to the local climate. All the participants adjusted their clothing according to their perceptions of temperature change in the city. For the Xinghai Park, 341 volunteers (180 males and 161 females) submitted 337 valid questionnaires. For the Xi'an Road, 531 volunteers (262 males and 269 females) submitted 502 valid questionnaires. The ages of the male and female respondents were 12–91 and 13–82 years, respectively. The subjects included 9.8% children (age <18 years), 66.5% adults (age 18–60 years), and 23.7% seniors (age >60 years). The proportion of seniors in the coastal area was 41.3%. The average clothing thermal resistance of the

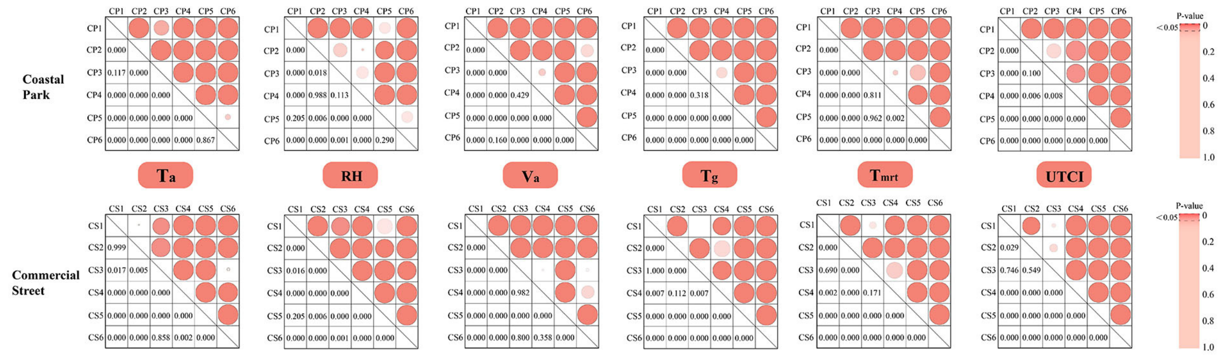

FIGURE 3
Results of *post-hoc* Tukey's test for different pairs of measurement points for the meteorological variables considered in this study.

respondents was 0.26 clo and 0.32 clo for the Xinghai Park and Xi'an Road, respectively (Appendix B, Table B1).

Meteorological parameters

The meteorological variables measured in the coastal park and commercial street are listed in Appendix C (Table C1). The *post-hoc* Tukey's test is generally used to determine the variability of the meteorological variables across different spaces (40). In this study, the test was applied to confirm that the meteorological variables for the measurement sites in the two study areas differed significantly (Figure 3).

Overall, the meteorological indicators for CP3 in the coastal park were not significantly different from those of CP1 (T_a), CP2 (*RH*, *UTCI*), CP4 (*RH*, V_a, T_g, T_{mrt}) and CP5 (T_{mrt}); the meteorological indicators for CP6 (V_a) were not significantly different from those of CP1 (V_a) and CP5 (*RH*, T_g).

The meteorological indicators of CS3 in the commercial street were not significantly different from those of CS1 (T_g, T_{mrt}, *UTCI*), CS2 (*UTCI*), CS4 (V_a, T_{mrt}) and CS6 (V_a, T_g); Measured values in CS1 and CS4, were not significantly different from CS2 (T_g), CS5 (*RH*) and CS2 (T_g), CS6 (V_a); all other measurement points portrayed strong variability.

Thermal sensation vote (TSV)

In outdoor spaces, the meteorological variables (T_a, *RH*, V_a, and T_g) can significantly affect human thermal sensation (72). To quantify the effects of these variables on the TSV, we conducted the Spearman's correlation analysis of meteorological variables and TSV for both study areas and compared the results with other studies (Table 3).

In summer, T_g ($\rho_{\text{coastal park}} = 0.381$, $\rho_{\text{commercial street}} = 0.359$) and T_a ($\rho_{\text{coastal park}} = 0.319$, $\rho_{\text{commercial street}} = 0.329$) were considered to be the main factors that influenced the respondents' thermal perceptions, which was consistent with the results of most studies (19, 25, 52, 73). The RH ($\rho_{\text{coastal park}} = -0.197$, $\rho_{\text{commercial street}} = -0.236$) and V_a ($\rho_{\text{coastal park}} = -0.178$, $\rho_{\text{commercial street}} = -0.060$) had negative correlation with the TSV, and for the commercial street, V_a ($\rho_{\text{commercial street}} = -0.060$) did not show a correlation with the TSV, which could be attributed to the lower wind speed in the urban high-density central area. Compared to those in Harbin and Xi'an, the correlations of T_a, T_g, RH, and V_a (except for commercial street) to TSV in CP and CS did not differ significantly, indicating that each climate indicator had an impact on the OTC in the coastal city in summer.

TABLE 3 Spearman's correlation results for thermal sensation vote (TSV) and meteorological parameters of both the study areas.

City	T_a	RH	V_a	T_g
CP (this study)	0.319**	−0.197**	−0.178**	0.381**
CS (this study)	0.329**	−0.236**	−0.060	0.359**
Harbin (19)	0.577**	−0.319**	−0.129**	0.560**
Xi'an (16)	0.63**	−0.55**	−0.20**	0.70 **

**Significance at 0.01 level; T_g, Globe temperature; T_a, Air temperature; RH, Relative humidity; V_a, Wind speed.

There were some differences between the TSVs of the coastal and commercial areas (Figure 4A). The TSV values tended toward points that indicated a hot perception (TSV > 0), with 70% for the commercial street and 58% for the coastal park. The coastal park had the highest percentage of "neutral" scores (TSV = 0; 41%), followed by "hot" (TSV = 2; 31%). In the commercial street, the proportions of "neutral" (TSV = 0), "slightly warm" (TSV = 1), and "hot" (TSV = 2) scores were about the same (∼27%). The proportion of commercial street (17%) considered to be "hot" (TSV = 3) was twice as high as the proportion of the coastal park (9%).

The majority of people (82%) had hot feeling (TSV ≥ 1) and 23% felt "hot" (TSV = 3) at the exposed beach (CP1) in the

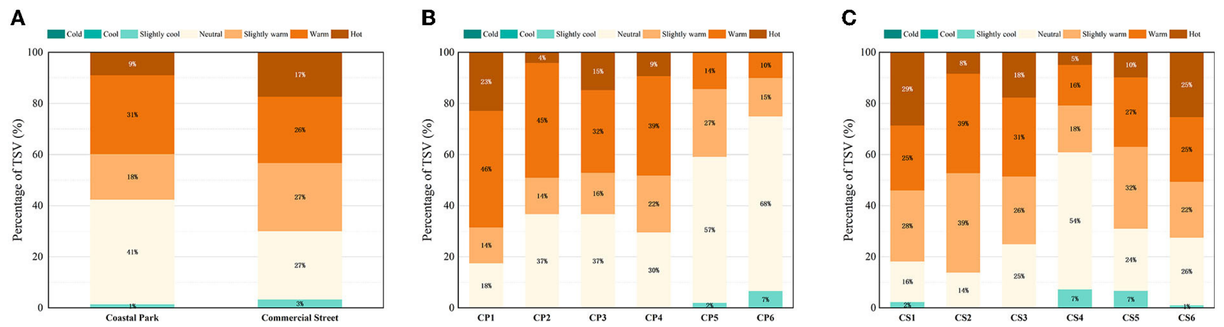

FIGURE 4
TSV in open spaces during summer: **(A)** Both study areas, **(B)** coastal park, and **(C)** commercial street.

comparison to the sites in the coastal park (Figure 4B). The TSVs at CP2, CP3, and CP4 were similar, with about 40% choosing "warm" (TSV = 2). The TSV of CP5 and CP6 were considered "neutral" (TSV = 0) by more than half of the respondents, probably because the measurement points were in the shade, and the perceptions of CP6 indicated "neutral" heat (TSV = 0; 68%); moreover, 7% of volunteers chose "slightly cool" (TSV = −1), which indicated that people felt more comfortable in a natural sheltered environment in the coastal zone.

In the commercial street, the proportion of the respondents who felt hot at each measurement point was significantly higher than of those in the coastal park (Figure 4C). More than 80% of the respondents felt warm (TSV $\geq$ 1), and approximately 50% felt extremely warm (TSV $\geq$ 2) in the front plazas of CS1 and CS2, with the highest proportion (29%) feeling "hot" (TSV = 3) in CS1. Among the "neutral" (TSV = 0) votes, those for CS3, CS5, and CS6 were accounted for ∼25%, but interestingly, the proportion for CS4 was more than half, which may be caused by the proximity of CS4 to high-rise buildings and the fact that the area was in the shade (due to building shadows). Overall, the more open the commercial spaces (CS1 and CS2) were, the hotter the perceived climate, while the more shaded the space (CS4), the more moderate was the perceived climate, which was consistent with the results obtained for the coastal park.

In addition, in the preference poll for meteorological variables, the two regions portrayed consistency (Appendix D), with the respondents preferring lower T_a, solar radiation and no change RH, V_a. with the factors being more pronounced for the commercial street. Surprisingly, the proportion of preferring stronger wind in commercial streets (32%) less than that in coastal park (36%).

Thermal comfort vote (TCV)

In summer, there were some differences in the thermal comfort vote (TCV) between the coastal park and commercial street (Figure 5A). The proportion of votes that indicated "neutral" climate was about the same in both the zones (around 65%); those indicating "comfortable" climate was same as those that indicated "uncomfortable" climate in the coastal park (16%). However, the proportion of "uncomfortable" votes was much higher than that of "comfortable" votes, at 33%, while "comfortable" votes only accounted for 5% of the total votes. Overall, people in both zones were mostly accepting of the thermal environment, but the coastal park was significantly more comfortable than the commercial street.

In the coastal park, for the CP1 area, most votes tended to indicate a strong "uncomfortable" (33%) climate, with only a few votes indicating a "comfortable" (2%) climate, in contrast to CP6, which portrayed the most votes for "comfortable" (35%) climate and least votes for "uncomfortable" (2%) climate (Figure 5B). The CP4 and CP5 sites had the highest percentage of votes for "neutral" climate, at 80 and 88%, respectively, with the other regions portraying proportions close to 60%. Similar to the heat sensation poll, the two shaded areas, CP5 and CP6, in the coastal zone were the most popular areas.

In the commercial street, more areas were considered to be "uncomfortable," compared to the coastal park (Figure 5C), with CS2 portraying the highest votes indicating an "uncomfortable" climate (50%), followed by CS1. Surprisingly, for the votes obtained for CS4, more than half of the TSV poll was "neutral" (54%), and 7% considered the climate to be "slightly cool," with 35% voting "uncomfortable" in the TCV poll. The CS3 site portrayed the most "neutral" rating (69%), while CS5 and CS6 both portrayed the lowest "uncomfortable" rating of 26%. It is possible that both measurement points were in shaded areas (located in the shadow regions of large buildings to the south).

The TCV voting results were consistent with most studies (25, 47, 74), concluding the fact that, in summer, outdoor spaces shaded by trees or buildings were more comfortable than the areas with lower SVF.

Different TSV levels were matched to the corresponding weighted mean TCV (mTCV) (Figure 6). The coastal park

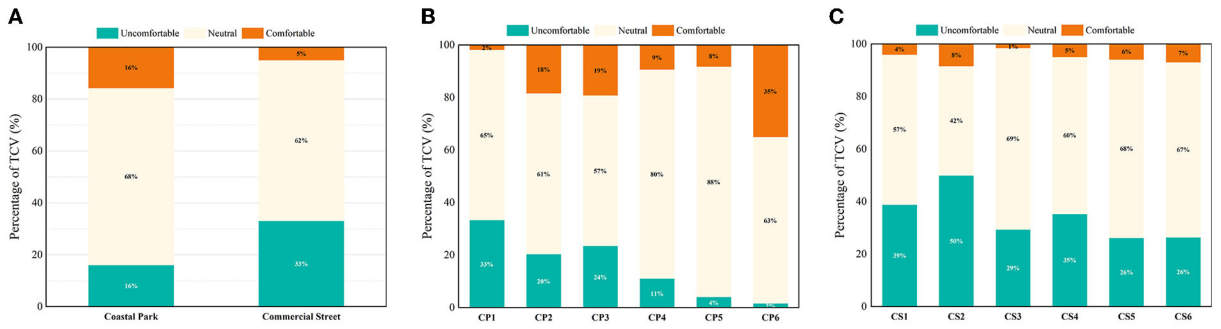

FIGURE 5
TCV in open spaces during summer: **(A)** Both study areas, **(B)** coastal park, and **(C)** commercial street.

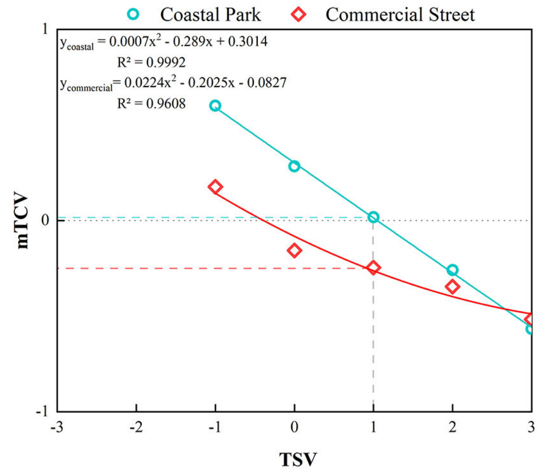

FIGURE 6
Correlation between TSV and TCV for coastal park and commercial street.

portrayed a strong correlation between the TSV and the thermal comfort of the respondents, i.e., the higher the heat sensation, the more uncomfortable the respondents were. When these respondents felt thermally comfortable (TCV>0) in summer, TSV<1.05 for coastal park and TSV<−0.47 for commercial street, it reflected the fact that people in the coastal park are more capable of thermal adaptation than those in the commercial street. When the respondents felt "slightly warm" (TSV = 1), the TCV values were 0.01 and −0.26 for the coastal park and commercial street, respectively, in the "slightly warm" condition, respondents in the coastal area felt "neutral" (TCV = 0), while those in the commercial area felt slightly uncomfortable (TCV < 0). The results indicated that psychological factors and environmental factors influenced the comfort level of people in the same feeling of heat.

Outdoor thermal benchmarks

Neutral UTCI (NUTCI) and neutral UTCI range (NUTCIR)

Neutral temperature is defined as the temperature at which people feel neither cold nor hot (75), and it is considered to be a valid indicator for evaluating thermal comfort.

In this study, we calculated the NUTCIs for the coastal park and commercial street to analyze the difference in the thermal sensation between the waterfront and built-up areas of the coastal city of Dalian. The weighted average of summer TSV and 1°C UTCI was calculated and fitted using linear regression (73). The UTCI was considered to be neutral when mTSV = 0. The NUTCI was significantly higher in the commercial street (26.0°C) than that in the coastal park (24.1°C), and this difference may be closely related to air temperature, clothing thermal resistance, and psychological expectations (44, 76) (Figure 7).

The UTCI range of the mTSV (−0.5, 0.5) was the neutral range (70), which represented the range generally accepted by most people. The NUTCIR of the coastal park (20.8–27.4°C) was slightly wider than that of the commercial street (23.3–28.7°C). The upper and lower limits of the NUTCI and NUTCIR of the coastal park were smaller than those of the commercial street, which indicated that the respondents in the commercial street were more adapted to the high-temperature environment in the high-density built-up area, whereas the reinvents in the coastal park preferred a cooler environment.

Thermal acceptable range (TAR)

The thermal acceptable range (TAR) is often used to assess OTC conditions, and the ASHRAE standard 55 defines the TAR as the range of temperatures acceptable to at least 80% (normal conditions) or 90% (strict conditions) of the residents (60). To explain the subjective thermal sensations of the UTCIs at different conditions, it is necessary to define the NUTCIR in

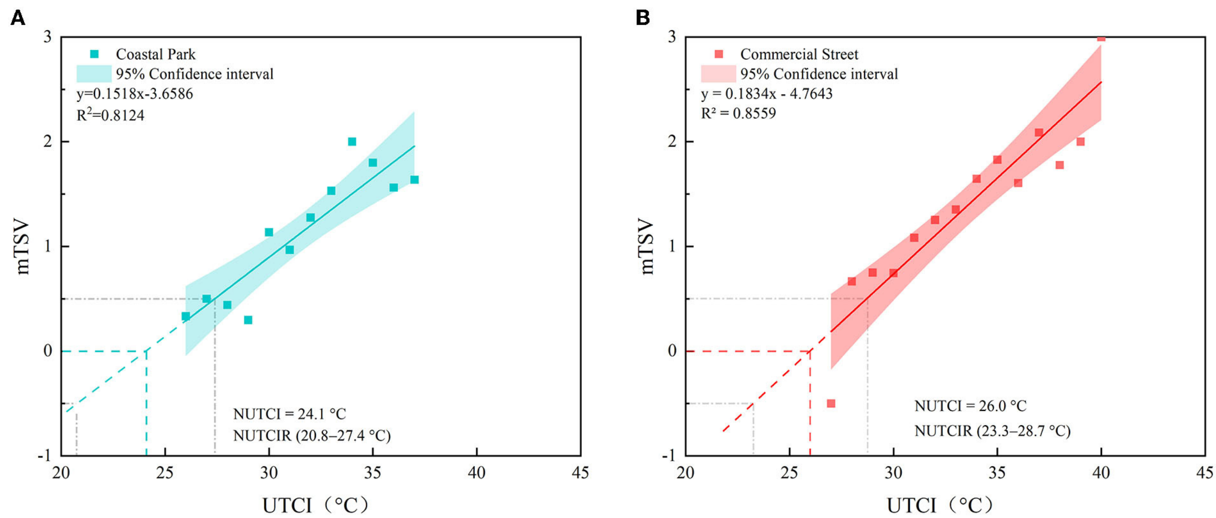

FIGURE 7
Neutral temperatures calculated using a linear regression: **(A)** Coastal park and **(B)** commercial street.

TABLE 4 UTCI calibrations for different stress categories.

Thermal stress	Modified UTCI (coastal park) (°C)	Modified UTCI (commercial street) (°C)	UTCI (°C)
Extreme heat stress	>38.9	>39.4	>46.0
Very strong heat stress	37.1–38.9	37.9–39.4	38.0–46.0
Strong heat stress	34.4–37.1	35.7–37.9	32.0–38.0
Moderate heat stress	30.2–34.5	32.1–35.7	26.0–32.0
No thermal stress	<30.2	<32.1	9.0–26.0

which respondents feel comfortable. In this study, we used the range of acceptable temperatures for 80% of the respondents.

Since our survey was conducted during hot weather and almost no respondents felt cold, as evidenced by the TSV, this study lacks subjective perceptions related to cold stress (only a limited range of thermal sensations was studied). Therefore, we calculated the thermal unacceptable rate of the UTCI in the 1°C interval, fitted it to an exponential function, and corrected it only for the four thermal stress levels of the UTCI scale, which corresponded to unacceptable levels of 40, 60, 80, and >80% (77, 78) (Table 4). In hot summer weather, the upper limit of the TAR was 32.1°C in the commercial street and 30.2°C in the coastal park (Figure 8).

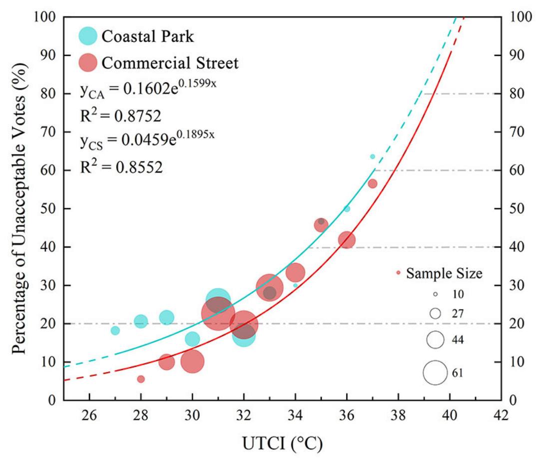

FIGURE 8
Relationship between the thermal unacceptable rate and UTCI for the coastal park and commercial street.

Thermal adaptations

We selected the respondents' subjective opinions and analyzed the differences in their environmental improvements and needs in different spaces (Figure 9). The respondents in the coastal park preferred "moving to shaded areas" to relieve discomfort (47.6%), followed by "putting on a hat or using an umbrella" (36.3%) and "drinking water" (20.1%). The option of "removing clothes" was the least preferred (3.5%) because, in general, people in coastal zones had less thermal clothing resistance (0.22 clo), compared to those in the commercial street (0.32 clo), due to the fact that clothing blocks a majority of ultraviolet rays. The choices of the respondents in the commercial area were more balanced, with the majority choosing "moving to shaded areas" (35.7%) and "putting on

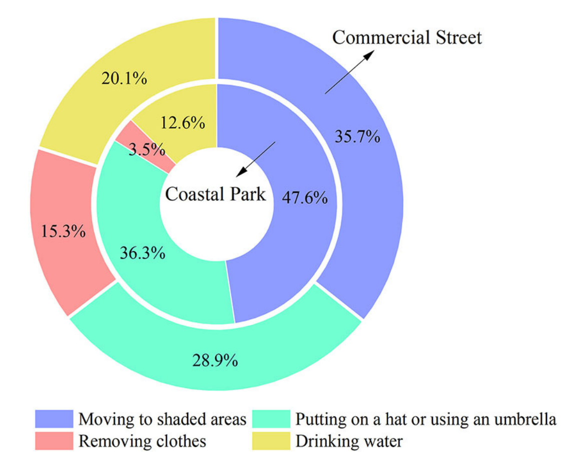

FIGURE 9
Comparison of preferred thermal adaptation behaviors for both the study areas.

a hat or using an umbrella" (28.9%) to relieve discomfort, followed by "drinking water" (20.1%) and "removing clothes" (15.3%). The results indicated that people in both regions preferred to adjust their thermal comfort by moving to shaded areas.

Thermal environment optimization

The calendar, combined with the modified thermal benchmark, can visualize the thermal environment conditions and changes in outdoor spaces and provide a reference for viable optimization strategies for thermal environments (75). In this study, we divided the thermal stresses in 30-min intervals for each space in the two regions and used the corresponding thermal stresses of "Modified $UTCI_{Coastal\ park}$" and "Modified $UTCI_{Commercial\ street}$" to describe the thermal environment of each space. As shown in Figure 10, each thermal stress corresponds to a different color.

In the coastal park, the shaded spaces (CP5 and CP6) had comfortable thermal conditions most of the time, with "moderate heat stress" experienced only from 09:30 to 12:00 h (CP5), 13:30 to 14:30 h and 15:00 to 16:30 h (CP6), which was related to the orientation of the shade. Semi-open spaces (CP2, CP3, and CP4) were under "moderate heat stress" most of the morning time and "strong heat stress" briefly between 13:30 and 16:30 h. According to our findings, we recommend that seating areas must be set up in the shade around the semi-open space. The beach (CP1) was exposed to sunlight and subjected to "strong heat stress" for extended periods of time; however, most people visit the beach to experience the sun and see the natural scenery, and therefore, simple sun protection devices (e.g., tarps, gazebos, and parasols) can be installed along the beach shoreline. Additionally, during 09:30–11:30 h and 14:00–15:00 h, people should avoid visiting the beach unless adequate protective measures have been taken (Figure 10A).

All spaces in the commercial street experienced thermal discomfort, the thermal conditions of the spaces were not stable, and the conditions at some measurement points were highly variable due to the shades of building and self-shading (Figure 10B). The CS1 site was in "strong heat stress" for a long time and "extreme heat stress" or "very strong heat stress" from 09:30 to 12:00 h and 12:30 to 14:00 h. The CS2 and CS3 sites were in "moderate heat stress" in the afternoon (14:00–17:30 h) as a result of building shadow, and in "strong heat stress" or hotter in the morning and noon (9:30–13:30 h). The CS4 site experienced "strong heat stress" or "very strong heat stress" from 11:30 to 16:00 h but was more comfortable in the morning and evening h. Both CS5 and CS6 sites were located on the north side of the buildings and were in "moderate heat stress" most of the time, but CS5 experienced "strong heat stress" in the afternoon (12:00–13:00 h), while CS6 experienced it or stronger in the morning and evening (09:30–11:30 h, 16:00–17:30 h). The difference was mainly due to the different heights and forms of the south side of the building. In the commercial street, most of the measurement points showed different heat stress in the morning, mid-day and evening due to the differences in openness, street orientation, building height and morphology. Therefore, we recommend planting large-canopy street trees at the curb of south-facing roads to provide shade, along with permeable paving, temporary sprinklers, and shading devices, according to the UTCI calendar. In addition, optimizing the building form and promoting urban ventilation may be a better way to improve the thermal environment of the commercial street (79).

Discussion

Neutral UTCI (NUTCI)

In Dalian, during summer, the NUTCI of the coastal park (24.1°C) was significantly lower than that of the commercial street (26.0°C), which corresponded to the difference in the mean UTCI of the two areas (mean $UTCI_{Coastal\ park}$ = 31.1°C; mean $UTCI_{Commercial\ street}$ = 33.6°C). In addition, the clothing preference, age and psychological expectation of the respondents may influence individual thermal assessment in different environments; for example, the air temperature was cooler in the coastal park, but the clothing thermal resistance (0.22 clo) was lower than that in the commercial street (0.32 clo), which was because most people who visited the coastal area had increased physical contact with nature (e.g., swimming and experiencing sea breeze). The respondents in commercial district chose clothing with greater thermal resistance to withstand the large temperature difference between

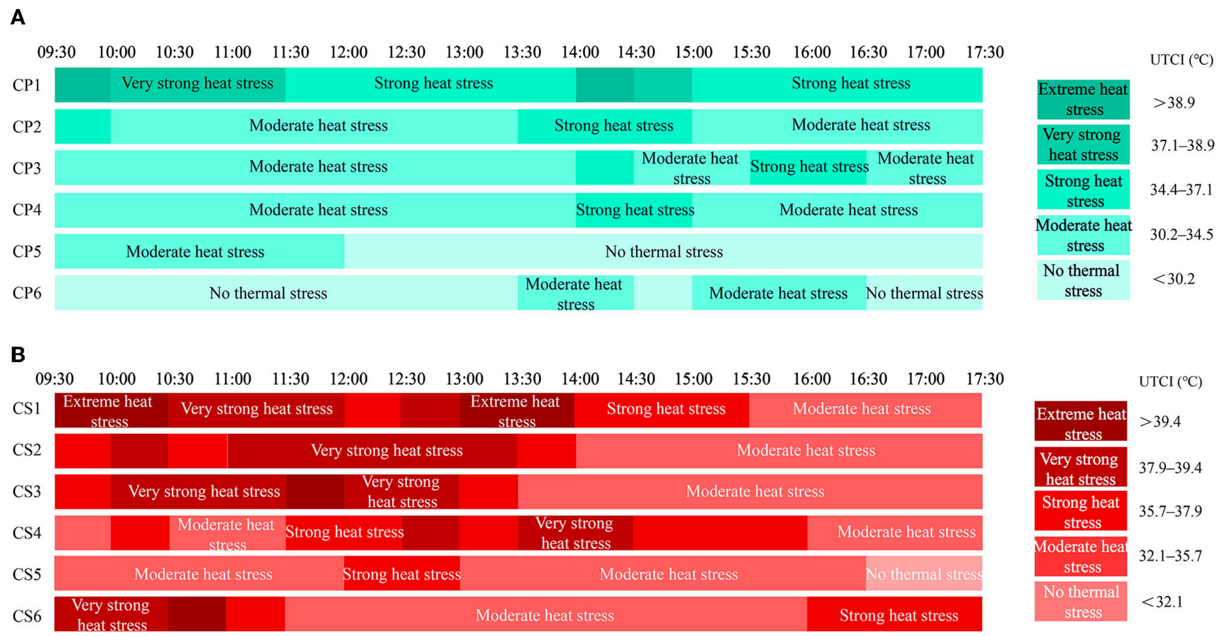

FIGURE 10
UTCI calendar for the 12 measuring sites considered in this study: **(A)** Coastal park and **(B)** commercial street.

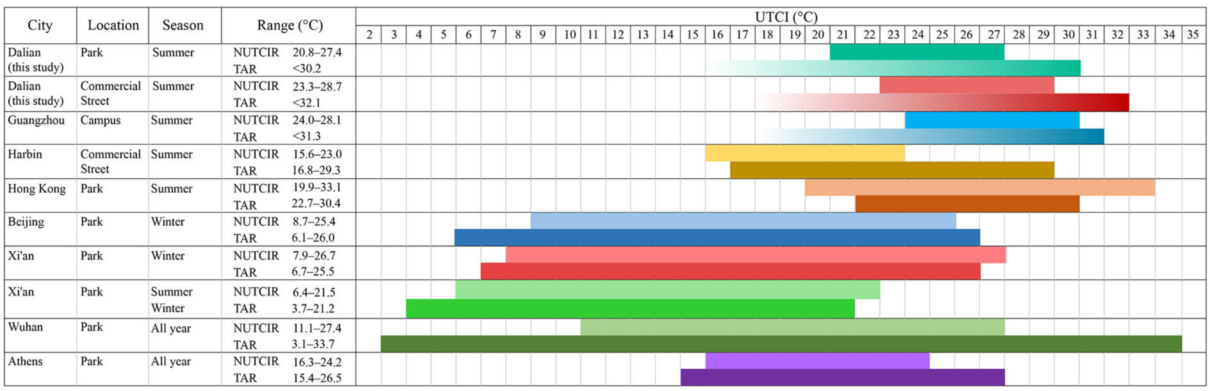

FIGURE 11
Relationship between NUTCIR and TAR.

the indoor and outdoor environments, while to follow social etiquettes. Also, the proportion of older people, who were less thermally sensitive than younger people, in the coastal park (41.3%) was significantly higher than that in the commercial street (12.4%).

Previous studies have proven that the variations in the NUTCIs of the cities in the same climate zone may be significant, depending on the study scope, method, season, and background climate (80) (Appendix E, Table E1). The findings of the present study were compared to those of the previous studies conducted during the same season and using the same method. Dalian and Harbin are in the same climate zone (Dwa), however, in our study, the NUTCI of the Harbin Commercial Street (19.3°C) (19) was lesser than that of the Dalian Commercial Street (26.0°C). This can be attributed to the fact that Harbin is located in an extreme cold region (whereas Dalian is a cold region), and the average summer temperature in Harbin (21.9°C) is significantly lower than that of Dalian (23.9°C) (27, 56). Additionally, time of test period also has a large impact on the test results (19), Harbin's test time span is larger (2 months), while this study concentrates on the hottest period of summer (2 weeks).

Nagoya in Japan and Umeå in Sweden are coastal cities like Dalian, and in summer, the NUTCI in Umeå Park is only

14.4°C (42), which is nearly 10°C lower than that of the Xinghai Park in Dalian. This may be because Umeå is located in a subarctic region, with short and warm summers, and the locals have adapted to this colder climate. The campus NUTCI in Nagoya was 10°C higher than that in the Xinghai Park in Dalian (47); such a large difference may be directly related to the age, gender, and cultural background of the respondents. First, the volunteers in Nagoya came from a narrower age group (college students) and were all male, whereas the age range of the respondents in this study (12–91 years) was broad. Second, cultural background and thermal environment influenced the individual NUTCI (11); for example, Japanese men still choose heavy suits in extremely hot weather to adhere to social etiquette. Notably, the NUTCI of the Xinghai Park in Dalian was slightly lower than that of the cities, such as Chengdu (24.8°C) (20), Iran (25.8°C) (18), and Guangzhou (26.0°C), that experience hot summers (71). The NUTCI of the coastal park in Dalian was significantly higher than that of children's park in Xi'an (17.8°C) (81), because the study participants in Xi'an were children and had less heat tolerance.

Neutral UTCI range (NUTCIR)

The UTCI range of MTSV (−0.5, 0.5) is a neutral range (60), which represents a generally acceptable range. In this study, the NUTCIR for the coastal park (20.8–27.4°C) was significantly wider than that for the commercial street (23.3–28.7°C), indicating that the respondents in the marina area were more accepting of the coastal park, which may be due to the fact that the beach area was cooler than the urban center. The upper and lower limits of the NUTCI and NUTCIR for the commercial street were higher than those for the coastal park; therefore, the respondents in the commercial areas were more accustomed to the warmer environment.

Generally, geographic location and local climate characteristics have a strong relationship with the NUTCIR (Appendix E, Table E2). In the park and campus studies, the NUTCIR of the costal park in Dalian was wider, compared to that of the inland cities (Guangzhou, Tehran, and Chengdu), because in Dalian, the variations in the meteorological indicators were more stable. The comparative analysis with other cities indicated that, among the seaside cities considered in this study, the ΔNUTCIR of Umeå (5.7°C) was close to that of Dalian, whereas Nagoya had a small ΔNUTCIR (3.7°C), this may be related to the over-concentration of the respondents' age groups (all respondents were male college students). Hong Kong portrayed a higher and wider NUTCIR than Dalian, owing to that fact that Hong Kong is a high-density city, with extremely hot summers, and the long-term thermal experience and adaptation of the residents has enabled them to adapt to higher temperatures. In the commercial area study, the NUTCIR of the commercial street in Dalian (23.3–28.7°C) was higher than that of Harbin (15.6–23.0°C), due to the higher summer temperatures in Dalian; however, Dalian's ΔNUTCIR (5.4°C) was significantly smaller than that of Harbin (7.4°C), which may be caused by hot summer weather in Dalian during the testing period.

Thermal acceptable range (TAR)

Table E3 (Appendix E) portrays the results of several OTC studies on TAR. Because our tests were conducted during the hottest time of summer in Dalian and lacked cold stress samples, we could only measure the upper limit of the TAR, similar to a previous study conducted on Guangzhou (71). During the hot summer weather in Dalian, the upper limit of the TAR was 32.1°C in the commercial street and 30.2°C in the coastal park. We compared these results with the thermal comfort study conducted on the Guangzhou campus; the upper limit of the TAR in the campus was between the Dalian coastal park and the commercial street, which was because Guangzhou had a typical subtropical climate, with hot and humid all year round and higher temperatures than Dalian in summer; therefore, the upper limit of the TAR was higher than that of the coastal park in Dalian, while the temperature and the UTCI levels in the commercial street of Dalian during the test period were higher than those in Guangzhou, thus indicating that the upper limit of $TAR_{Commercial\ street}$ was higher.

Further, we combined the results of the TAR and NUTCIR and discussed the difference between their predicted and actual comfort ranges (Figure 11). In most studies, the difference between the intervals of the TAR and NUTCIR was not significant, such as that observed in studies conducted on Beijing and Xi'an (80). Notably, the upper limits of TAR in the coastal park and commercial street of Dalian were both significantly higher than the upper limit of the NUTCIR, which was similar to the results of the study conducted on Guangzhou (71). We believe that, in the coastal park, although the residents felt hot in summer, the temperature was still acceptable, because most of the respondents actively engaged in outdoor leisure activities such as beach excursions or commercial shopping and had strong psychological expectations for the hot environment. In contrast, Harbin, an inland city with severe cold, portrayed a surprisingly high TAR ceiling of 6°C (19), compared to the NUTCIR, which could be related to Harbin's long and severe winter weather; therefore, the local residents looked forward to the warm weather in summer and thus portrayed extreme high acceptance for warm environments. In Hong Kong, which is also a coastal city, the upper TAR limit was lower than the upper NUTCIR limit (21), which may be due to the long hot summers in Hong Kong and the urban heat island effect caused by high-density construction, resulting in the citizens' non-acceptance of the local thermal environment. This difference in the psychological and physical sensations of the residents can be explained by estimating the complexity of their thermal sensations.

Implications

The thermal comfort survey of coastal park and commercial street showed that people's thermal perception and adaptive behavior in coping with summer heat reflected consistency, i.e., people preferred shaded areas during summer daytime, the percentage of "comfort" was significantly higher for TSV and TCV in both areas with measurement points in the shade of trees, structures, and buildings, and people were more willing to move to shaded areas to cope with thermal discomfort. In the coastal park, the proportion of feeling comfortable (TCV = 1) in the shade of trees was significantly higher (CP6, 35%) than under the pavilion (CP5, 8%), which indicates that the optimal design of landscape features can improve the OTC of citizens (40). In addition, in the correlation analysis between meteorological variables and TSV in both areas, the wind speed in the coastal area showed a significant correlation, while the commercial street did not, but in the preference votes for meteorological variables, the proportion of "preferring stronger wind" in the coastal area was greater than in the commercial street, probably because the wind speed in the commercial street area was unstable, with high winds and static winds were more frequent. Combining the above discussion and related results, the following five suggestions for urban design and landscape design are proposed: (1) Setting up plant shade in outdoor resting places in the coastal area, and planting more street trees in the commercial area to relieve heat pressure on residents (82); (2) In outdoor open areas, such as beaches and squares, structures such as shade shelters can be set up for shade, which combined with spraying, can cool the temperature and increase humidity; (3) Optimizing the building form layout to increase building shading in open areas to reduce the risk of thermal exposure in high-density areas (83); (4) Providing the public with a thermal calendar for different areas in summer and advice on the risks associated with the thermal environment; (5) Optimizing the wind environment of the pedestrian layer in high-density neighborhoods in combination with sea breeze, and set wind-guiding or wind-blocking measures according to seasonal characteristics (84–86).

Limitations

Due to the uncontrollable nature of outdoor testing, in the future, our study can be supplemented on an ongoing basis. First, in this study, we considered the thermal comfort in coastal cities only during summers. Compared to that of studies conducted in multiple seasons, the range of the NUTCIs for the studies conducted during summers was smaller (Figure 11), and the discussion of influences and design strategies to promote and extend the outdoor activity period could be continued in the winter and transition seasons while refining the revised UTCI scale. Second, our study focused more on the spatial differences of important metrological factors, and the effects of different levels of natural environmental elements (e.g., vegetation, sea breeze, and white noise) on individual comfort need to be explored in the future. Third, the intensity of pre-test activities could lead to metabolic changes, which could affect individual comfort. For example, the study on Guangzhou was limited to the thermal comfort of students during summer military training (71), and some elderly people in our study at the coastal park engaged in activities of different intensities, such as square dancing, jogging, and swimming, which could be discussed in future studies.

Conclusions

In this study, we considered two tourist-friendly places, a coastal park (Xinghai Park) and a high-density commercial street (Xi'an Road), in Dalian, China. Six spatial measurement sites were selected in each of the two areas to compare the differences in the thermal environment of outdoor leisure activity sites in a coastal city in summer. The differences in the thermal benchmark and adaptation were compared through meteorological measurements and questionnaires, and the following conclusions were obtained.

(1) During summer, in the coastal city, there was a significant correlation between the TSV and all outdoor thermal ambient meteorological parameters. The coastal park and commercial street portrayed consistent characteristics, with T_a and T_g being positively correlated with the TSV and V_a and RH being negatively correlated with the TSV. Notably, T_g had the strongest correlation with TSV and was the main factor that influenced the OTC in coastal cities. The TSV and TCV results were consistent with other studies, with respondents feeling more comfortable in the shade of buildings or trees and a general uncomfortable feeling in areas with high openness and exposure.

(2) There was a significant difference in the range of thermal comfort between the coastal area and the city center in summers. The $\text{NUTCI}_{\text{Coastal park}}$ was 24.1°C and the $\text{NUTCIR}_{\text{Coastal park}}$ was 20.8–27.4°C. The $\text{NUTCI}_{\text{Commercial street}}$ was 26.0°C and $\text{NUTCIR}_{\text{Commercial street}}$ was 23.3–28.7°C. This indicated that most respondents in the commercial street were

adapted to the high temperatures of high-density built-up areas while those in the coastal area preferred cooler environments and were more adaptable to hot weather.

(3) The TAR results indicated that people had different levels of acceptance to different environments, with an upper limit of 30.2°C in the coastal park and 32.1°C in the commercial street. Notably, unlike previous studies, in our study, the upper limits of the TAR and NUTCIR were significantly different in both the study areas, suggesting that people in coastal cities in colder regions had a high thermal sensitivity to hot weather and strong adaptive capacity.

This study confirmed the applicability of UTCI in summers in coastal areas, explored the subjective satisfaction and objective parameters of thermal comfort in outdoor environments in coastal parks and commercial streets, and analyzed the spatial differences in peoples' thermal comfort evaluation. The results of the study can be used as a criterion to evaluate the OTC in Dalian and provide a reference for designing a comfortable thermal environment in different outdoor spatial environments in the coastal cities in summers. Notably, our study results can improve the overall comfort of different outdoor environments and supplement tourism in coastal area, thereby contributing to the economic development of coastal regions.

Data availability statement

The original contributions presented in the study are included in the article/Supplementary material, further inquiries can be directed to the corresponding author/s.

Author contributions

HZ: investigation, data curation, and writing-original draft preparation. FG: conceptualization, methodology, writing-reviewing and editing, and supervision. KL and JW: investigation and resources. JD and PZ: investigation and data curation. All authors contributed to the article and approved the submitted version.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Publisher's note

Supplementary material

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/fpubh.2022.1024757/full#supplementary-material

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Physical environment research of the family ward for a healthy residential environment

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Climate change and population aging are two of the most important global health challenges in this century. A 2020 study by the Environmental Protection Agency showed that average people, particularly older adults, spent 90% of their time at home. This is even more evident during the coronavirus disease 2019 (COVID-19) pandemic. Home-based care models have become a new trend. The health and comfort of the living environment profoundly impacts the wellbeing of older adults. Therefore, research on the physical environment of the family wards has become an inevitable part of promoting the health of older adults; however, current research is still lacking. Based on the study and analysis of continuous monitoring data related to elements of the physical environment (thermal comfort, acoustic quality, lighting quality, and indoor air quality) of family wards, this paper explores the living behaviors of the participants in this environmental research (open or closed windows, air conditioning, artificial lighting, and television) on the indoor physical environment. (1) While referring to the requirements of international standards for an indoor aging-friendly physical environment, we also discuss and analyze the physical environment parameter values according to Chinese standards. (2) People's life behaviors have different degrees of influence on the elements of indoor physical environments. For example, opening doors and windows can alleviate the adverse effects of indoor environmental quality on the human body better than simply turning on the air conditioner. (3) Owing to the decline in physical function, older adults need special care. Studying the status quo of physical environmental elements and proposing suitable environmental improvement measures for aging are of great significance. (4) This research aims to address global warming and severe aging and to contribute to sustainable environmental development.

KEYWORDS

physical environment, healthy building, indoor environment quality, family ward, aging, healthy residential environment

Introduction

In the face of climate change and increasing aging, China's home quarantine policy in response to the coronavirus disease 2019 (COVID-19) has forced older adults to contend with even more significant challenges in seeking medical care. China entered the state of an aging society at the end of the 20th century, and the degree of aging has continued to deepen. Climate change and population aging are two of the most critical global health challenges of the 21st century. According to the Population Division of the United Nations Department of Economic and Social Affairs (1), in 2050, China's over-60 population will account for 23.8% of the total population. China is promoting the concept of "home-based care" or "in-place care" through adaptation and transformation to encourage older adults to obtain higher-quality living conditions in a healthy and sustainable living environment (2–4). A 2020 study by the Environmental Protection Agency shows that average people, particularly older adults, spent 90% of their time at home. This is even more evident during the COVID-19 pandemic. Another study also showed that older adults spend ∼22 h a day at home, mainly in bedrooms and living rooms (5–9). However, little is known about the physical environment, closely related to wellbeing and living healthily in older adults (10–12). The World Health Organization (WHO) proposed an active aging framework, with safe housing for older adults as a critical theme in the physical environment dimension (13). Creating age-friendly environments is a strategic objective in the World Health Organization's (14). Global Strategy and Action Plan on Aging and Health (2016–2030). It also relates to many of the United Nations' (UN) (15). Sustainable Development Goals and the European Union' (EU) new Smart Healthy Age-Friendly Environments (2019–2023) policy development program as well as the recently launched Center for Active Aging and Innovation established by the Association of Southeast Asian Nations (16).

With improvements in living standards, human health and environmental quality have received widespread attention from researchers. China's carbon neutrality challenge reveals the increasingly apparent negative impact of human construction activities on the environment (17, 18). Sustainable development is a global consensus that promotes the healthy development of society, with more environmental issues involved increasingly (19). The built environment accounts for 40% of the world's annual final energy (20), with residential buildings accounting for a significant proportion. Environmental sustainability is a growing concern in developing the living environment, driven partly by calls for sustainable and eco-friendly lifestyles (21–24). Therefore, the need to create green living environments for residents, especially older adults, by incorporating a healthy environment is increasing (25). Older adults are essential contributors to environmental sustainability (26). Occupants often cope with environmental discomfort by adapting to it or adapting themselves (27). The role of adaptive behavior in improving occupant comfort and environmental quality as well as in improving occupant satisfaction has been confirmed by scholars (28–31). Occupant behavior is a significant source of uncertainty in building performance (32–34). Different disciplines and fields of work, from health to urban planning, social care, and information technology (35–37), recognize the value of involving occupants in environmental design.

Family wards that meet and safeguard the health needs of older adults must ensure a sustainable, safe, and comfortable indoor physical environment (38). Some scholars have explored the relationship between the living environment of older adults and physiological and psychological factors (39). Others have concluded that the thermal and acoustic environment has a more critical impact on the overall indoor physical environment quality than that on indoor air quality (40, 41). Moreover, research has shown that the four elements of the physical environment have different degree of importance in the existing standards for assessing and certifying residential indoor building environments (42). Other scholars have compared older adults' thermal comfort with the current predicted mean vote (PMV) comfort models and concluded that their thermal sensitivity is lower than the sensitivity level of the PMV model used in many standards (43). They found that older adults were more tolerant than non-older adults and preferred higher temperatures (44). The thermal behavior and living conditions of older adults (45) in naturally ventilated dwellings (46, 47) have also been reported.

After considering the wellbeing and physical and mental health of older adults, there is a consensus on developing a high-quality residential environment for them (48). A two-way link exists between the built environment and human behavior, health, and wellbeing (49). The quality of the indoor physical environment depends on the indoor environmental performance of the building as well as human behavior (50). Environmental gerontological theories suggest that indoor physical environment is a crucial factor affecting the wellbeing of older adults (51). Therefore, understanding the complex interactions between humans and the indoor built environment (52) and how the behavioral activities of occupants affect the quality of the indoor physical environment is crucial (53, 54). The current study considered different combinations of physical environmental factors, such as the thermal and acoustic environments, light and acoustic environments, light environment and indoor air quality, and acoustic environment and indoor air quality. Researchers are most interested in the effects of dependent variables, such as occupant comfort, feelings, preferences, and satisfaction (55–57). For example, scholars have assessed the extent to which window opening/closing behavior is driven by outdoor climatic conditions, indoor air quality, or other parameters. Studies have concluded that indoor and outdoor air temperature, indoor air quality, and solar radiation are the main drivers of occupant control of window opening and closing (58, 59). Some scholars have proved *via* experimental approaches that the clothing of occupants and the interaction between people and the built environment affect behavior patterns, impacting the physical environment (60). Occupant interaction with the thermostat affects energy consumption and the quality of the indoor physical environment. The thermal adaptation behavior of occupants includes adjusting fans, heaters, and thermostats when they feel uncomfortable (61). Humans generally adapt to indoor physical environments through behavioral, physiological, and psychological adaptations (62); for example, by opening or closing windows and curtains, the thermal and light environments in the physical environment elements can be regulated (63), including increasing indoor airflow (64). Another study found that occupants used ceiling fans much more than air conditioning systems and chillers to regulate a home's physical environment (65). Other studies have shown that window regulation is related to environmental factors such as temperature and seasonal changes, size, and distance to windows. However, it should be noted that while such measures improve occupants' comfort, they can also lead to a waste of energy (66). Therefore, scholars should find a balance among the various comfort-related factors (67).

Based on research on the indoor physical environment of a family ward in Guangzhou, China, this study focuses on the correspondence between occupant behavior and elements of the physical environment, analyzes the parameters of the physical environment suitable for aging, and proposes measures to optimize the indoor physical environment of family wards. This research aims to solve the problems of aging and the sustainable development of the living environment. Following existing standards, we measured the indoor physical environment quality to evaluate the relationship between residents' preferences and the physical environment in family wards. Our conclusions should be applied to existing buildings (to assess their present status), retrofit projects (to evaluate them before and after renovation), and new facilities (for design and benchmarking).

Research objects

Family ward

The family ward is located in the city of Guangzhou, China. Guangzhou has a southern-subtropical maritime monsoon climate. Because it is located close to the South China Sea and is affected by warm and humid tropical marine air masses, it has distinct climate characteristics. Guangzhou generally has hot summers (June–August) and relatively mild winters (December–February). The building where the family ward is located is close to where two main roads of the city intersect (Figure 1). A healthy female experimenter with a height of 1.6 m was selected for this study. The experimenter observed the changing aspects of the indoor physical environment by simulating activities of daily living in the family ward environment controlled by older adults or individuals with disabilities. This study measured the light, acoustic, and thermal environments as well as the indoor air quality of the four main activity areas of the family ward. These activity areas primarily consisted of the reception area, rest area, passing hall, and bathroom. The total area of the family ward was 26 m^2.

We chose the Weather Tool (Autodesk Analysis Ecotect software) to analyze the physical environment of the family ward area. According to our analysis of Guangzhou meteorological parameters, we were able to determine the family ward's overall environmental conditions. The analysis results of the meteorological tools can assist in verifying the reliability of the measured results and provide preliminary data for analyzing the impact of the outdoor environment on the indoor environment. According to the analysis results obtained using the Weather Tool, the annual average amount of solar radiation in the Guangdong area is primarily received in the direction of West South by 60°, the subcooling period is concentrated in the South direction, and the overheating period is focused on the North West by 5° (Figure 2A). The Figure 2B shows that the supercooling period in the blue area is from late November to early April. In this study, the experimental subjects in the family ward sat north and faced south, and the measured time was during the supercooling period. The Guangdong area, where the family ward is located, has low solar radiation intensity and low heat from direct sunlight. The outdoor cold air radiation adversely affects the indoor thermal environment. Based on the above analysis results and other constraints, we selected December 13–15, 2021, as the test time for the supercooling period.

Physical environment

The indoor micro-environment performance of family wards can be assessed in terms of thermal comfort, lighting quality, acoustic quality, and indoor air quality, generally and collectively referred to as the indoor physical environmental quality (IPEQ). The IPEQ of family wards is also affected by outdoor sources, building characteristics, and indoor pollutants. Physical environment comfort is usually defined as "that condition of mind that expresses satisfaction with the physical environment." Providing comfort indoors is a fundamental objective of architects, engineers, and the allied building sector professions.

Thermal comfort

Recently, an increasing number of researchers have devoted themselves to investigating and analyzing the indoor thermal environment of residential buildings (68, 69). The impact

FIGURE 1
Location characteristics of experimental building.

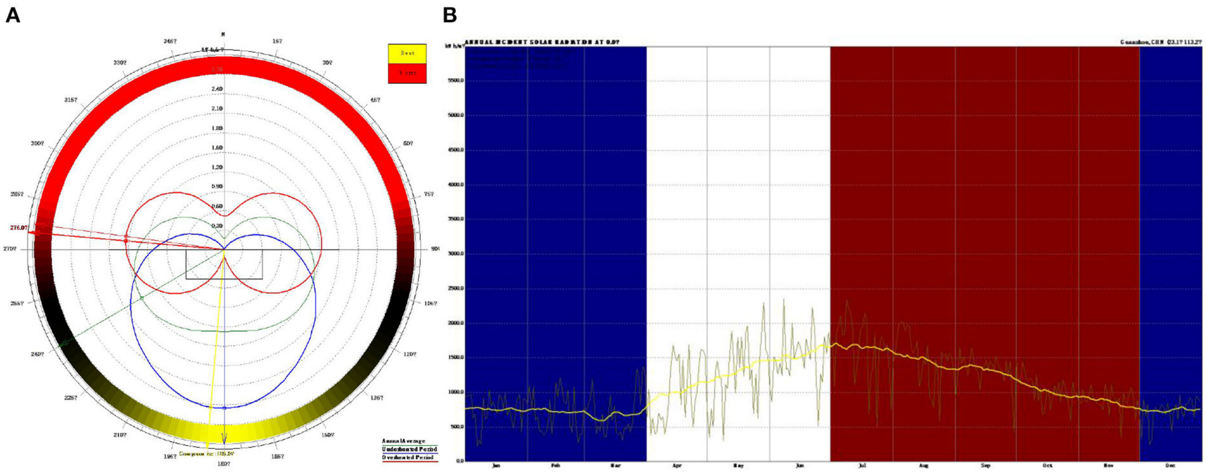


FIGURE 2
Analysis results obtained by the weather tool. **(A)** Solar radiation; **(B)** The overheating period and the supercooling period.

of thermal environments on the emotional wellbeing of occupants is complex (70). The indoor thermal comfort of an indoor environment can be estimated using a thermal adaptation model based on the currently applicable standards the American society of heating, refrigerating and air-conditioning engineers, Ins. (ASHRAE) 55–2020 and the energy performance of buildings (EN) 16798–2019. Thermal comfort is a psychological and physiological condition that expresses a human's perception of the temperature, humidity, and wind environment of their surrounding indoor and outdoor environments (71). Objective factors of environmental quality include air temperature, the average radiant temperature of the surrounding surfaces, relative humidity, and wind speed (72). Thermal comfort significantly impacts occupant health, particularly the perception of household indoor environmental quality, which is especially important for vulnerable groups such as older adults (73).

Since the invention of air conditioners in the early 20th century, people have become accustomed to manually controlling indoor climates. Despite continuous improvements in control technology, room temperature has remained the dominant control variable in air-conditioning technology for over a century. Research has shown a definite link between occupants' exposure to low or high indoor temperatures and their health. Relevant organizations and documents outlined indoor temperature range limits. In 1987, the world health organization (WHO) guidelines in indoor temperatures recommended indoor temperatures be maintained at 18°C, or 20–21°C in rooms used by older adults (74). Several other relevant studies suggest that indoor temperatures should be close to 25°C in the absence of physical activity (75) and should be lowered but maintained above 20°C. In addition, according to T18883-2002, the standard temperature for heating in winter should be in the range of 16–24°C, and the typical temperature for air conditioning in summer should be 22–28°C (76).

Exposure of sensitive individuals to low temperatures can lead to decreased resistance to respiratory infections and increased blood pressure. Thermal fatigue and heat stroke can occur when sensitive individuals are exposed to high temperatures. The risks are thus substantial for older adults. Scholars have presented different research results regarding the thermal comfort of older adults. Relevant research shows that physically and psychologically, older people prefer a warm environment. Thermal sensation of older adults is general 0.5 scale units (on a 7-point thermal sensation scale, Table 1) lower than thermal sensation of younger adults (77). Other scholars have also proved that during the heating period, controlling the indoor temperature within the range of 22–26°C has a positive impact on the health and comfort of occupants, particularly older adults, and helps improve the quality of the indoor environment (78).

The temperature and humidity are critical indicators of the comfort of a room. Indoor humidity is vital to human thermal comfort, indoor air quality, and feelings of dryness. Some scholars have argued that the humidity level should be maintained between 25 and 55%. The humidity limit is 12 g/kg in ASHRAE 55-2013, 40–70% in the chartered institution of building services engineers (CIBSE) guide A: environmental design (79), and I: 30–50%, II: 25–60%, III: 20–70%, and <12 g/kg in EN (European Committee for Standardization) 15251 (80). Owing to differences in climate, the living habits of residents, and older adults' physical fitness in different countries and regions, the results obtained by scholars vary. The thermal environment parameters obtained by researchers were controlled within a clear limit range. Considering that older adults constitute a vulnerable group, the discussion of thermal environment parameters requires further case support.

TABLE 1 The thermal comfort index PMV and its relationship to thermal sensitivity (96).

−3	−2	−1	0	+1	+2	+3
Cold	Cool	Slightly cool	Neutral	Slightly warm	Warm	Hot

Thermal sensation votes were recorded using the American Society of Heating, Refrigerating, and Air-Conditioning Engineers (ASHRAE) 7-point scale of thermal sensation (97), with questions ranging from hot (+3) to cold (−3) (98).

The indoor thermal environment includes the relative humidity (RH), indoor airflow velocity (Va), earth thermometer temperature (Tg), predicted mean votes (PMV), and many other elements. In winter, the Va is usually small, and the average radiant and air temperatures have a greater impact on human thermal comfort. In addition to taking temperature and humidity measurements, the measurement of the indoor physical environment also includes the average radiant temperature of the room. In this study, the mean radiant temperature was approximated as the area-weighted average of each surface temperature. To present the research results more intuitively, a thermal imager was selected for the visual recording in this study. The subjects here had a metabolic rate of 1.2 met and a thermal resistance of 1 clo of clothing. The area where occupants often stay and three measurement points near the hospital bed were selected. The location of selected points are shown as the temperature and humidity measurement point location in Figure 3.

Lighting quality

One of the most direct environmental factors affecting the comfort of older adults is the lighting intensity in the room. Occupants' requirements regarding their lighting environment change with age owing to physiological changes. Research

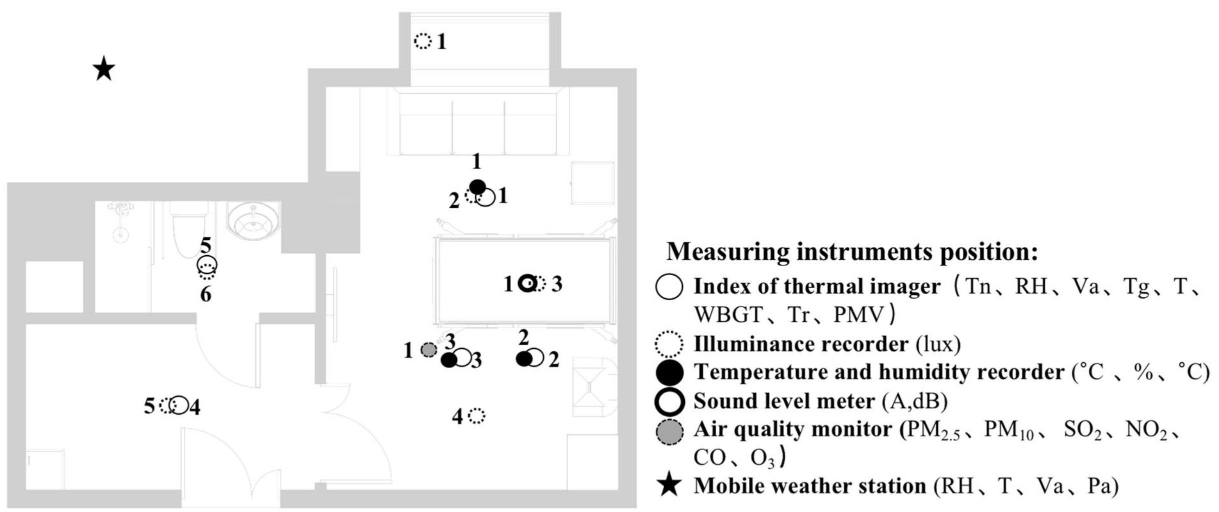


FIGURE 3
Instruments' position plan.

shows that vision changes are among the most important physical changes that occur with aging (81, 82). Compared to non-older adults, older adults require higher illumination levels, especially short-wavelength light, to experience visual and circadian effects (83).

A Japanese company's study showed that the overall comfort level of a room for older adults varies between 50 and 250 lx. The comfortable illuminance value of young people accounts for ∼2/3 of this illuminance. The findings of this study suggest that older adults have a greater need for lighting (81, 84, 85). China's "Architectural Lighting Design Standard GB50034-2013" stipulates the standard value of lighting at different heights of residential buildings. For example, at a level of 0.75 m, in an older adult's bedroom, the general activity area should meet a standard illuminance value of 100 lx, and the bedside and reading areas should complete the mixed lighting of 300 lx. In an older adult's living room, general activity should meet a 200 lx standard and a mixed illuminance standard of 500 lx for writing and reading. For the bathroom, an illuminance of 100 lx is required. According to China's "architectural lighting design standard GB50033-2013," the natural light intensity of bedrooms and living rooms in residential buildings should be at least 300 lx.

The following conclusions can be drawn from the above analysis combined with the existing standard requirements. A bedroom area with a partial reading function and mixed lighting should meet the requirements of 100–300 lx, and the natural lighting should meet the requirements of at least 300 lx. A living room needs to meet the mixed lighting standard value of 200 lx and natural lighting illuminance value of 300 lx. An auxiliary hall must meet the requirements of 100 lx mixed lighting intensity. Finally a bathroom must meet the illuminance requirement of 100 lx for mixed lighting.

Acoustic quality

According to the "Code for Sound Insulation Design for Civil Buildings GB20118-2010," the regulations on the allowable noise level (A sound level, dB) for residential buildings with higher requirements are as follows: bedroom daytime ≤45 dB (A), nighttime ≤37 dB (A); living room all day ≤45 dB (A). According to the "Acoustic Environment Quality Standard GB3096-2008," acoustic environment functions are divided into five types. Type 0 refers to areas requiring special quietness such as rehabilitation and recovery areas. The family ward in this study can be considered this type of area and requires a higher standard of improvement and control of indoor environment quality. For the Type 0 sound environment functional area, the environmental noise limit was ≤50 dB (A) during the day and ≤40 dB (A) at night. According to the Chinese Industry Standard "Architectural Design Standards for Elderly Facilities JGJ450-2018," when the occupants are older adults, the interior should have good sound insulation and noise reduction devices. The noise of the indoor living environment (86) should be <40 dB (A), and the air sound insulation should not be >50 dB (A). The impact sound should not exceed 75 dB (A) (87). Older adults are more tolerant of sound, but they are also more sensitive. Excessive and unnecessary noise can harm older adults' health and hinder their recovery from hearing loss. Long-term exposure of older adults to noise above 65 dB (A) can cause serious health problems, such as sleep disturbances, hearing loss, tinnitus, hypertension, and cardiovascular disease. According to relevant Chinese standards, for rooms with a residential building area of <30 m^2, the measuring point is the center of the room. The family ward used in this study was 26 m^2. Therefore, the center point of the room was selected to measure the acoustic environment parameters. The area is also an activity area for the occupants. The measurement point was 1.2 m away from the ground and 1.0 m away from the indoor wall.

Indoor air quality

The indoor air quality standards have improved over the past few years. Indoor air quality can have a wide range of effects on occupants' health and immune systems. The cleaner the indoor air, the more resistant the occupants are to viruses and infections. In winter, occupants are more likely to move indoors, shortening the distance among them, and increasing their risk of disease. According to the European environment agency (EEA), air pollution is Europe's most significant environmental health risk, especially in urban areas. Particulate matter (PM), nitrogen dioxide (NO_2), and ground-level ozone (O_3) cause the most significant damage, leading to ∼400,000 premature deaths annually.

This study primarily refers to the regulations on indoor environmental parameters during the winter heating period in China's "Indoor Air Quality Standard GB/T18883-2002." Regarding physical parameters, the indoor temperature was set to 16–24°C; the relative humidity was controlled at 30% to 60%, and the air volume was 0.2 m/s. The indoor chemical parameters were as follows: the sulfur dioxide (SO_2) concentration should be <0.5 mg/m^3, the nitrogen dioxide (NO_2) concentration should be controlled at 0.24 mg/m^3, the carbon monoxide (CO) concentration should be <10 mg/m^3, and the inhalable particles 10 (PM_{10}) concentration should be controlled at 0.15 mg/m^3. According to standard requirements, when the room area is <50 m^2, 1–3 sampling points are selected as the setting. The sampling point should not be near the ventilation opening, and the distance from the wall should be more than 0.5 m. The instrument should be set at a height of 0.5 m to 1.5 m. According to the standard requirements, the doors and windows were closed for 24 h before the measurement in this experiment.

Methods

Parameters and instruments

A portable Delta Ohm HD32.2 instrument and a thermal imager were used to measure the thermal environment. The instrument mainly measures indoor thermal environment parameters and records data every minute. The parameters include Air temperature (Ta), RH, mean radiation temperature (Tr), natural wet-bulb temperature (Tw), Tg, and wind speed (WS). This study used Tg, Tw, and Ta to estimate a composite temperature index and the wet bulb globe temperature (WBGT), following the International Organization for Standardization (ISO) standard. These measurements were then used to evaluate the influence of temperature, humidity, and solar radiation on people. The most commonly used heat balance estimates PMV model was utilized to evaluate the thermal comfort of the family ward in this study. The PMV model was initially developed by Fanger based on indoor experiments to establish a thermal balance model for the thermal comfort of air-conditioned buildings (88). Fanger and Toftum (89) was among the first to study the parameters affecting indoor environmental quality. Other researchers have since validated its applicability to naturally ventilated buildings (42, 90, 91). In this study, the thermosensory scale from the PMV model (from 3 cold to + 3 hot) was obtained from the ASHRAE Standard 55 (1992, 2013, 2020; Table 1) (92–94). They were also combined with Ta, Tr, WS, HR, occupants' activity level (met), and occupants' clothing insulation (Clo) to determine the thermal comfort of the family ward.

In this study, the room acoustic environment parameter, the A-weighted sound pressure level, was recorded every minute. A portable sound level meter AWA5633 instrument and the NoiseLab-Lite mobile application were calibrated for each other. The sound pressure level measured by the A-weighting network was expressed as LA in dB (A).

This study used a portable ONSET MX1104 instrument to measure indoor lighting environment parameters (illuminance value, lux). The temperature and humidity at the corresponding measuring points were also recorded. The data form a contrasting condition designed to reduce measurement errors due to sensor drift (data are recorded every minute).

To obtain relevant data on indoor environmental quality parameters, this study used a portable Sniffer4D Mapper instrument to record indoor air quality parameter data, such as SO_2 ($\mu g/m^3$), CO ($\mu g/m^3$), NO_2 ($\mu g/m^3$), $PM_{2.5}$ (Particle size is 0.3∼2.5 μm, $\mu g/m^3$), PM_{10} (Particle size is 0.3∼10 μm, $\mu g/m^3$), every minute. Air pollution is a recognized risk factor for cardiovascular and respiratory diseases. In this study, existing instruments were used to detect and analyze indoor environmental quality parameters as much as possible.

The indoor and outdoor environments are closely related, and the outdoor climate causes periodic changes in the indoor environment (95). In this study, we selected the 2000 series WatchDog mobile weather station to monitor the outdoor physical environment quality of the family ward.

The monitored meteorological parameters mainly included temperature, relative humidity, wind speed, wind direction, and rainfall. The weather station was installed on the open roof of the building and coincided with the time measured in this study, December 13–15, 2021. All instruments and their corresponding physical environment parameters for the family ward are listed in Table 2.

Measurement settings

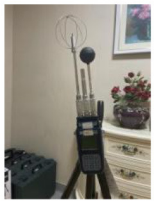
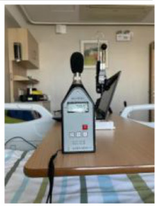
The analysis based on ASHRAE Standard 55, Building Thermal Environment Test Method Standard JGJ/T 347, Civil Building Lighting Design Standard GBJ 133, Acoustic Environment Quality Standard GB 3096, Indoor Air Quality Standard GB/T 18883 and other approaches showed that these standards correspond to environmental measuring instruments. There are different requirements for placement position, quantity, and height. In this study, the instrument's positioning considered older adults. The geometric center point of the small space and the measurement points were arranged in six rows along the long axis as the instrument placement point. These were located in areas that do not receive direct solar radiation. The height is 0.6 and 1.2 m above the ground, depending on the position of the older adults. When the older adults are seated, the instrument is located at 0.6 m. When they stand, it is located at 1.2 m. Each instruments should be at least 1.0 m away from the walls and windows. Some instruments require flexibility based on occupant activities or comparative data. The device was stabilized for 10 min and recorded measurements for ∼2 days (Figures 3, 4).

Results

Outdoor environment

Based on the valuable data obtained by the 2000 Series WatchDog weather station monitoring the building roof's outdoor weather parameters for 2 days, some results were accepted after sorting and analyzing. The measured data for the outdoor physical environment are shown in Figure 5. From December 13–15, 2021, the outdoor temperature, relative humidity, and solar radiation changed periodically. The maximum outdoor temperature was 26.39°C at 1:30 p.m. and the minimum temperature was 15°C at 1:30 p.m. The

TABLE 2 Basic characteristics of the experimental instruments.

Environmental parameters	Instruments	Measuring range	Accuracy	Time interval/min	Experimental instruments
Thermal comfort	Delta Ohm HD32.2	−40 to 100°C (TP3207.2, dry-bulb temperature)	Classe 1/3 DIN	1 min	
		−10 to 100°C (TP3276.2, black-bulb temperature)			
		4 to 80°C (HP3201.2, natural wet-bulb temperature)	Class A		
Acoustic quality	AWA5633 and NoiseLab-Lite mobile application	35 dB−130 dB (A)	2 level	1 min	
Lighting quality	ONSET MX1104	0–167,731 lux (lighting)	±10%, direct sunlight	1 min	
		−20 to 70°C (temperature)	±0.20°C: 0–50°C		
		0–100% (relative humidity)	±2.5% RH		
Indoor air quality	Sniffer4D mapper	0∼1000μg/m³ (PM1.0, PM2.5, PM10)	1μg/m³	1 s	
		0∼11ppm (NO_2)	<1.1ppb		
		0∼11ppm (CO)	<0.6ppb		
		0∼15ppm (SO_2)	<0.8ppb		
Outdoor environment	2000 series WatchDog weather station	−40 to 125°C (air temperature)	±0.4°C at −40 to 90°C	1 min	
		0%-100% (Relative Humidity)	±0.2%RH at 25°C		
		0–1,500 W/m²	±5%		

temperature difference was thus more than 11°C, and it must be accounted for through adjustment measures, such as long-sleeved clothes or doors and windows. The highest relative humidity was 76.1% at 6:00 a.m. and the lowest was 35.5% at 4:00 p.m. Studies have shown that most people feel more comfortable with a relative humidity of 30–80%. Therefore, the humidity of the outdoor environment reached a comfortable standard. The solar radiation reached 789 wat/m^2 at noon, and the lowest recording was 0 wat/m^2. The family ward is located in southern China, which has a humid and cold climate.

Evaluation of the thermal environment

The temperature and humidity data of the six measurement points in the family ward in this study were obtained through actual measurement (Table 3). The monitoring results showed differences in the temperature and humidity obtained by different measurement instruments, and the data from other measurement points also showed consistent variation. The testers were mainly active at measurement points 1 and a. Based on the results, the temperature and humidity data of these two measurement points were generally higher

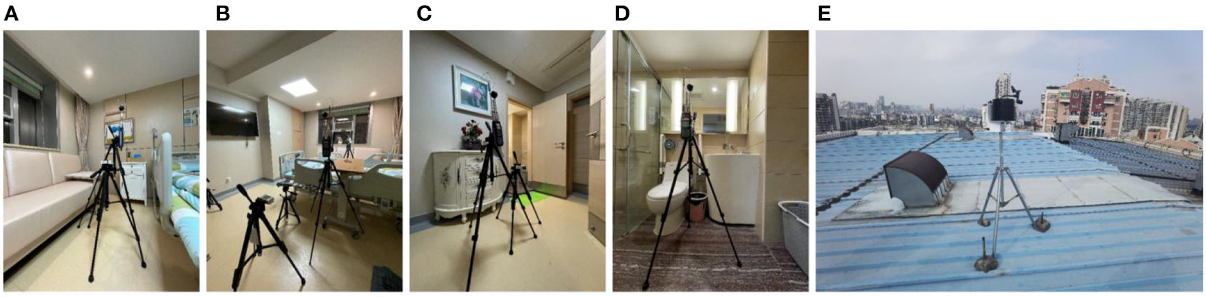


FIGURE 4
Instruments' position, real scene. **(A)** Rest area; **(B)** Reception area; **(C)** Lobby; **(D)** Toilet; **(E)** Roof.

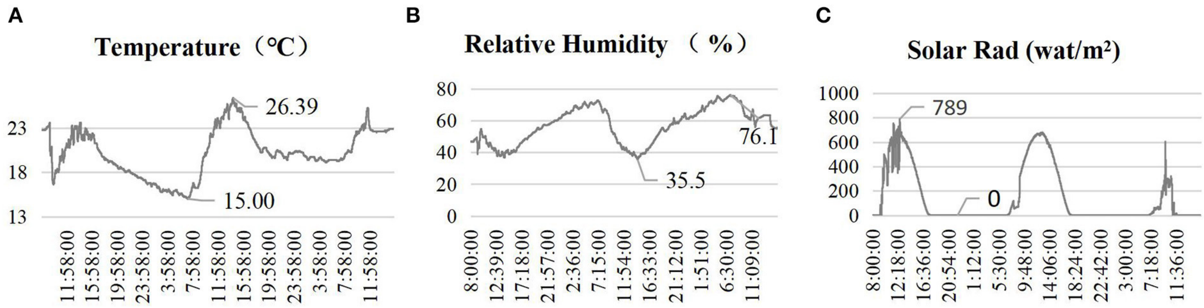
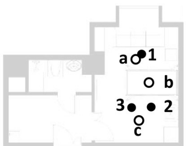


FIGURE 5
Outdoor environment. **(A)** Temperature; **(B)** Relative humidity; **(C)** Solar rad.

TABLE 3 Measured results of thermal environment elements.

	Measuring instrument: HOBO-MX2301A			Measuring instrument: HOBO-MX1104A		
	Measurement point 1	Measurement point 2	Measurement point 3	Measurement point a	Measurement point b	Measurement point c
Relative humidity (%), MAX	54.10	53.78	54.37	56.77	55.99	55.74
Relative humidity (%), MIN	42.68	41.87	42.49	43.37	42.27	42.31
Temperature (°C), MAX	23.49	23.66	23.49	23.57	23.36	23.41
Temperature (°C), MIN	21.28	21.47	21.50	20.92	21.48	21.63

than those of the other measuring points. It is possible that some of the data were affected by the tester's mobile debugging instrument, such as measurement point 3. The temperature fluctuation range of each measuring point was about 2–3°C. Furthermore, the maximum temperature was below 25°C, and the minimum temperature was controlled above 20°C. The humidity fluctuation range of each measurement point was maintained at 12–13%. The maximum humidity was below 55% and the minimum was above 40%. From the test data, the indoor temperature and humidity of the family ward in this study were within a comfortable range. Whether it is suitable for older adults with different physical conditions requires follow-up experimental support.

The thermal imager recorded the inner surface temperature of the internal walls, windows, and furniture of the family ward. Some of the measurement results are shown in Figure 6. The surface temperature of the air quality measuring instrument reached the commanding height of the surface temperature of the hospital bed area, locally reaching 27.8°C. For other indoor walls, it was between 20 and 22°C. In the indoor ceiling section, the air conditioning system contributed to a lower

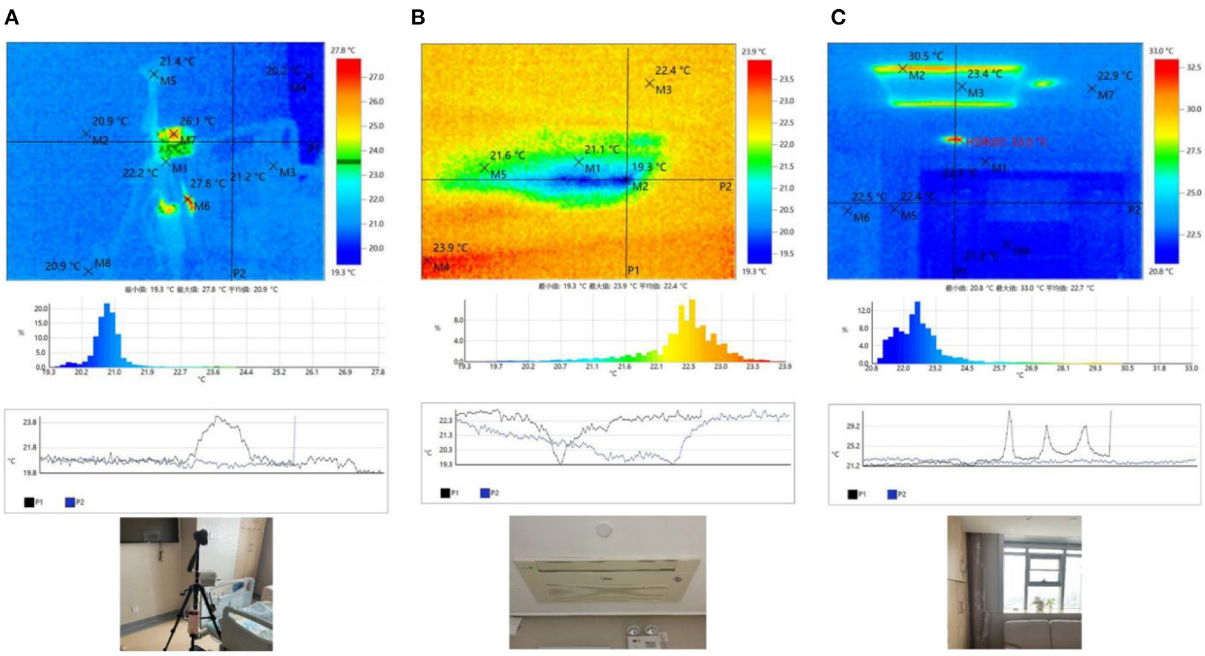


FIGURE 6
Surface temperature. **(A)** Bed area; **(B)** Air conditioning area; **(C)** Window area.

temperature, as low as below 20°C. The indoor network signal monitoring device contributed a temperature of 23.9°C. The roof temperature was 22.4°C. In the area of the room with windows and lamps, the temperature of the visible lights was as high as 33.0°C, the minimum temperature of the window glass was 20.8°C, and the other walls were all above 22°C. The above data analysis shows that the indoor temperature of the family ward in this study was within the standard range but was slightly cold. The indoor wall temperature was consistent with the average indoor air temperature measured by the measurement instrument. Therefore, the mean radiation temperature in the family ward is reflected by the temperature of each surface. The specific positions of measurement points 1, 2, and 3 are shown in Figure 6. The indoor PMV was calculated based on the actual measured environmental parameters, and the corresponding thermal environment index values at different time points were obtained (Figure 7). The PMV was between −0.5 and +0.5, indicating an overall comfortable and good thermal environment index within the family ward. The sudden change in some data was mainly caused by the experimenter's debugging of the instruments.

Evaluation of the acoustic environment

Different interference measures in different periods affected the indoor acoustic environment of the family ward. As shown in Figure 8, the indoor acoustic environment exhibited irregular fluctuations. For example, three unfavorable noise domains appeared on the evening of December 13, when the doors and windows were closed. The first was caused by the closing of the outdoor construction site at night. Despite the doors and windows acting as barriers, the noise value still exceeded the recommended limit. The second and third were due to the routine activities of laboratory personnel. On December 14, there were two more constant noise values, both due to the activities of laboratory personnel. For example, the experimenter turned on the air quality monitoring instrument, the ventilation mode of the air-conditioning system, and the TV. The two noises that exceeded the standard on the morning of December 15 were also caused by indoor personnel activities and the adjustment of the indoor testing equipment.

Due to the activities of indoor occupants and outdoor urban dwellers, certain incidental factors can affect the results during a sound test. The noise level in this study for the entire day of December 14 was slightly higher than the specified value. Some abnormal sound levels are 55 dB (A) to 70 dB (A). From December 13 to 15, although there were still abnormally fluctuating noise values during this period, the overall sound environment was good and met the standard requirements. It is worth noting that the higher noise values that appear for a short period can be reduced by taking appropriate measures in subsequent renovations.

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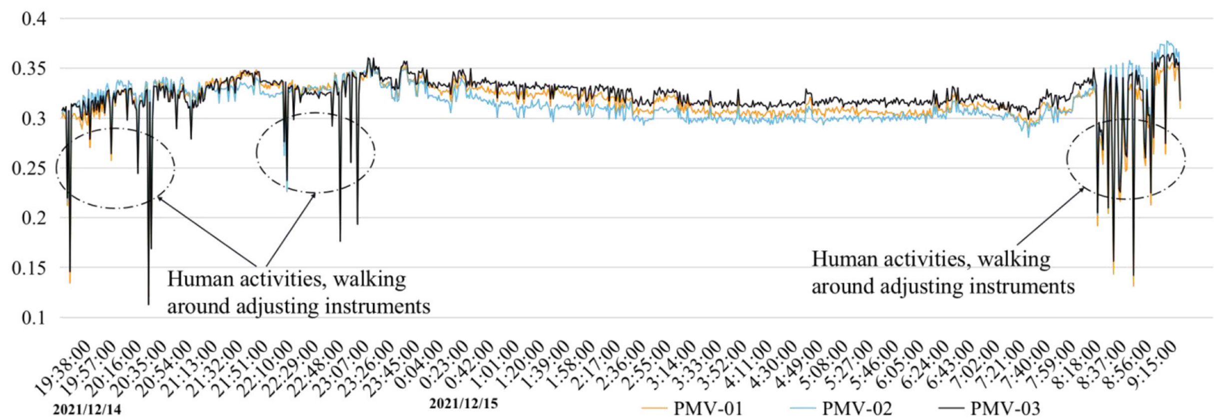

FIGURE 7
Main area of activity measurement points and calculated PMV value.

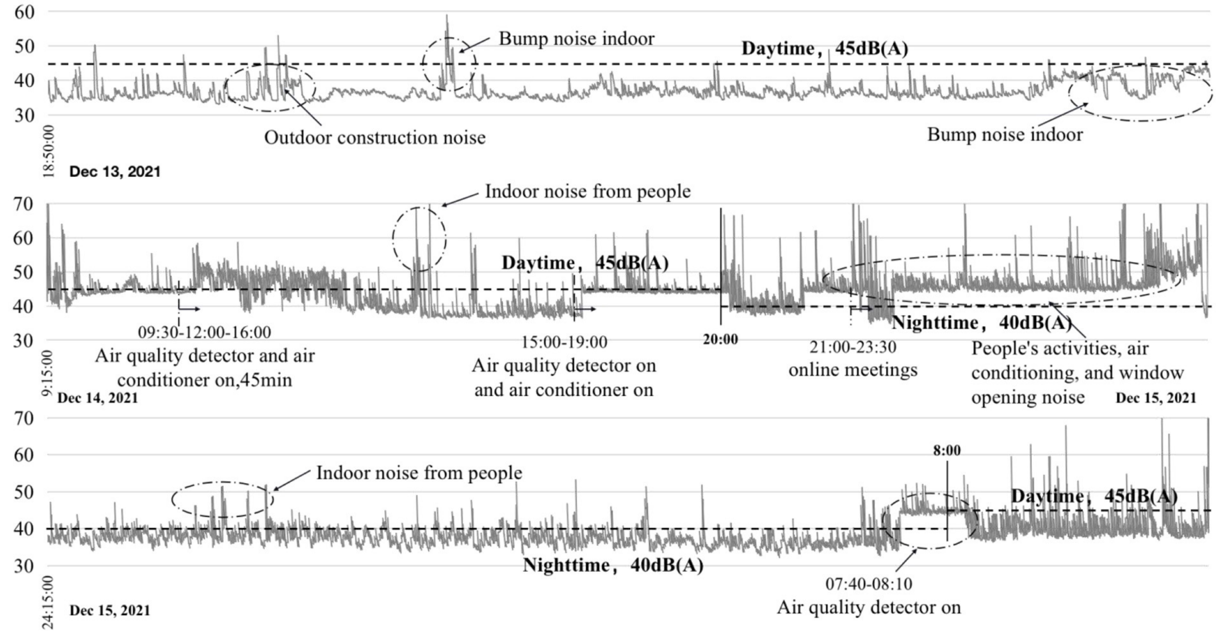

FIGURE 8
Recorded noise values from December 13 to 15.

Evaluation of the lighting environment

In this study, we selected six measurement points in the family ward (Figure 9). Measurement point 1 was a comparison test point on the windowsill. Measurement point 2 was located in the sofa activity area, measurement point 3 above the hospital bed, measurement point 4 in the reception area, measurement point 5 in the hall, and measurement point 6 in the bathroom. Measurement points 2 and 3 were in the bedroom area with a partial reading function; the mixed lighting thus should meet the requirements of 100–300 lx, and the natural lighting should meet the requirements of at least 300 lx. Measurement point 4 was located in the living room and needed to meet the mixed lighting standard value of 200 lx and a natural lighting illuminance value of 300 lx. The passage of measurement point 5 needed to meet the requirements of a 100 lx mixed lighting intensity. Measurement point 6 was located in the bathroom and needed to meet the illuminance requirement of 100 lx for mixed lighting.

Figure 10 shows the three set working conditions: working condition 1 with artificial lighting turned on and the curtains open, working condition 2 with artificial lighting turned off and the curtains opened, and working condition 3 with closed curtains and artificial lighting turned on. Based on the results of the three working conditions, measurement point 2 met the standard requirements of mixed lighting, but its natural lighting illuminance still needed to be increased by 100 lx. The mixed and natural lighting at measurement points 3 and 4 did not meet the standard requirements. Measurement point 5 met the requirements with the assistance of artificial lighting, but the natural lighting in this area was poor. Measurement point 6 relied entirely on artificial lighting, which met the illumination requirements, but the area lacked natural lighting and thus needs improvement. In general, the quality of the light environment in the family ward was poor and needed to be improved.

Evaluation of the indoor air quality

In this study, a measurement control group was established to analyze indoor environmental quality (Table 4). The measurement started at 9:00 a.m. on December 13, and there was one participant in the room. This study selected a control group for discussion. From 17:00 to 17:45 on December 13, the working conditions were to open the windows for ventilation, introduce fresh air, and turn off the air conditioner. Another set of control experiments was conducted from 17:00 to 17:45 on December 14. The working conditions were to turn on the air conditioner in the two-grid ventilation mode and close the doors and windows.

Figure 11 shows the content levels of the various elements in the indoor environment of the family ward. In general, the content levels of each element on December 14 were significantly higher than those on December 13. The SO_2 content level was 2 $\mu g/m^3$ higher, the CO content level was 0.35 mg/m^3 higher, the NO_2 content level was 4 $\mu g/m^3$ higher, the $PM_{1.0}$ content level was 5 $\mu g/m^3$ higher, the $PM_{2.5}$ content level was 4.5 $\mu g/m^3$ higher, and the PM_{10} content level was higher than 10 $\mu g/m^3$. Thus, the CO content increased most dramatically.

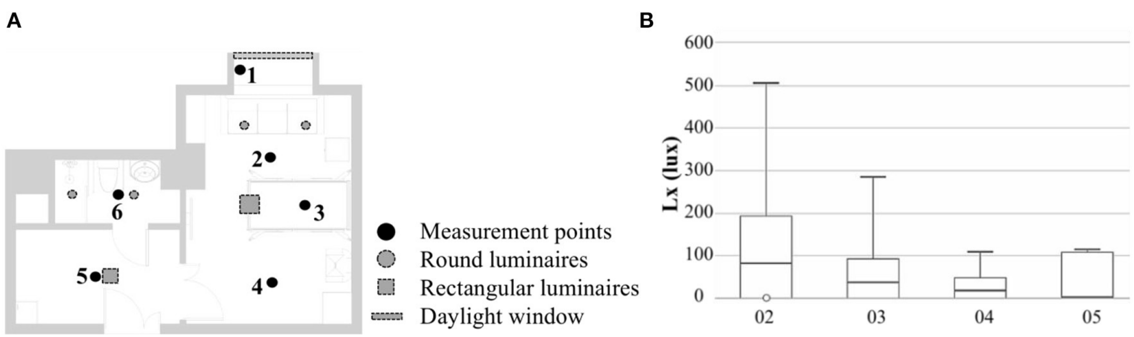

FIGURE 9
Lighting environment measurement points. **(A)** Point positions; **(B)** Illuminance intervals.

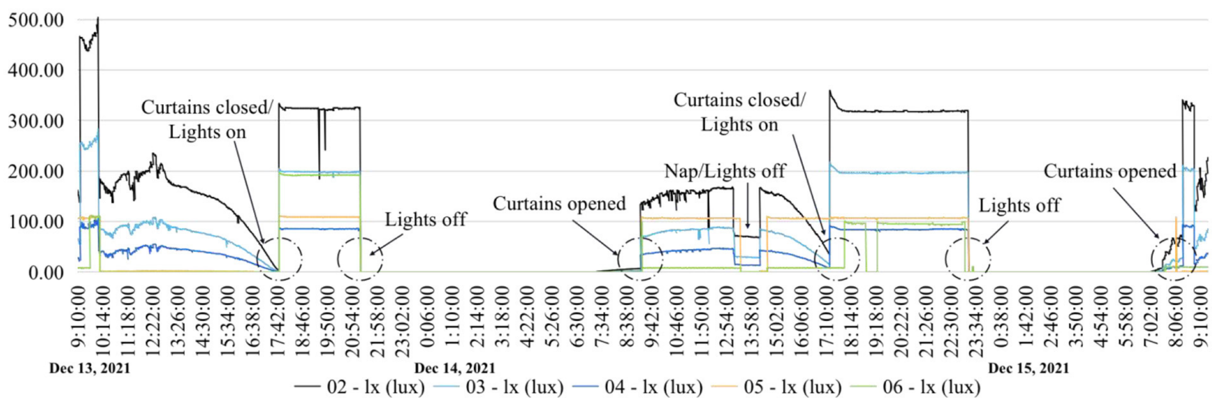

FIGURE 10
Recorded lighting values from December 13 to 15.

Discussion

Summary

Through experimental analysis, it was concluded that the occupants' behavior affects the quality of the indoor physical environment and directly affects the comfort and health of the occupants. Therefore, allowing occupants to control the indoor physical environment during the supercooling period, such as by heating, cooling, and introducing fresh air, should be considered in the designing of a family ward. It is important to note that in residential environments, occupants' environmental preferences and regulatory behaviors vary widely, especially among older adults, and buildings must be designed to accommodate these changes while simultaneously increasing building energy use and reducing emissions. These issues are significant in the context of climate change and rapid aging.

This study found that family wards performed better in terms of thermal environment and indoor air quality. However, some improvements to the light and acoustic environments are needed. In addition, the living habits of the occupants, especially older adults, directly affect the quality of the indoor environment. To improve the livability of the indoor environment of family wards, this study puts forth several optimization suggestions.

a) There are abundant international standards and documents across societies, and the purpose of optimizing the physical environment is achieved by strictly limiting the standard values of various physical environment parameters. However, considering the living environment in China, resident characteristics, and the habits of adjusting to the environment, regional features should be taken into account in the design of a family ward. We compared the test results of this study with Chinese and international standards. This study aims to achieve a more scientific evaluation of the quality of the physical environment in family wards. For example, according to ASHRAE research on acoustic environments, the maximum appropriate noise level in a family ward ranges from 39 dB (A) to 44 dB (A). If the room is small and private, the maximum noise level should be 39 dB (A) to 48 dB (A). Moreover, the maximum appropriate noise level is 35 dB (A) to 39 dB (A) for bedrooms and 39 dB (A) to 48 dB (A) for living rooms. The ASHRAE research results are somewhat different from the Chinese standards. The Chinese standards state that bedrooms should be $\leq$45 dB (A) during the day and $\leq$37 dB (A) at night, and the living room should be $\leq$45 dB (A) throughout the day. Therefore, based on Chinese standards, in this study, the acoustic environment quality of wards was judged according to the provisions. The same applies to other physical environmental factors, as explained above.
b) The family ward met the general comfort standard and performed well in terms of the thermal environment. To optimize the thermal environment of the family ward examined in this study, we first considered preventing the room from overheating or overcooling. The cooling and heating functions of the air-conditioning system were not used in this experiment; therefore, the results obtained showed a slightly colder state at night. In optimizing the ward's physical environment in the future, the heat source and cooling system can be effectively controlled so that the indoor physical environment can be adjusted to a temperature suitable for older adults' thermoregulation. In addition, fresh air can be introduced by adjusting the temperature and moisture content of each surface in the room, while enhancing the natural ventilation rate. We deal with thermal comfort under different control modes, and alternative methods can be selected, such as correcting the clothing value by changing the occupants' clothing to from a level at which they feel uncomfortable (such as 1.0 clo) to a relatively comfortable level (such as 0.5 clo).
c) Considering the existing standard values for the acoustic environment of residential buildings in China, limits of 45 dB (A) during the day and 40 dB (A) at night were suggested. From this study, it can be observed that the indoor acoustic environment is influenced by occupant behavior. It is also significantly influenced by outdoor-specific sound sources (e.g., traffic noise, outdoor construction noise, adjacent dwellings), home technical installations, and occupants' ability to adjust these factors. Considering the family ward's particular function room and considering the physical characteristics of older adults, from this perspective, the investigated family ward needs to strengthen its noise control. In particular, at night, the outdoor ambient noise needs to be eliminated. In indoor acoustic environments, there are many optimization strategies, such as, applying sound insulation materials to reduce the noise in the living environment as much as possible, using doors, windows, and other enclosures with good sound insulation effects, and the use of soft indoor decoration that adjusts indoor reverberation time and weakens noise intensity. In addition, noise sources should be avoided, such as reducing the noise generated by indoor equipment.
d) Optimizing the indoor light environment, on the premise of meeting the standard requirements should focus on the weakening physical functions of occupants with age as well as the occupants' need for high-quality light environments. In this study, the quality of the light environment in the family ward was poor, and the requirements of relevant standards could only be met when natural and artificial lighting were used in conjunction. The color, temperature, and warmth of the light environment of the family ward in this study need to be further investigated. Based on the current experimental results, we first need to strengthen the illuminance standards

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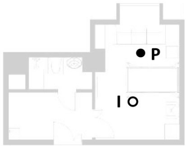
TABLE 4 Recorded values of indoor air quality elements.



	Measurement instrument: Sniffer4D mapper (P: experimenter, 1 person; I: Instrument location)					
	SO2 μg/m^3	CO mg/m^3	NO2 μg/m^3	PM1.0 μg/m^3	PM2.5 μg/m^3	PM10 μg/m^3
Dec. 13, 17:00–17:45 (Average value)	6.75	0.97	67.94	23.79	37.99	41.43
Dec. 14, 17:00–17:45 (Average value)	8.72	1.34	71.29	29.43	47.28	51.54
Standard limit value (Average value)	1 h ≤500 μg/m^3	1 h ≤10 mg/m^3	1 h ≤240 μg/m^3	–	24 h≤150 μg/m^3	24 h≤100 μg/m^3

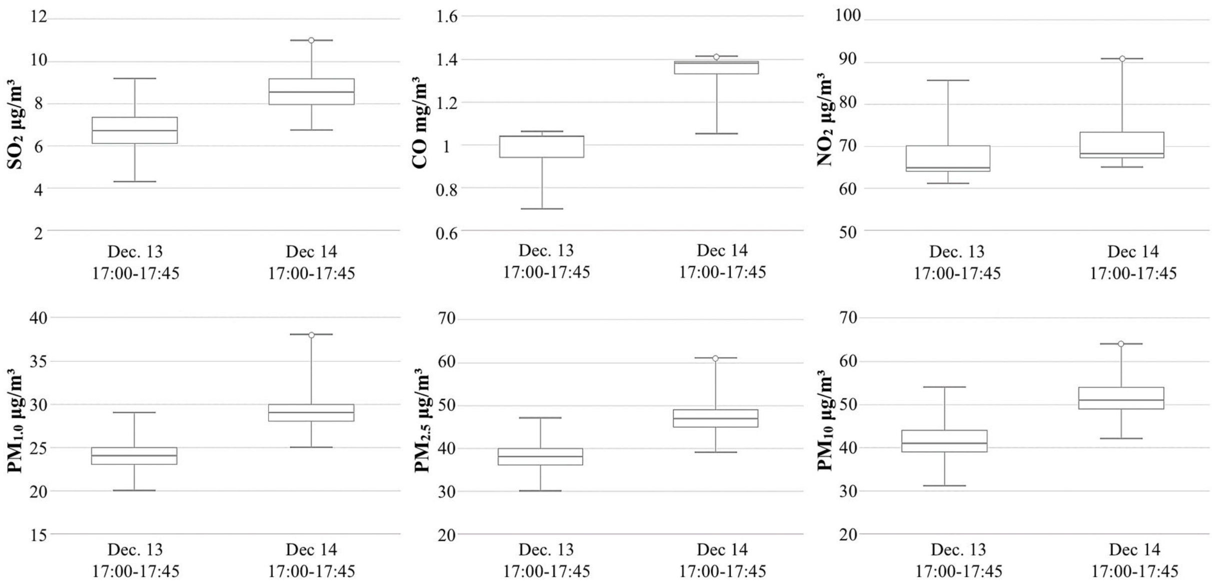


FIGURE 11
Comparison of indoor air quality elements.

of natural and artificial lighting, achieve a better lighting state, and improve the overall light environment quality of the ward with different light color effects. Many specific approaches can be employed to optimize the physical environment of this family ward. Examples include using illuminance that matches the visual function of older adults, adjusting the intensity of sunlight during different seasons, quantifying the measurement of visible light passage, and using movable visors and window glass to control color rendering. In addition, artificial lighting can be used to supplement natural lighting when necessary. An indoor mixed-light environment can satisfy the standard requirements with the inclusion of high-performance lamps. In winter, or when natural lighting is insufficient, consideration should be given to incorporating artificial lighting environments.

e) After 2 days of actual measurement, the indoor environment of the family ward was of good quality and fully met the limits specified by the standards. Regarding air quality, the environment can be optimized for elements that have detrimental effects on human health and comfort. Specific measures included filtering the air coming in from the outdoors, increasing the frequency of natural ventilation and the ventilation rate of mechanical ventilation, increasing the purification effect of green plants, and choosing low-polluting home improvement materials. When occupants living alone, opening windows for ventilation can bring better indoor environmental quality than turning on an air conditioner. This study involved the observation of the changes in indoor air quality brought about by occupants' adjustment to the indoor environment. When designing a healthy family ward environment, designers must also consider the environmental impact of building materials and functional layouts. Simultaneously, the focus is on the possibility of occupants adapting to these conditions.

Limitations

In the future, people, especially older adults, will have higher requirements for the indoor physical environments in their daily lives. This study lacks systematic, scientific, and reasonable guidelines for optimizing the interior environment of existing residential buildings and appropriate design guidance for interior space design. The four physical environment elements—the acoustic environment, light environment, thermal environment, and indoor air quality—involve considerable content. This study made some attempts in terms of research, but more scholars need to discuss these issues as key research objects. Based on the current research data, the home-based care environment in South China needs to be optimized. The environmental needs of the different types of rooms for older adults are poorly understood. For example, in the bedroom, the acoustic, thermal, and light environments interact more closely with older adults' health. Indoor air quality may be a more important factor for older adults in living rooms. Therefore, studying the interaction between the indoor physical environment and the behavioral habits and health status of older adults is of great importance for improving their quality of life.

The limitations of this study are that the sample size of the family ward was insufficient, and the total time of the physical environment test was inadequate. The research still requires the participation of older adults as an experimental subject to better support the research results. It is important to note that this study did not measure these factors during a time outside the supercooling period; therefore, the measurements were not well validated. Although the supercooling period was selected for measurement, it did not represent the environmental conditions of the family ward during winter and summer. Fortunately, the family ward has been renovated for older adults, and it plans to admit older adults as the next step, laying a good foundation for follow-up research. In addition, this study has certain limitations in terms of benchmarking. Owing to the lack of international discussions on the research object of family wards, there are no building norms and standards directly aimed at the physical environment of this research object. This study is based on the consideration of older adults and individuals with disabilities, combined with the relevant content of the norms and standards of hospital buildings, residential buildings, green buildings, and healthcare buildings. In the future, as scholars focus more on family wards and advance research on its physical environment, it is expected that this research and subsequent discussions will contribute to the specifications and standards for the physical environment of these family wards.

Conclusions

This study presents the results of a short-term physical environment monitoring project in a Guangzhou family ward. Our research provides a comprehensive understanding of the current state of indoor and outdoor environments during the supercooling period using measured data and software to determine the indoor and outdoor physical environments of family wards. Our findings suggest that occupant activity directly affects the indoor physical environment. This is primarily reflected in the control activities of the occupants. During the supercooling period, by adjusting the opening and closing curtains and turning lamps on and off, adjusting windows and air conditioning systems, and adjusting the activity types of indoor functional areas, methods to improve the quality of the indoor physical environment can be discovered and harnessed to relieve discomfort.

The study also found that traditional indoor environmental quality judgments are mostly subjective judgments based on vision, hearing, and smell, which are usually inaccurate. This study combines subjective and objective measurements and software analysis with personal judgment to achieve a scientific study of the indoor physical environment and propose a reasonable optimization path. Taking internationally recognized standards as the research background, this subjective and objective analysis of the environment will help the occupants, especially older adults, better understand their environment and inform future indoor environment optimization measures.

Although this study has certain limitations, the analytical methods used here have general implications in terms of artificially setting different indoor environment control modes, comprehensive interpretation, and the analysis of the changing characteristics of the four elements of the indoor physical environment. This study focuses only on family wards during the supercooling period. A similar method will be used at other times of the year to conduct control experiments. By observing the characteristics of the interactions between people and the environment, we can summarize the paths that optimize the indoor physical environment. This study provides guidance for environmental modification and for the living habits of future occupants' during the supercooling period.

This study found that there is currently a lack of research on the interaction mechanism between occupants' living patterns and elements of their living environment, and the proportion of older adults among the subjects of sustainable environmental research remains to be assessed. Our study is the first step toward bridging this gap. Future research will address the issue of environmental health by exploring the impact mechanism of older adults' living behaviors in different seasons throughout the year on elements of their physical environment. This research has implications for the health of older adults, sustainable environments, healthy cities, and policy and suggests introducing better indoor physical environment requirements for family wards to optimize their indoor environmental parameters, prevent health disorders, and improve the quality of life of older adults.

Data availability statement

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

Author contributions

YZ and XL: conceptualization. XL: methodology, formal analysis, and funding acquisition. YZ: software, resources, and data curation. XL, QM, and LC: validation. YZ and BL: investigation and visualization. YZ, XL, and BL: writing—original draft preparation and writing—review and editing. QM and LC: supervision. All authors have read and agreed to the published version of the manuscript.

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Conflict of interest

Author XL was employed by Architectural Design and Research Institute Co., Ltd.

The remaining authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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Community public health safety emergency management and nursing insurance service optimization for digital healthy urban environment construction

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The purpose of this paper is to promote the construction of digital healthy cities and improve the living standards of urban residents. Based on this, this paper analyzes the development of healthy cities, and studies community public health safety emergency management and nursing insurance service optimization methods for healthy urban environment construction. First, the concept of digital healthy urban environment construction is discussed. Then, the role of environmental health is discussed. Finally, two methods are designed to study the emergency management of public health safety and nursing insurance services in urban communities under the condition of environmental health. The results show that in the environmental health score of the city, the scores of X1 (the urban air quality excellent rate) and X6 (citizens' satisfaction with the environmental quality) were relatively low between 2016 and 2018, below 0.5 points. The scores for the remaining 3 years were relatively high, above 0.5. The scores of X2 (green coverage rate of built-up area), X3 (average grade sound effect of environmental noise in urban area), X4 (harmless treatment rate of domestic waste) and X5 (centralized treatment rate of domestic sewage) were relatively high from 2016 to 2018, above 0.5 points, and relatively low in the remaining 3 years, below 0.5 points. Meanwhile, residents are very satisfied with information collection and information management in public health and safety emergency management, and the number of very satisfied people is basically more than 40%. Satisfaction with resource allocation and privacy management is high, and the number of very satisfied people is basically above 30%. However, the satisfaction with risk perception and management measures is very low, and the number of very satisfied people is basically below 20%. It shows that the current construction of the community's public health and safety emergency management system is relatively poor in terms of X2–X5, while the development of X1 and X6 is relatively mature. The research not only provides a reference for the construction and improvement of a digital healthy city, but also contributes to the improvement of the healthy life of urban residents.

KEYWORDS

digital cities, health city, emergency management, nursing insurance system, community structure

Introduction

With the development of science and technology, digital and healthy cities have become important goals for future urban construction. The improvement of residents' life is crucial based on healthy city construction, and the healthy life of residents is the main purpose of healthy city construction (1). Based on this, the construction of a healthy city is mainly based on the living conditions of urban residents. Environmental health is the most critical issue affecting residents' living conditions, so improving urban environmental health plays a vital role in promoting the construction of healthy cities (2). In urban environmental health research, community public health safety emergency management and nursing insurance services are the most direct factors affecting residents' living standards (3). Although the current management of these factors is not perfect, many studies have provided references for its future development.

The development of digital healthy cities plays an important role in the overall development of society. The development of digital healthy cities can not only change the way of life of human beings and provide more convenience for human beings, but also promote the efficiency of urban construction and comprehensively promote social development. However, the current construction of public health safety emergency management and nursing insurance services in digital healthy cities is not perfect, so more research is needed to provide support for its development.

Based on this, this paper first discusses the construction needs and specific construction concepts of digital health cities. Then, the important role of urban environmental health in the construction of healthy cities is discussed. Finally, the public health security emergency management and nursing insurance service in a community are studied. The innovation is that it not only studies the development of digital healthy city, but also studies the comprehensive development of digital healthy city and community public health security emergency management system through the entropy weight method. The research not only provides a reference for community public health security emergency management and the optimization of nursing insurance services, but also contributes to the construction and development of healthy cities.

Literature review

Although the current social achievements in the construction of the community public health security emergency management system in digital healthy cities are not outstanding, many studies have provided references for its development. First in foreign research, Sánchez (4) designed the architecture of the geospatial information sharing platform and the SOA (service-oriented architecture)-based spatial data sharing model based on the SOA architecture. Based on the development framework, the prototype system of the urban multi-source spatial information sharing platform is realized, which fully explains the development and design concept of the digital city (4). Park et al. (5), from the perspective of urban and regional informatization and digital city engineering construction, combined with digital city engineering practice, integrated urban construction field, 3S field, surveying and mapping science field, computer science field experts and scholars ' research results on digital city. A preliminary study on the basic concept of digital city, the theoretical framework of digital city, the engineering framework of digital city and other theoretical issues is made. The basic theoretical framework of digital city is put forward (5). Azzaoui et al. (6) pointed out that building healthy cities is a global action strategy advocated by the World Health Organization in the 1980s in response to the challenges to human health posed by urbanization. It aims to build a city that is constantly developing and developing its natural and social environment and expanding its social resources so that people can support each other in enjoying life and realizing their full potential (6). Rivani and Mei (7) pointed out that the good health of the population is the basic premise and condition of social and economic development, and public health is responsible for promoting and protecting the health of the population. Therefore, public health always adapts its strategies to promote and protect the health of the population according to the health problems faced by the population (7). To sum up, foreign research has entered a relatively mature stage for the construction of public health and safety emergency management system, and has formed relatively comprehensive research results. In addition, many studies in China have provided research references for public health security emergency management in digital health cities. Chen

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et al. (8) pointed out that under the influence of various factors, emergencies occur frequently, and public health emergencies are at the forefront, bringing many negative impacts on human life safety, social harmony and stability, and healthy economic development. Therefore, effectively responding to emergencies in the field of public health and strengthening research on public health emergency management have become one of the practical problems that governments at all levels need to solve urgently (8). Kang et al. (9) constructed an emergency management system framework for urban public health security based on data warehouse, emergency response support platform, unified management of information, and interconnection with other e-government systems, and elaborated on the basic functions of each business module and key technical methods for system implementation (9). Song et al. (10) pointed out that as the global aging process continues to accelerate, countries around the world have begun to establish long-term care insurance systems to deal with the long-term care risks of the elderly brought about by aging. Different countries have their own advantages and disadvantages in the system design of long-term care insurance due to differences in their own political environment, welfare system traditions, and cultural customs, especially in the design of long-term care insurance payment systems (10). Huang et al. (11) pointed out that the large scale of the elderly population and the continuously increasing and deeply aging population have led to a rapid increase in the number of disabled elderly people. Establishing a long-term care insurance system in line with the current social needs as soon as possible will undoubtedly become an important means to resolve the risk of disabled elderly care (11).

In summary, the current research on digital cities, public health security, emergency management and mutual insurance services in China and other countries has been very comprehensive. However, the practical application research of community public health emergency safety management and nursing insurance service in the construction of digital healthy cities has not yet appeared, so this paper is breakthrough research.

Research theory and methods

Construction of the digital healthy urban environment

Digital city

With the development of science and technology, digital construction has become the main direction of current social development. Digital city refers to the tendency of urban construction to be digitized. It is embodied in the informatization of the surveying, mapping, and statistical process of the earth's surface, the informatization of government management and decision-making process, the informatization of the people's life process, and the informatization of the management and decision-making process of enterprises in society (12). If urban construction can meet these four constructions needs, it will enter the era of urban informatization. Urban informatization construction is mainly based on computer, multimedia, and large-scale storage technology, with the broadband network as the link. Remote sensing, global positioning system, geographic information system, engineering measurement technology, simulation-virtual technology, and other technologies are used to carry out multi-resolution, multi-scale, multi-space-time, and multi-type three-dimensional descriptions of cities. Information technology means are used for digitizing and virtualizing all the content of the city's past, present, and future on the network (13).

Specifically, the digital city refers to the use of spatial information to build a virtual platform and to obtain and load urban information in digital form, including urban natural resources, social resources, infrastructure, humanities, and economy, to provide a wide range of services for the government and all aspects of society. Digital cities can realize comprehensive analysis and effective utilization of city information. It supports urban planning, construction, operation, management, and emergency response through advanced information technology. It can effectively improve government management and service levels, enhance urban management efficiency, save resources, and promote sustainable urban development. On the one hand, 80% of the content in human life and the production process is related to urban space and its location, so the digital city is constructed and operated based on the spatial information platform (14). On the other hand, the spatial information platform is the infrastructure construction in the process of digital city construction. Various high-end digital city applications need to be realized through the spatial information platform and are restricted by the construction of the spatial information platform. Therefore, the relationship between spatial information platforms and digital cities is very close. In building a digital city, it is necessary to consider constructing a spatial information platform (15).

The speed of urban development is getting fast based on the construction of information cities. The quality of urban construction is also constantly improving, so the role of information city construction is vital.

Healthy city

With the continuous acceleration of urbanization, the demand for urban construction is also increasing. In the current urban construction, a healthy city is an important indicator to regulate the quality of urban construction (16). According to statistics, about 60% of people will live in big cities by the middle of the 21st century. The increasing number of people in cities will bring many problems to urban construction, including environmental pollution, traffic jams, high unemployment,

TABLE 1 The urban environmental health evaluation system of the WHO and the CRSUD.

Organization	First-level indicator	Secondary indicators
WHO	Industry (W1)	Air pollution (W11)
		Water quality (W12)
		Sewage treatment rate (W13)
	Life (W2)	Domestic garbage collection (W21)
		Domestic waste disposal (W22)
	Construction (W3)	Green space coverage (W31)
		Green space accessibility (W32)
		Vacant industrial land (W33)
	Infrastructure (W4)	Sports and leisure facilities (W41)
		Sidewalk (W42)
		Bicycle lane (W43)
	Public works (W5)	Public transit (W51)
		Coverage of the public transport network (W52)
		Living space (W53)
China Urban Development Research Association	Basic environment (W1)	Air quality compliance days (W11)
		Centralized treatment rate of urban sewage (W12)
		Harmless treatment rate of domestic waste (W13)
		Greening rate of built-up area (W14)
		Urban population density (W15)
	Cultural environment (W2)	The number of theaters and theaters per square kilometer in the urban area (W21)
		The total number of books in public libraries per thousand people (W23)
		Internet penetration (W23)
	Social conditions (W3)	Number of medical institutions per square kilometer in urban areas (W31)
		Hospital and health care beds per 1,000 people (W32)
		Number of practicing (assistant) physicians per thousand people (W33)
		Number of people insured by basic medical insurance (W34)

and housing shortages (17). These problems can affect the progress of urban construction, the final quality, and the health of residents. Therefore, in the current urban construction, a healthy city has also become one of the main goals of urban construction (18).

The healthy city is the concept of urban construction proposed by the WHO at the end of the 20th century. A healthy city mainly refers to the three main factors of urban construction to meet residents' health, environmental health, and social health. In the construction of a healthy city, the realization of these three goals may be in line with the construction of a healthy city. The specific operation is to improve residents' health, improve the urban environment's condition, and optimize the utilization of social resources (19). Healthy residents are urban residents who are in a healthy state. A healthy urban environment refers to the environment in the city that can ensure the healthy life of urban residents. It guarantees the physical and psychological healthy living needs of urban residents. Healthy social resources refer to the rational use of social resources to ensure urban residents' healthy life and development (20).

Based on the above theories, a healthy digital city is a new type built by combining digital and healthy city concepts. A healthy digital city can satisfy the digital development of the city, improve the effect of urban development and the efficiency of management, and provide support for the healthy development of the city.

Analysis of the role of environmental health

Environmental health is an important indicator for building healthy cities. Environmental health refers to ensuring the healthy growth of urban residents in urban construction. The urban environmental health evaluation method has five aspects to the standard proposed by the WHO. In the China Research Society of Urban Development (CRSUD), the evaluation of environmental health is different (21). Table 1 shows the urban environmental health evaluation system of the WHO and the CRSUD (22).

From Table 1, the WHO has proposed an evaluation system for environmental health in healthy cities, similar to the environmental health evaluation system proposed by the CRSUD. However, the evaluation system of the WHO mainly includes the basic environmental evaluation of the city. The evaluation system proposed by the CRSUD contains comprehensive contents (23). The ultimate goal of these evaluations is to provide references for building a healthy urban environment, thereby providing important support for the healthy life of urban residents.

Urban community public health safety emergency management and nursing insurance service under environmental health

The urban community is the smallest unit of urban management and an important object in urban construction. The concept of urban residents' autonomy can be well realized based on the urban community (24). Public health security emergency management and mutual insurance services are serious problems facing urban communities. These problems will cause damage to the health of the urban environment and affect the health of residents. Public health security directly affects the health of residents, and it has the characteristics of great harm, poor controllability, poor persistence, and high complexity (25). As a result, the response to public health events should not be limited to the field of public health, and the causes of events and the particularity of their hazards should be comprehensively analyzed. Based on this, targeted emergency management work is conducted to minimize the impact of public health emergencies on the country, society, and individuals, ensure the safety of human life and property, and maintain social stability and harmonious development (26).

Emergency management refers to a series of management activities to ensure public safety, control the situation, and reduce losses when a public emergency occurs (27). Community emergency management capability is one of the essential modules of the government's public management system. Improving community emergency management capacity is critical to improving government administrative capacity. It is also an indispensable and important guarantee to enhance the sense of urban security and improve people's happiness (28).

Nursing care insurance refers to insurance that provides compensation for the cost of nursing services for those insureds who need long-term care due to old age, illness, or disability (29). With the continuous improvement of urbanization, the demand for nursing care insurance services is increasing rapidly. The needs for nursing services mainly include the nursing needs of the elderly, post-critical illnesses, and the disabled. Therefore, improving the quality of community nursing services to improve urban environmental health cannot be ignored (30).

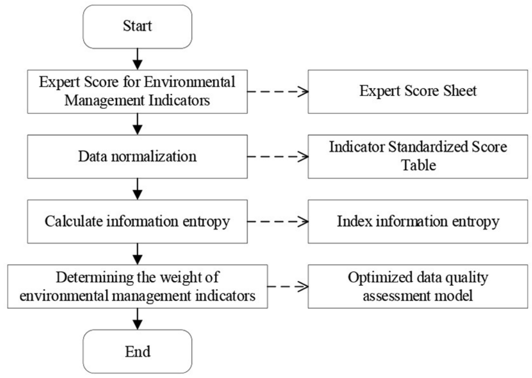

FIGURE 1
Community public health safety emergency management evaluation process.

TABLE 2 Questionnaire survey information.

Classification by	Classification	Number of people	Proportion (%)
Gender	Male	200	50
	Female	200	50
Age	18–30	92	23
	30–40	112	28
	40–50	124	31
	50–60	72	18

Based on the above discussion, community public health safety emergency management and nursing insurance service are two very important parts of the optimization of urban environmental health. Therefore, this paper designs and evaluates the current situation of community public health safety emergency management and nursing insurance service in the current urban environmental health optimization to provide a reference for future community public health safety emergency management and nursing insurance service optimization.

Community public health safety emergency management and nursing insurance service evaluation method

Based on the above theories, a comprehensive investigation and analysis of a community's urban environmental health transition are carried out. Research and analysis of the changes in community public health safety emergency management and nursing insurance services are also conducted. The specific

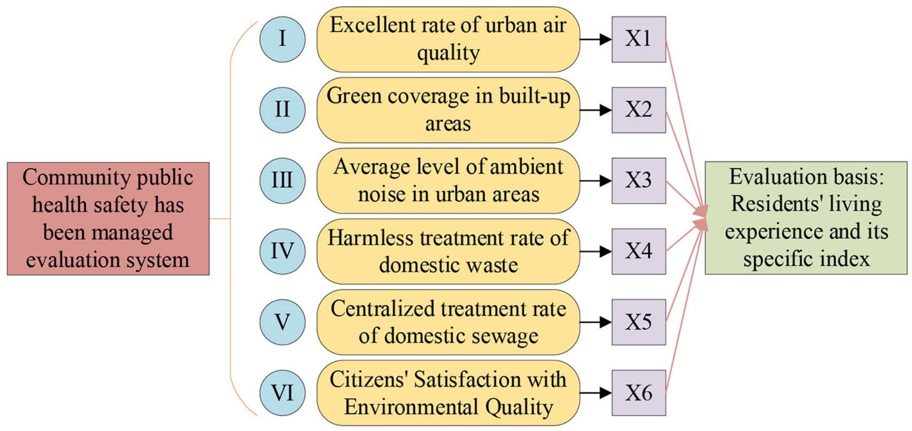

FIGURE 2
Basic information on urban environmental health assessment.

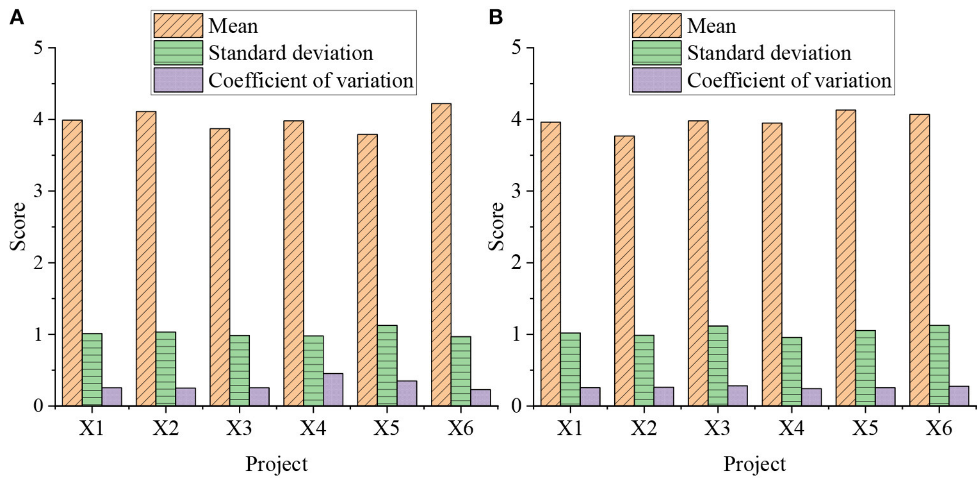

FIGURE 3
The specific parameters of the city's evaluation of each indicator in 2020 and 2021 [**(A)** is 2020; **(B)** is 2021].

methods used are the entropy weight method and questionnaire survey method. The entropy weight method research needs to determine the research object set as X, and its evaluation matrix is:

$$X = (X_{ij})_{n \times m} \tag{1}$$

In Equation (1), n represents the number of evaluation objects, and m represents the number of evaluation indicators. i and j mean the position of the evaluation object in the matrix (31). The data is standardized, and the positive indicator is processed according to Equation (2).

$$Z_{ij} = \frac{X_{ij} - X^i_{min}}{X^i_{max} - X^i_{min}} \tag{2}$$

In Equation (2), Z_{ij} represents the standard value, X^i_{min} represents the minimum value of the original data, and X^i_{max} represents the maximum value of the original data. Inverse indicator data can be processed according to Equation (3).

$$Z_{ij} = \frac{X^i_{max} - X_{ij}}{X^i_{max} - X^i_{min}} \tag{3}$$

Then, the weight of the data is calculated.

$$P_{ij} = Z_{ij} / \sum\nolimits_{i=1}^{m} Z_{ij} \tag{4}$$

All elements in the Equation (4) have the same meaning as the above equations. Then the entropy value of the data is calculated, and the calculation equation is:

$$e_j = -k \sum\nolimits_{i=1}^{m} (P_{ij} * \ln P_{ij}) \tag{5}$$

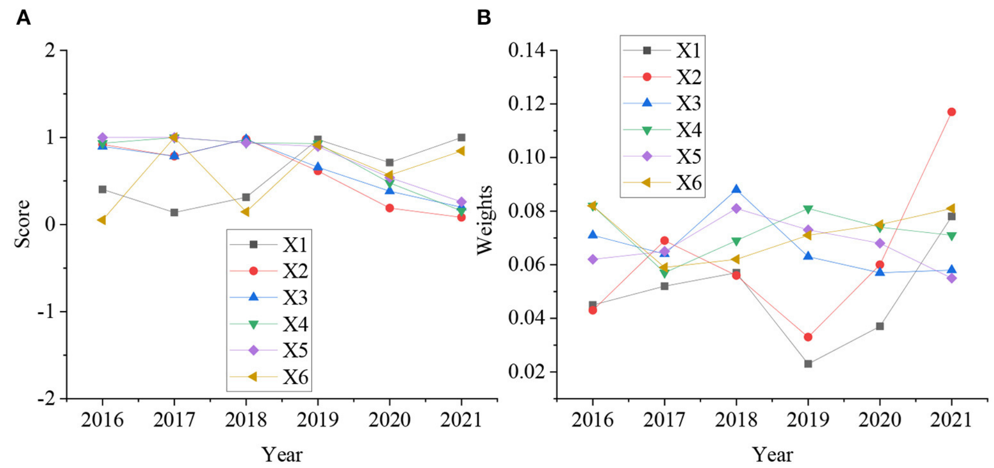

FIGURE 4
Evaluation results of urban environmental health scores and weights [**(A)** is environmental health assessment; **(B)** is environmental health weight].

In Equation (5), $k > 0$. Besides, the coefficient of variance is calculated for the data.

$$d_j = 1 - e_j \tag{6}$$

Finally, the weights of the data are calculated.

$$w_j = d_j / \sum_{j=1}^{n} d_j \tag{7}$$

Based on the above analysis, an investigation and evaluation of the urban environmental health status of a community is conducted. Then, through a questionnaire survey, the community public health safety emergency management and nursing insurance service status are investigated and evaluated (32, 33). Figure 1 shows the specific process of community public health safety management evaluation using the entropy weight method.

Figure 1 shows that this paper mainly evaluates the community public health safety emergency management system through the entropy weight method. Table 2 shows the specific content of the questionnaire survey method.

Table 2 shows that the surveys and evaluations of community users are based on gender and age. Age classification starts from 18 years old and conforms to the basic norms of the questionnaire. A total of 400 questionnaires are distributed, and 392 valid questionnaires are recovered, with an effective rate of 98%, which is in line with the norms of the questionnaire survey. Therefore, the research is valid. The subject of the questionnaire is to evaluate the public health security emergency management and nursing insurance services in the community.

The design evaluates the urban construction in which a community is located, mainly to investigate and evaluate the environmental health status of the digital healthy city. Among them, the environmental health assessment includes the assessment of urban infrastructure and services. The evaluation system is made according to the evaluation indicators of WHO and China Urban Development Research Association in Table 1, and constitutes six indicators X1–X6. They are the excellent rate of urban air quality, the green coverage rate in built-up areas, the average level of ambient noise in urban areas, the harmless treatment rate of domestic waste, the centralized treatment rate of domestic sewage, and the citizens' satisfaction with environmental quality. Figure 2 shows the basic information of a city's environmental health assessment.

Figure 2 shows that the research contents include the excellent rate of urban air quality, the green coverage rate in built-up areas, the average level of ambient noise in urban areas, the harmless treatment rate of domestic waste, the centralized treatment rate of domestic sewage, and the citizens' satisfaction with environmental quality. The main evaluation basis includes residents' feelings and specific parameters of various indicators. Based on the above basis, this paper conducts a comprehensive survey on the environmental health status of the city where a community is located. First, the changes of various indicators of the city are counted, and the statistical method is the coefficient of variation of the city's recognition of the indicator when it was formulated to determine the specific basis for the city's environmental health assessment.

Assessment of results

Digital health city environmental health assessment

Through the evaluation system established above, the current situation of community public health safety emergency management and nursing insurance services

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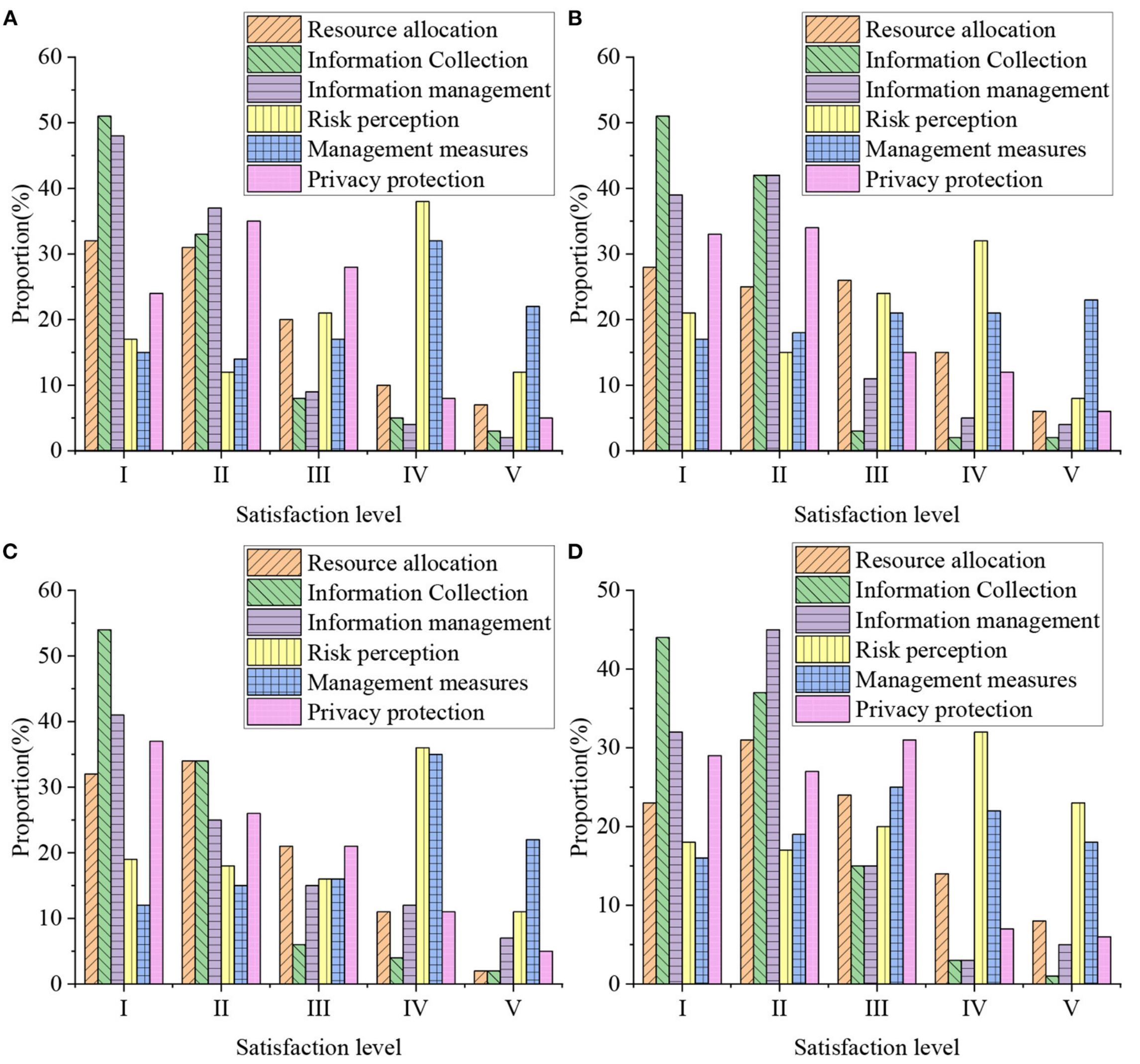

FIGURE 5
Evaluation results of community health and safety emergency management [**(A)** is 18–30 years old, **(B)** is 30–40 years old, **(C)** is 40–50 years old, and **(D)** is 50–60 years old].

is evaluated. Figure 3 shows the specific parameters of the city's evaluation of each indicator in 2020 and 2021.

Figure 3 shows that in the establishment of the urban environmental health assessment index, the average scores of the indicators such as the excellent and good rate of air quality in the urban area of the city in 2020 and 2021, the green coverage rate in built-up areas, the average level of ambient noise in urban areas, the harmless treatment rate of domestic waste, the centralized treatment rate of domestic sewage, and the citizens' satisfaction with environmental quality are all around 4 points. It shows that it is reasonable to evaluate the environmental health construction of the city through the excellent rate of urban air quality, the green coverage rate in built-up areas, the average level of ambient noise in urban areas, the harmless treatment rate of domestic waste, the centralized treatment rate of domestic sewage, and the citizens' satisfaction with environmental quality. Figure 4 shows the scoring and weight evaluation results of various indicators of the city.

From Figure 4, through the evaluation, it is found that the scores of X1 and X6 in the environmental health score of the city are relatively low between 2016 and 2018, below 0.5. The scores for the remaining 3 years are relatively high, above 0.5. The scores of X2, X3, X4, and X5 are relatively high from 2016 to 2018, above 0.5. The remaining 3 years are relatively low, below 0.5. The weights of all indicators are above 0.4 every year.

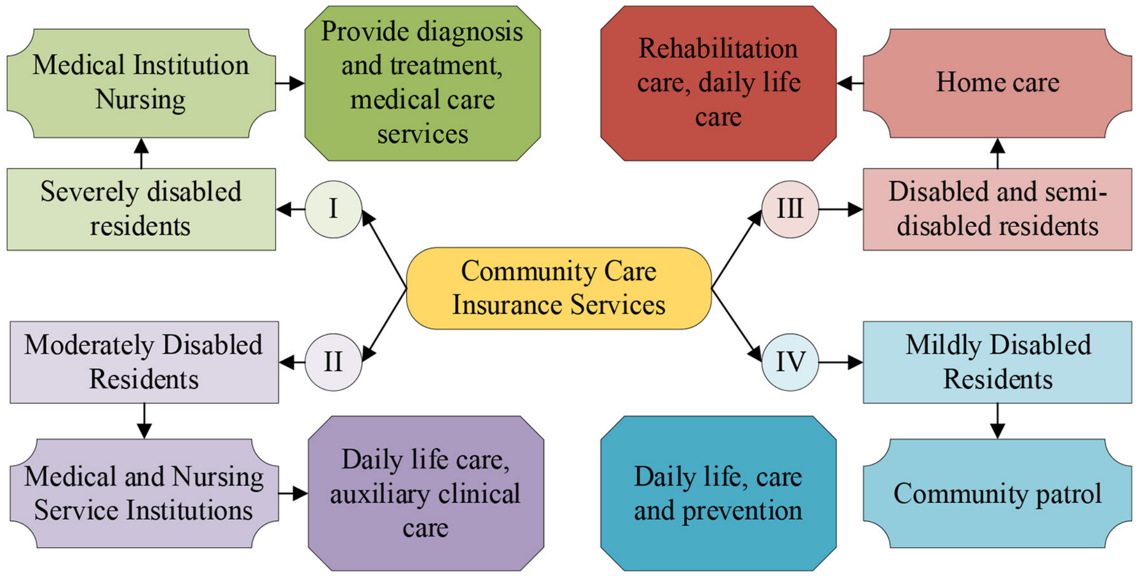

FIGURE 6
Optimal design of community nursing insurance services.

Community public health safety emergency management and nursing insurance service optimization evaluation

In terms of emergency management of social public health security, this paper mainly evaluates the management of the COVID-19. The main assessment is based on the emergency management situation during the disaster, including factors such as resource allocation, information collection, information management, risk perception, management measures, and privacy protection during the epidemic. Therefore, this paper conducts research and evaluation on the residents of a certain community based on this evidence through a questionnaire survey. The evaluation of the community's public health security emergency management status is mainly based on the residents' satisfaction, and then provides a reference for the optimization of community public health security emergency management. In the research, the user classification in Table 2 is mainly used as the standard to investigate and the current public satisfaction is evaluated. Figure 5 shows the results of the assessment of community health security emergency management.

In Figure 5, I–V represent very satisfied, satisfied, general, dissatisfied and very dissatisfied, respectively. In the evaluation of community public health security emergency management, residents are very satisfied with the information collection and information management in public health security emergency management, and the number of very satisfied people is basically more than 40%. Satisfaction with resource allocation and privacy management is high, and the number of very satisfied people is basically above 30%. However, the satisfaction with risk perception and management measures is very low, and the number of people who are very satisfied is basically below 20%. It indicates that at present, the optimization of public health safety management in this community needs to focus on risk perception and management measures. Meanwhile, it is necessary to strengthen the improvement and maintenance of other aspects.

Digital health city nursing insurance service optimization measures

Based on the optimization of community nursing insurance services, Figure 6 shows the optimized design of community nursing insurance services.

Figure 6 shows that, based on the survey of residents in this community, the current community nursing insurance service has not been fully established. Therefore, in order to optimize the nursing insurance service in this community, a more comprehensive community nursing insurance service design is proposed for the community. First, the groups of residents who need nursing insurance services are classified into four levels in total, namely severely disabled residents, moderately disabled residents, disabled and semi-disabled residents, and mildly disabled residents. And different community nursing insurance service projects and methods are designed for residents of different levels to provide a reference for the overall optimization of nursing insurance services in the community. Meanwhile, it also provides support for the overall community care insurance services in the city. As mentioned above, this paper comprehensively studies the current situation of public health emergency safety management and nursing insurance services in digital healthy urban communities, and conducts research on their optimization, thus providing an important reference for the construction and development of digital healthy cities across the country.

Conclusion

With the continuous development of urban construction, a digital healthy city has become an important goal of urban development. Therefore, in order to promote the development of healthy cities and improve the living conditions of urban residents, this paper first discusses the construction process of digital healthy cities. Secondly, the important role of environmental health in the improvement of residents' lives in digital health cities is discussed. Finally, through two methods, namely questionnaire survey and entropy weight method, research on environmental health and community public health security emergency management and community nursing insurance service in a city is designed. The research results show that the environmental health scores of X1 and X6 in the city were relatively low between 2016 and 2018, below 0.5, and the scores in the remaining 3 years were relatively high, above 0.5. The scores of X2, X3, X4, and X5 were relatively high from 2016 to 2018, above 0.5 points, and the remaining 3 years were relatively low, below 0.5 points. And the weight value of all indicators is above 0.4 every year. Residents are very satisfied with information collection and information management in public health and safety emergency management, and the number of very satisfied people is basically more than 40%. Satisfaction with resource allocation and privacy management is high, and the number of very satisfied people is basically above 30%. However, the satisfaction with risk perception and management measures is very low, and the number of very satisfied people is basically below 20%. Meanwhile, this paper also provides guidance on the emergency management of public health security in the urban community and the optimization of community nursing insurance services. Although a relatively comprehensive study of the environmental health status of a city, community public health emergency safety management and nursing insurance service status has been provided, and important guidance has been provided, the overall study of the city is not comprehensive enough. Therefore, in the future, the research scope will be expanded, and the construction of the public health security emergency safety management system in the process of digital city construction will be optimized to provide reference for the future construction of digital healthy cities.

Data availability statement

The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding authors.

Author contributions

GH and ZW: conceptualization, validation, and supervision. YD and GH: methodology, project administration, and funding acquisition. YL and SJ: software. YD and YL: formal analysis. SJ and GH: investigation. SJ and YT: resources. YT and GH: data curation. GH, ZW, and YD: writing—original draft preparation and writing—review and editing. YL: visualization. All authors contributed to the article and approved the submitted version.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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A topology-based evaluation of resilience on urban road networks against epidemic spread: Implications for COVID-19 responses

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Road closure is an effective measure to reduce mobility and prevent the spread of an epidemic in severe public health crises. For instance, during the peak waves of the global COVID-19 pandemic, many countries implemented road closure policies, such as the traffic-calming strategy in the UK. However, it is still not clear how such road closures, if used as a response to different modes of epidemic spreading, affect the resilient performance of large-scale road networks in terms of their efficiency and overall accessibility. In this paper, we propose a simulation-based approach to theoretically investigate two types of spreading mechanisms and evaluate the effectiveness of both static and dynamic response scenarios, including the sporadic epidemic spreading based on network topologies and trajectory-based spreading caused by superspreaders in megacities. The results showed that (1) the road network demonstrates comparatively worse resilient behavior under the trajectory-based spreading mode; (2) the road density and centrality order, as well as the network's regional geographical characteristics, can substantially alter the level of impacts and introduce heterogeneity into the recovery processes; and (3) the resilience lost under static recovery and dynamic recovery scenarios is 8.6 and 6.9%, respectively, which demonstrates the necessity of a dynamic response and the importance of making a systematic and strategic recovery plan. Policy and managerial implications are also discussed. This paper provides new insights for better managing the resilience of urban road networks against public health crises in the post-COVID era.

KEYWORDS

transport resilience, road networks, epidemic spreading, COVID-19, emergency management

1. Introduction

Since 2020, the global COVID-19 pandemic has not only triggered major shifts in city operations, but has also had a considerable impact on people's travel behaviors, as well as their abilities to work and their mental health (1–4). Many countries have adopted strict public health control measures to contain the spread of this unprecedented and highly infectious virus, such as travel restrictions, road closures, and social distancing. While road closures, for instance, are considered effective in isolating certain high-risk areas and communities so that the infectious spread may be quickly controlled, such "no access" restriction measures could substantially harm not only the local accessibility and road network connectivity but also many other unexpected aspects of our daily life. For example, a recent study on the impact of COVID-19 related "stay-at-home" restrictions on food prices in Europe showed that vegetable prices increased by 3.36% in the high restriction group compared to the low-restriction group (5). Despite the knowledge of the general impacts of the access control measures, there is still very little known about how those strict control measures, as responses to the various types of virus spreading, could affect the resilience performance of the road networks in megacities. More importantly, investigation on this topic might reveal useful implications for better preparing for the challenges in the post-COVID time.

The key theme this paper is focusing here is about the resilience of the urban road networks, and this topic has been extensively studied by many scholars, under the context of various types of natural and man-made disasters. However, studies on the resilience of urban road networks against infectious diseases have been relatively limited, which leads to a lack of knowledge on building resilient urban transportation systems in the context of emergency response management for public health crises. Such scarcity is even more prominent when considering various types of contagious spreading mechanisms including the sporadic and trajectory-based occurrence of the disease. The former refers to the cases that are scattered or are in a small cluster and separated in place so that little or no connection exists among them, and more importantly, those cases also do not show a recognizable common source. The latter is also known as the superspreader spreading mode. A superspreader is often considered an infected individual who has infected others disproportionately (6, 7). In this paper, we adopt the definition as those who infect many others along their trajectories of movement. Furthermore, from the perspective of quickly recovering the systemic serviceability in emergency responses, it is also not very clear how much dynamic recovery strategies outperform static recovery strategies under the two abovementioned spreading mechanisms. Addressing these unclear questions has both practical and managerial implications for a better urban management. As a result, the objectives of this paper can be summarized as follows.

1. To conduct an in-depth assessment of resilience on urban road networks against the two aforementioned epidemic spreading mechanisms and reveal their dissimilar negative effects in terms of the performance loss;
2. To perform comparative studies between the static and dynamic recovery strategies and quantitatively reveal the effectiveness and shortcomings in terms of the performance restoration.

To achieve the objectives, this paper conducts a simulation-based comparative investigation to understand the epidemic spreading and the recovery processes on urban road networks. Taking Beijing, China, as an illustrative case study, we used the classic susceptible-infectious-recovery (SIR) model and network analytics to simulate the *sporadic occurrence* and *trajectory-based occurrence*. Additionally, we comparatively analyze the performance of urban road networks under two recovery strategies, namely the *"First-Close-First-Reopen" (FCFR)* recovery strategy and the *dynamic* recovery strategy. The resilience, in terms of performance loss, from all cases is evaluated to quantitatively benchmark their heterogeneous effectiveness, which yields several critical implications for practical COVID-19 emergency responses in megacities. The main contributions of this paper can be summarized as following:

- This paper quantitatively measures the advantages of the dynamic road recovery strategy over the widely applied static one under the context of various epidemic spreading mechanisms, providing additional new evidence and insights for relevant decision makers and stakeholders.
- This study lays a foundation for better understanding the impacts of the emergency road closures (either temporary or permanent) on the efficiency of road networks, which is useful for local authorities to manage more efficient responses to future public health crises in urban emergency management.
- To the best of our knowledge, this paper is one of the earliest studies that discuss the superspreader spreading mechanism in the field of transportation resilience, which fills a clear gap for the development of the frontier.

The remainder of this paper is organized as follows: Section 2 reviews the state-of-the-art knowledge on two resilience-related topics, namely resilience assessment and infectious spreading on urban roads, and identifies and further clarifies the knowledge gaps and missing links. Section 3 describes the proposed simulation-based analytical approach and the applied methods, including details on two spreading mechanisms and two recovery strategies. Section 4 outlines the essential background information about the case study and data. Section 5 presents the main findings of this investigation. Then, Section 6 discusses and summarizes several managerial implications, followed by the conclusion and future research directions of the paper in Section 7.

2. Literature review

2.1. Assessment of resilience on urban road networks

The resilience of urban road networks is crucial to the operation of modern cities, especially when disruptions occur and prompt responses are needed. This particular stream of research occupies a large share of the resilience-related fields in infrastructure studies. Many studies discussed the assessment of road network resilience against natural disasters such as earthquakes, floods, landslides, heavy snow, etc. For example, Aydin et al. (8) developed a method to assess the resilience of urban road networks under seismic hazards using graph theory and stress testing methods, and Zhou et al. (9) studied the connectivity of post-earthquake road networks by using percolation based method. Gao et al. (10) used the Bayesian network (BN) as a modeling tool to assess road network resilience and component importance under different earthquake magnitudes, which showed that the higher the earthquake level is, the lower the system resilience. Morelli and Cunha (11) proposed a novel method for measuring urban road resilience against floods based on travel distribution, and Zhang et al. (12) quantitatively assessed the vulnerability and resilience of urban traffic under different rainfall intensities. Aside from those previous examples focusing on single events, some scholars approached the issue from the perspective of multiple hazards. Der Sarkissian et al. (13) assessed road resilience to different natural hazards with a developed network analytic method and Zhou et al. (14) developed a novel two-layer framework to assess the robustness of transportation networks considering multiple hazard events. Additionally, there are many studies on the resilience of road networks, readers can refer to some recent studies in this field such as Zhou et al. (15) and Serdar et al. (16).

From the above, resilience assessment highly hinges on different scenarios, causing difficulties in simulation-oriented studies. Recovery modeling and simulation on different infrastructure networks, such as interdependent utility networks and electric power networks, have been not uncommon in the relevant fields (17–23). For example, Li et al. (24) simulated the effect of road closures caused by pluvial flash floods in multiple scenarios with a GIS-based model. Wang and Liu (25) proposed a mathematical model for measuring the recovery of urban road networks in snow events and established snow removal resource location and allocation optimization models to resolve the issue. In addition, some studies also introduced other methods to discuss the simulation recovery on road networks. For instance, Vodák et al. (26) introduced a modified ant colony optimization algorithm to study the recovery process of road networks after disasters, which can be used for planning construction work when damage occurs. Zhan et al. (27) employed traffic congestion on road networks as a case study and proposed a new framework for modeling the evolution of functional failures and recoveries in complex road networks. Sohouenou and Neves (28) compared the effects of several link-repair strategies on road network resilience across a multitude of perturbation scenarios and analyzed the characteristics of the optimal recovery strategy. The findings showed that it was important to consider and model the recovery processes for critical disruption scenarios that affect a large number of links. In addition, Tang et al. (29) tested the effect of different sensor recovery schedules on the resilience of traffic-sensor networks through the analysis of the spatial-temporal vehicle patterns in Cambridge, UK. The simulation results suggested that a prioritized sensor maintenance recovery plan would enable more efficient use of public resources.

2.2. Infectious spreading on urban roads

The spread of infectious diseases has had great impacts on the public health and transportation sectors and thus, has been well-documented in many previous studies (30–33). The rapid development of the urban built environment and transportation infrastructure can facilitate the spread of infectious diseases and amplify their scale (34). For years, numerous efforts have been dedicated to building models for studying infectious diseases in public transportation systems. For example, Qian and Ukkusuri (21) developed a novel Trans-SEIR modeling approach to connect urban transportation systems with the spread of infectious diseases. The results can guide the optimal placement of entrance control over the public transportation system, such as buses and metros, and thus, help to mitigate the risks of infectious diseases. Mo et al. (35) proposed a time-varying weighted public transit (TWPT) encounter network to model disease spreading through transit systems, considering social activity contacts at both local and global levels. The results showed that early identification and isolation of infected passengers can effectively reduce the spread. Using the susceptible-or-infected (SI) and susceptible-infected-recovery (SIR) models, Chatterjee et al. (36) studied the dynamic process of epidemic outbreaks and information diffusion on urban bus networks in six Indian cities. They discovered that the characteristic path length is vital for information diffusion and epidemic spreading. In addition, Zhang et al. (37) analyzed the transmission mechanism of the COVID-19 epidemic along traffic routes based on population migration, using an improved SEIR model.

Moreover, a few studies have also addressed the relationship between transportation systems and several specific diseases such as dengue and tuberculosis. Li et al. (38) studied the spatial and temporal changes in dengue spread and its spatial relationship with road networks in southern Chinese cities. Their results indicated that cases were concentrated near narrow roads and that the epidemic spread mainly along high-density road network areas, which partially explains the underlying mechanism of the occurrence of sporadic epidemic hotspots during the early spreading stage. Ge et al. (39) examined the association between tuberculosis (TB) incidence and four types of transportation networks at the provincial level, identifying spatial clusters of TB incidence linked with transportation networks in different regions. COVID-19 has been a popular research focus in transportation studies in recent years (40, 41). Among them, analyzing the control measures and policy implications is of great value for the transportation sector (42, 43). For instance, Zhou et al. (44) studied the impact of different entry restriction policies on international air transport connectivity during COVID-19 and Zhou et al. (45) proposed a layered weighted network efficiency (LWNE) metric to study the vulnerability of the worldwide air transportation network in response to different levels of disruptions. Anke et al. (46) investigated the impact of SARS-CoV-2 on mobility behavior and found a profound impact on mobility behavior with decreases in public transport and increases in car usage, walking and cycling. Furthermore, they also found that lockdown in the behavioral changes was minimal, which suggested isolated differences between policies with and without lockdown. Readers can also refer to further studies about infectious spreading on various transportation systems at different scales, including studies by Muley et al. (47), Kutela et al. (48), Choi (49), Hu et al. (50), Zhao et al. (51), and Severo et al. (52).

2.3. Research gap

From the above review, we found that recovery simulation of road networks, including many other types of infrastructure networks, based on different scenarios have been discussed extensively. All of them have substantially contributed to how we might effectively assess the resilience of urban road networks, optimize their recovery, and reveal the spreading mechanism of infectious diseases on urban transportation infrastructure. However, studies on recovery simulations of road closures in the context of public health crises, such as COVID-19 on road networks, with a good comparative analysis between static recovery strategies and dynamic recovery strategies are still needed. As stated in the previous section, we address this gap with two clear objectives in this paper.

3. Methodology

3.1. The analytical framework and basic assumptions

Figure 1 depicts the proposed simulation-based analytical framework that realizes the hybrid process of virus spread and policy interventions with a given road network (because most of the roads in the study area are dual-way roads, we therefore construct the network model as undirected). We design two spreading mechanisms (i.e., sporadic spreading and trajectory-based spreading) and two recovery strategies (i.e., static and dynamic recovery strategies) to simulate the spreading of infectious diseases and the recovery process of the network. Finally, we obtain the network performance profiles based on simulation outcomes and quantify the effectiveness of these two recovery strategies on road network resilience under different spreading mechanisms. Several basic, yet essential, assumptions should be presented as the prerequisites and cornerstones for the analysis.

1. ***In the simulation, we assume that all spreadings follow the topology of the road networks with a 100% infection rate.*** This is based on the fact that a contagious disease spreads among populations due to intensive human mobility activities, and human mobility often hinges on the urban road topology. The discussion of (1) the actual spreading pathways from one individual to another and (2) the effect of dynamic population changes on epidemic spreading are not in our scope.
2. ***Unlike many previous studies, the affected objects in the simulations are not individual human beings or acting agents but road segments.*** The infected road segments are assumed to be disconnected from the road networks. That is, once a confirmed positive case is identified along a particular road segment or in the community that is adjacent to a road segment, this segment is assumed infected, and as a response, this road segment is closed by the local government immediately; in other words, it is removed immediately from the network's accessibility due to its disconnection. Although this is a very strong assumption based on the "All-or-Nothing" principle (i.e., it is either full access or no access at all, limited or time-variant access is not considered), in real world practice, it is considered acceptable and realistic. For instance, for several countries that implement strict control policies, such as China, once a confirmed case is identified, the whole vicinity and community will be isolated and closed for full-screen sanitization, and thus, the roads around that area will be closed. Even in a less strict situation, if the vicinity is not completely isolated, people would still deliberately avoid those roads as soon as they know that there is a high risk of being infected around that particular vicinity, which is also roughly equivalent to road closure from a holistic perspective.

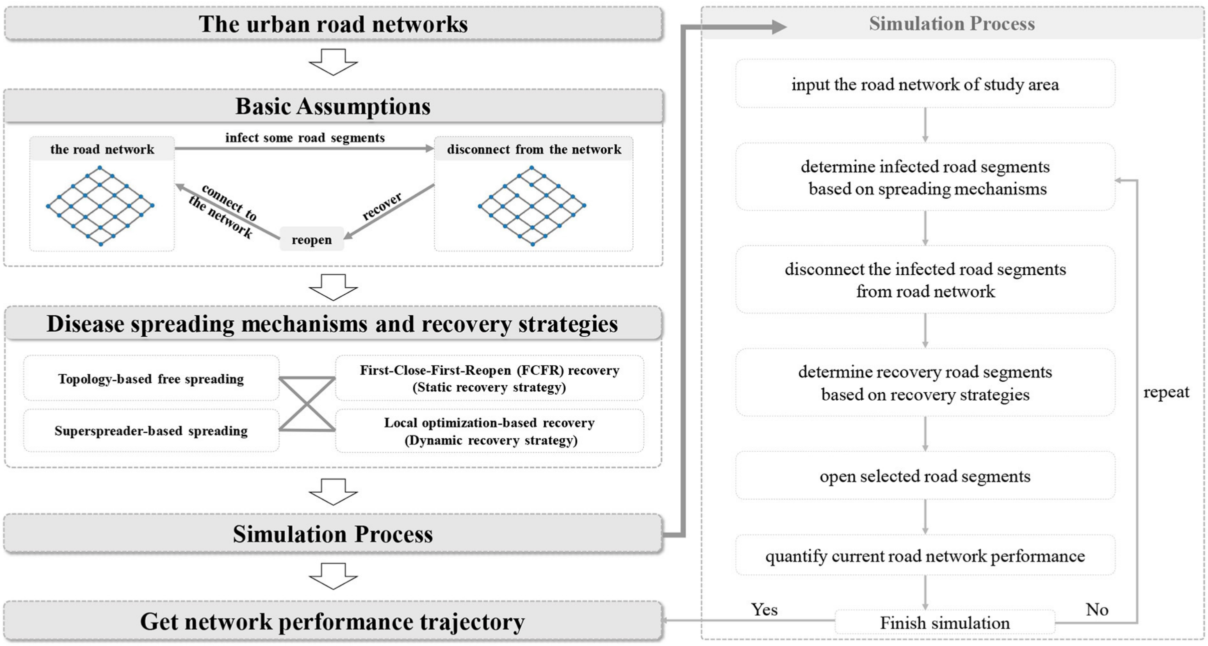

FIGURE 1
The proposed simulation-based analytical framework.

3. ***Disconnected road segments are assumed to be able to "reopen" after being treated with thorough sanitization or being identified as low-risk areas following restricted inspections (as an analog to the term "recover" in the typical failure-recovery paradigm)***. Moreover, in contrast to many previous studies assuming that recovery only starts after the completion of attacks/failures/removals, we let both the processes of closures and reopening happen simultaneously at each time step to simulate more realistic actions delivered by a city's emergency response team. In addition, we also assume that each road segment only experiences one closure in one round of simulation, i.e., we do not consider reinfections within those already-reopened segments.
4. ***Two types of spreading mechanisms are considered in this study, namely, the sporadic spreading mode and the trajectory-based spreading mode***. We assume that the former follows edge betweenness centrality and the latter has a certain associated infection range. Based on the previous study from Li et al. (38) and Tantrakarnapa et al. (53), the former spreading mode considers that the disease might sporadically occur at those highly populated spots where the density of roads and edge betweenness centrality are high, while the latter one mimics the negative impacts from superspreaders where the roads adjacent to (or within a certain range of) his or her trajectory will be considered high-risk areas that are very likely to be infected as well. Solid examples supporting this assumption in real world events can be found. For example, in January 2021, a super-spreader in Jilin Province, China, was identified to have had close contact with ∼140 other individuals (54) and most of them later became confirmed positive cases, which directly incurred a city-level emergency response, including massive road closures and large-scale screening and testing. Super-spreaders may have no symptoms or slight symptoms, but they are highly infectious and unpredictable, i.e., scholars have dedicated considerable effort to decoding its fundamental mechanism, yet it still remains unclear (55).
5. ***The risk of infectious disease spreading based on a topological road network considers the following three scenarios:*** (1) all roads are assumed to be pedestrian accessible; (2) the commuting mode of super-spreaders on the road network could be both public transport trips or private car trips. The former may generate risks due to direct contact with other passengers. The latter may exacerbate risks due to random stops, such as staying at service stations and waiting at toll booths.

3.2. Road network performance

As mentioned in the literature review, various methods have been applied for road network performance quantification (56–59). Related topics are also popular in the field. In this study, one of the network connectivity indicators, network efficiency, is used to compute the network performance at each time step, as it is a well-defined indicator that considers both the network topology and the connection situation, which can directly link to the performance of the mobility flows on road networks. The network efficiency of the current road network G is defined in Equation (1). The equation computes the average reciprocal nearest distance among all the junction pairs in the network. As seen, the shorter the distance between nodes i and j is, the larger the network efficiency, and therefore, the better the connectivity of the road network.

$$E(G,t) = \frac{1}{n(n-1)} \sum_{i \neq j \in G(t)} \frac{1}{d(i,j)} \tag{1}$$

where $E(G,t)$ is the network efficiency of network G at time t. $d(i,j)$ is the shortest distance between nodes i and j in the network structure at time t. n is the total number of nodes in network G.

To facilitate multilateral comparison and the calculation of the resilience in the later stages, we normalize the network efficiency to ensure that the initial network performance before any edge removals starts from 1 (i.e., 100% efficiency). The normalized network efficiency is determined by Equation (2), where $E(G,0)$ is the initial network efficiency of network G.

$$\overline{E}(G,t) = \frac{E(G,t)}{E(G,0)} \tag{2}$$

3.3. Disease spreading mechanisms for simulations

3.3.1. Sporadic spreading mode

The sporadic spreading mode considers that the infectious may sporadically occur at populated locations with high edge betweenness. In network theory, the edge betweenness centrality strongly indicates the centrality of each edge based on the shortest paths in all possible origin-destination (OD) pairs and describes the probability that an edge may be frequently passed by the OD movements, which on road networks indicates frequent traveler visits. Therefore, the betweenness-based propagation intuitively shows that crowded places have a higher infection probability (53). The edge betweenness centrality can be defined as Equation (3). Among all the shortest paths between all OD pairs on the road network, the more paths that pass the edge, the higher betweenness centrality the edge possesses.

$$B(e) = \sum_{s \neq t} \frac{\sigma_{s,t}(e)}{\sigma_{s,t}} \tag{3}$$

where $s,t \in V$ and V is the set of vertices in the network. $\sigma_(s,t)$ is the total number of shortest paths among s and t. $\sigma_{s,t}(e)$ is the total number of shortest paths from s, t pairs that pass edge e.

At each time step in this spreading mode, the road edges with top $s(t)$ betweenness centrality values are set as infected. The betweenness centrality was recomputed at each time step to fully consider the dynamic influence of virus spread and updates of epidemic control policies. The spreading process is illustrated in Figure 2 by a grid network when the spreading speed is 1 edge/time step. At each time step, the edge with the highest betweenness centrality is identified as infected and therefore closed, which means this edge is removed from the network. Next, the betweenness centrality value of each edge is recomputed. The betweenness centrality value of each edge dynamically changes as the time step proceeds.

For the betweenness-based spreading mode, it is also essential to determine the spreading speed at each time step. Here, we select the most classic and widely applied SIR model. A typical SIR model can be depicted as Equations (4)–(6). For the basic theoretical implementation of this model, please refer to Hethcote (60) and Newman (61). This model describes the important temporal relationship among three groups during the epidemic propagation process, i.e., the susceptible group, the infected group, and the removed group (62). In this study, S indicates the group of edges that are susceptible to the virus in time step t. The number $S(0)$, however, is smaller than the total number of edges in the graph to mimic the typical characteristics in the sporadic spreading mode. The variable I indicates the group of infected edges in time step t. The variable R indicates the group of recovered edges at time step t. $R(0)$ equals 0 since no edge is reopened at the beginning of the propagation process.

$$\frac{\mathrm{d}S(t)}{\mathrm{d}t} = -aS(t)I(t) \tag{4}$$

$$\frac{\mathrm{d}I(t)}{\mathrm{d}t} = aS(t)I(t) - bI(t) \tag{5}$$

$$\frac{\mathrm{d}R(t)}{\mathrm{d}t} = bI(t) \tag{6}$$

where S is the number of susceptible edges, I is the number of infected edges, and R is the number of reopened edges. a and b are two real, positive constant parameters used to control the model.

Based on the SIR model, the spreading speed at each time step can be inferred by Equation (7). The spreading speed equals the total number of infected and reopened road segments at time step t minus that of the last time step $t-1$.

$$s(t) = I(t) + R(t) - I(t-1) - R(t-1) \tag{7}$$

where $s(t)$ is the propagation speed at time step t. Correspondingly, the recovery speed $r(t)$ at each time step can

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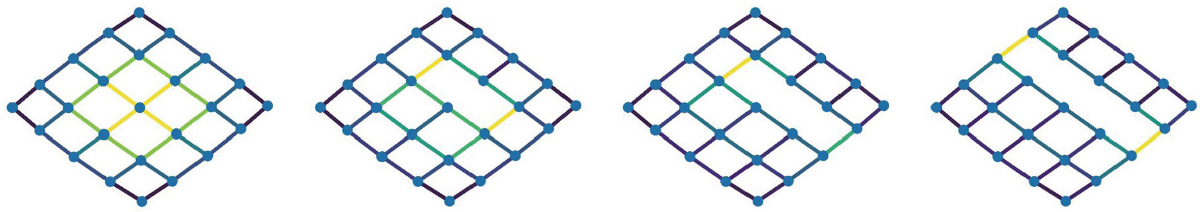

FIGURE 2
Network topology-based free spread model illustration (yellow: infected edge; green: travel path).

be determined based on the time differences of the total number of removed edges.

$$r(t) = R(t) - R(t-1) \quad (8)$$

3.3.2. Trajectory-based spreading mode

This mode is defined as the superspreader spreading mode in this paper. Super spread events have drawn increasingly high public attention in recent years (63). In this spreading mode, a superspreader's traveling path is first defined by assuming he or she would always go for the shortest distance to the destination (for simulating a shortest-path-based trip chain in daily commuting behaviors) and travel along this path with a predefined constant speed. At each time step, the surrounding road edges within a predefined given radius of the vicinity are identified to be high-risk segments that local authorities would close to prevent further cascading spreading, which might be caused by this particular superspreader in a worst case emergency response plan. Therefore, the spreading speed $s(t)$ is coupled with and determined by the superspreader's traveling speed and vicinal road density (i.e., the faster the traveling speed and the higher the vicinal road density are, the more road segments might be infected and then closed at each time step).

Figure 3 illustrates the mechanism of the trajectory-based spreading mode when a superspreader travels from the bottom corner to the middle of the grid. For a better visualization, the infected (closed) road segments are colored rather than removed. The green lines indicate the superspreader's travel path, and the yellow lines denote the closed vicinal road segments. The breadth first search algorithm proposed by Eppstein (64) is used to determine the vicinal road segments at each time step in this set of simulations.

3.4. Recovery strategies

3.4.1. First-close-first-reopen (FCFR) recovery (static recovery strategy)

The FCFR strategy, a common practice of recovery and maintenance schemes in previous studies and real world practices, is used as the benchmark for comparative analyses. As self-explained, this recovery strategy reopens the closed road segments based on their infection sequence; the first closed road segment will be treated and reopened first in the recovery process. Figure 4 shows an illustration of such a recovery process given the spreading mode from Figure 2. Although FCFR is the most widely applied and intuitive response principle in emergency events, it is obviously not a proactive approach as it does not dynamically consider the influence of the reopened road segment on the rest of the closed roads or the changes in the overall network performance. Thus, we refer to the FCFR recovery strategy as the static strategy here in this study.

3.4.2. Local optimization-based recovery (dynamic recovery strategy)

Given that the infections occurring on the road network follow either the spreading mode of Figure 2 or Figure 3, finding the global optimal reopening sequence of those closed segments is a nondeterministic polynomial (NP) problem. Especially as the number of infected edges increases, the complexity of this problem exponentially increased due to the increased number of combinations and system functionality quantification (65). Moreover, when the future propagation process remains unknown, making the global optimal recovery decision in the current time step is even more difficult. To ensure the simulations are both practically and computationally approachable, using the local optimization as the decision principle could be a simplified yet very feasible solution here. In this study, the dynamic recovery strategy is defined as reopening the road edges that can maximally improve current network performance (i.e., the network efficiency) compared to the last time step (Equation 9). Figure 5 illustrates the process of the local optimization-based dynamic recovery strategy when the reopening speed is 1 edge/time step.

$$argmax[p(t+1|a_i) - p(t)] \quad (9)$$

where $p(t)$ is the network performance at time step t, which is the efficiency in this paper (cross-referencing Equation 2),

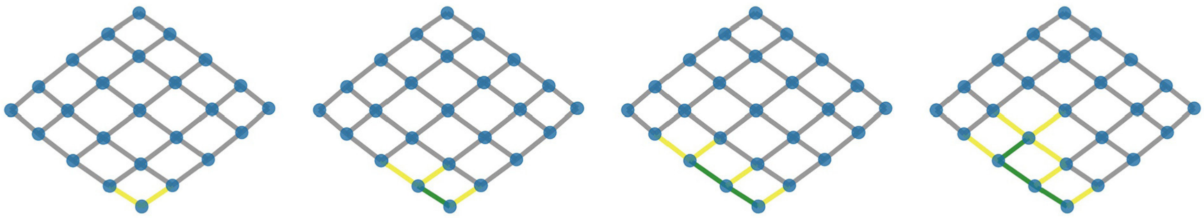

FIGURE 3
Trajectory-based cascading spread model illustration (yellow: infected edge; green: travel path).

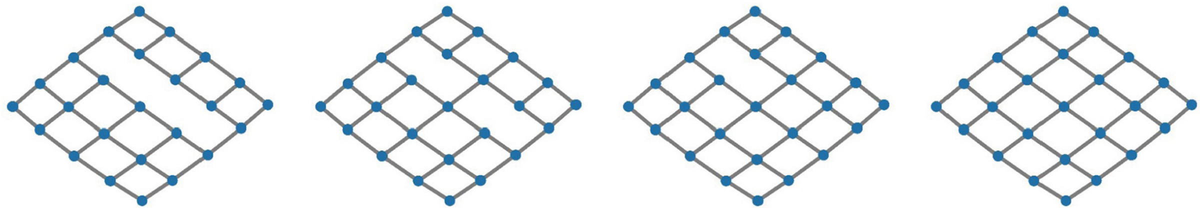

FIGURE 4
Trajectory-based cascading spread model illustration (yellow: infected edge; green: travel path).

$p(t+1|a_i)$ is the network performance at time step $t+1$ after reopening the road segment a_i, and *argmax* indicates that the optimization function is to find the best argument a_i that provides the maximum value from the function.

3.5. Simulation settings and pseudo codes

It has been proven that minor access roads play critical roles in maintaining the overall accessibility of road networks. Thus, we do not trim off those short and minor access roads in the selected network to simplify the topology for levitating computational burdens. In this vein, to facilitate the computation and ease the intense load, parallel computing and memory control processing techniques have been used in the iterative computations of the network efficiency in all simulations. The computing process is modified by the Python package, *Networkx* (64).

Two scenarios based on spreading mechanisms are simulated separately in this study to illustrate the influences of different emergency responses. Both recovery strategies are applied to these scenarios. Figure 6 represents the pseudocode for the sporadic spreading case, where the disease spreading speed and road reopening speed are determined by the SIR model. Hence, the input requires the road network information, the parameters from the SIR model, and the recovery strategy. The output is the resultant network performance which is quantified by Equation (1) at each time step.

Figure 7 represents the pseudocode of the trajectory-based spreading simulations. The input requires the road network information, the recovery strategy, and a predefined trajectory path of the superspreader. The spreader is assumed to travel along the trajectory with a fixed traveling speed. At each time step, the location of the traveler along the trajectory is used to identify the vicinal road segments within a given range. Here, this range is set as within N segments, i.e., all segments that can reach the current superspreaders location within the distance of N linked road segments. Hence, the number of total infected road segments predominantly hinges on the local road density. In contrast to the first scenario, the reopening speed of the trajectory-based spreading simulations is set as a constant for the purpose of simplification and later for comparative analysis.

4. Case study

Beijing, the capital city of China, was selected as an illustrative case study here. It is known as a representative megacity and ranked as one of the top 10 cities in the 2021 Global Cities Index (66). As a high-density megacity and an important hub of the Beijing-Tianjin-Hebei agglomeration, Beijing had a large population of 21.89 million permanent residents in 2020 and an unparalleled annual traffic volume (67). A virus outbreak in Beijing would lead to severe impacts on the management of urban operations and people's travel behaviors (68). However,

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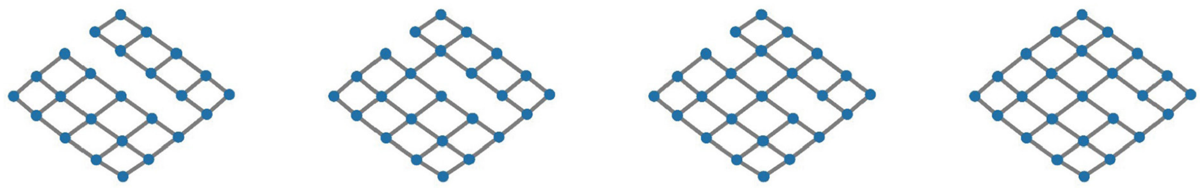
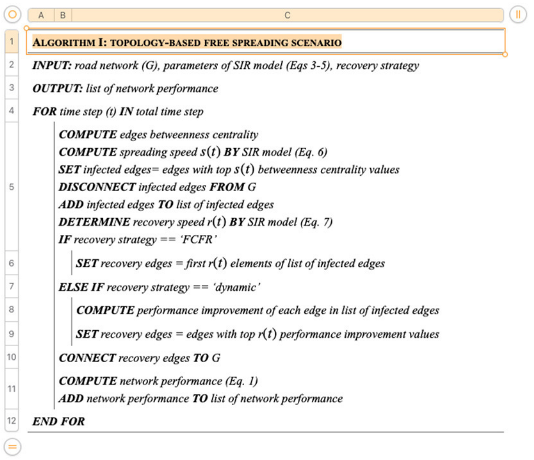


FIGURE 5
Illustration of the local optimization-based recovery process.



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ALGORITHM I: TOPOLOGY-BASED FREE SPREADING SCENARIO
INPUT: road network (G), parameters of SIR model (Eqs 3-5), recovery strategy
OUTPUT: list of network performance
FOR time step (t) IN total time step
    COMPUTE edges betweenness centrality
    COMPUTE spreading speed s(t) BY SIR model (Eq. 6)
    SET infected edges= edges with top s(t) betweenness centrality values
    DISCONNECT infected edges FROM G
    ADD infected edges TO list of infected edges
    DETERMINE recovery speed r(t) BY SIR model (Eq. 7)
    IF recovery strategy == 'FCFR'
        SET recovery edges = first r(t) elements of list of infected edges
    ELSE IF recovery strategy == 'dynamic'
        COMPUTE performance improvement of each edge in list of infected edges
        SET recovery edges = edges with top r(t) performance improvement values
    CONNECT recovery edges TO G
    COMPUTE network performance (Eq. 1)
    ADD network performance TO list of network performance
END FOR
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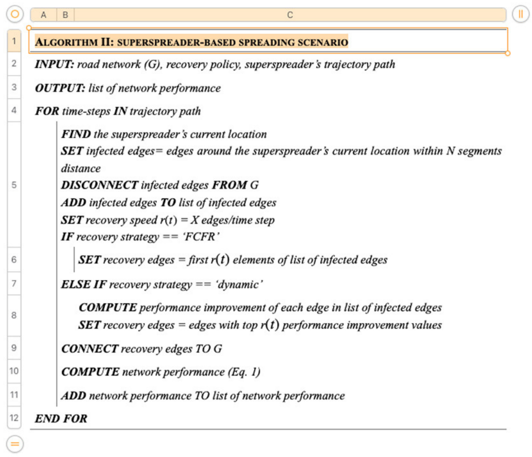
FIGURE 6
Algorithm I: Sporadic spreading scenario.



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ALGORITHM II: SUPERSPREADER-BASED SPREADING SCENARIO
INPUT: road network (G), recovery policy, superspreader's trajectory path
OUTPUT: list of network performance
FOR time-steps IN trajectory path
    FIND the superspreader's current location
    SET infected edges= edges around the superspreader's current location within N segments
    distance
    DISCONNECT infected edges FROM G
    ADD infected edges TO list of infected edges
    SET recovery speed r(t) = X edges/time step
    IF recovery strategy == 'FCFR'
        SET recovery edges = first r(t) elements of list of infected edges
    ELSE IF recovery strategy == 'dynamic'
        COMPUTE performance improvement of each edge in list of infected edges
        SET recovery edges = edges with top r(t) performance improvement values
    CONNECT recovery edges TO G
    COMPUTE network performance (Eq. 1)
    ADD network performance TO list of network performance
END FOR
```

FIGURE 7
Algorithm II: Trajectory-based spreading scenario.

Beijing suffered second wave of COVID spread in 2020, and there was no local transmission within 56 consecutive days under extremely strict control measures (69). Therefore, it is of practical importance to take Beijing as a case study to investigate how megacities should respond to the spread of the virus and learn from it. Here, the study area is confined within the inner third-ring road of Beijing (Figure 8). This study area covers the very core of its massive road network, including 16,008 junction nodes, 22,062 road segments, and a total road length of ~2,300 km.

Figure 9 shows the descriptive analysis of the road network statistics. Figure 9A indicates the edges' betweenness centrality values when all the road segments are functional. The road segments with higher betweenness centrality are shown in red, where we can clearly see that those high-betweenness edges are concentrated around the center of the study area and are mainly trunk roads or major urban streets. Figure 9B displays the degree distribution of the nodes; most of the nodes have a degree of 3, which often represents a "T" shape junction in the topology (a node with degree 4 represents a normal four-way intersection), and this number is in line with the findings from previous studies. A few nodes' degree is larger than 4, which may be caused by the extra ramps on highways or roundabouts. From the road edge length distribution (Figure 9C), it is clear that most of the road segment lengths are <500 m, and a few road segments have lengths of over 1,000 m.

5. Results

5.1. Sporadic spreading scenario

From the methodology, we utilize the SIR model to determine the spreading speed $s(t)$ and recovering speed $r(t)$ in this simulation scenario. Two parameters that control the SIR model, the infection rate a and recovery rate b, are selected from Cooper et al. (70) to imitate a real pandemic spreading process. The number of susceptible road segments is set as 1,000, which accounts for ~4.5% of the total road segments. a and b in Equations (3)–(5) are set as 0.35 and 0.035 based on the referred study (we reproduced the SIR simulation strictly following the instructions in the paper. Readers can refer to it for more details on the SIR model

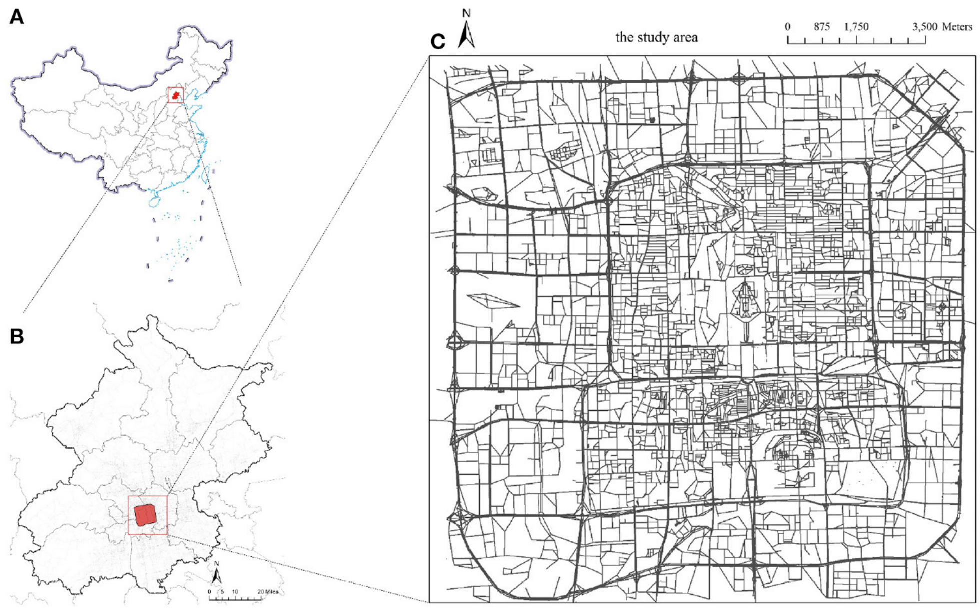

FIGURE 8
The study area. **(A)** China. **(B)** Beijing. **(C)** The study area.

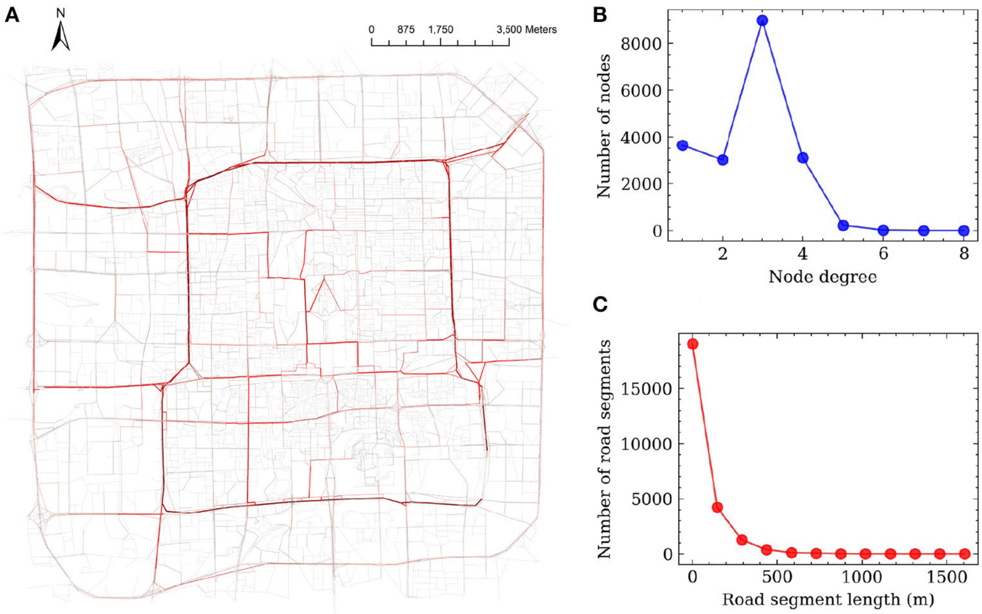

FIGURE 9
Node degree distribution of Beijing Road network. **(A)** Betweenness centrality degree. **(B)** Node degree distribution. **(C)** Road length distribution.

construction and simulation settings). The time-dependent evolving processes of the susceptible group, infected group, and reopened group are shown in Figure 10A. The results of the SIR model indicate that the number of susceptible road segments gradually decreases at the beginning as the disease begins to spread. After ∼5 time steps, the gradient of the curve of infected road segments increases, and a large portion of the susceptible group has been infected. The simulation is ended at 50 time steps (to cover a long enough wave of epidemic strike). All the susceptible road segments are infected,

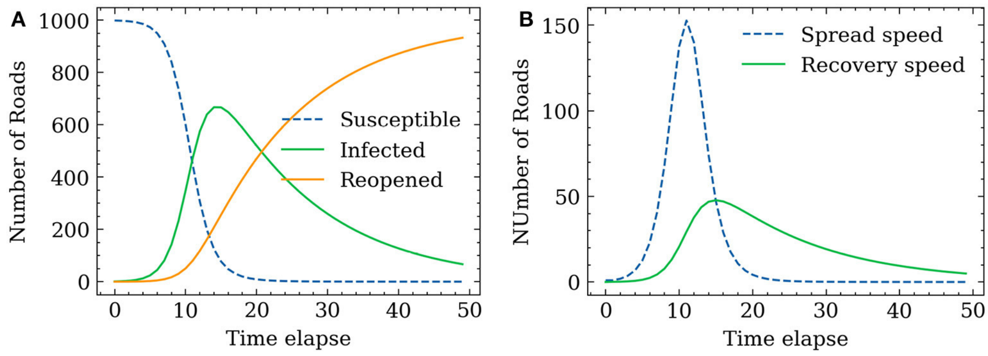

FIGURE 10
SIR model simulated propagation process. **(A)** Number of each group. **(B)** Propagation and recovery speed.

but a small portion of road segments are not recovered at the end of the simulation. The corresponding spreading speed and recovery speed are shown in Figure 10B. The largest spreading speed occurs at ∼12 time-steps, where most road segments are infected but the recovery process was just about to initiate, and then the spreading process almost finished after the 20 time-steps. As described in the study framework (cross-referencing Figure 1), the segments are dynamically closed and reopened based on the spreading speed and recovery speed. It should be noted that with the betweenness centrality of each edge being recomputed at each time step, the infected road segments at each time step can be different when using different recovery strategies.

Figure 11 shows the road network performance curves in the context of the two proposed recovery strategies. A relatively similar network performance decrement trend between the FCFR recovery and dynamic recovery can be observed at the initial stage of spreading process. The discrepancy between the two became more obvious after ∼10 time-steps, which corresponds to the increasing recovery speed as seen in Figure 10B. Although the network performance touches its lowest point at a similar time step regardless of the recovery strategy, the dynamic recovery clearly demonstrates a much higher performance value than the FCFR method, which indicates a better and more resilient performance by losing less total system functionality.

The advantage of using the dynamic strategy is even more critical during the later stage of the spreading process, and it can be observed that the dynamic recovery strategy almost achieves 100% of the original performance whereas the FCFR strategy only reaches ∼95% of the pre-event performance level. Overall, the performance loss of the dynamic recovery strategy is only ∼4.63, which is 9.1% of the total performance area, while that of the FCFR recovery strategy reaches 6.49 (12.7%), which again quantitatively confirms the advantages of the dynamic recovery compared to the FCFR recovery.

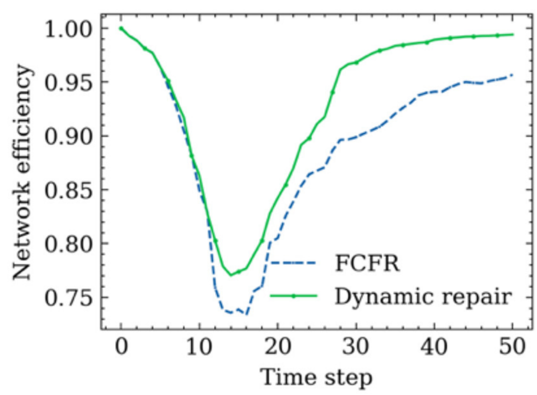

FIGURE 11
Hybrid influence of restriction and reopen influence of the different recovery models.

However, we can also see from the simulation result that the sporadic occurrence of disease can cause considerable harm to the road network as the performance level drops sharply within the first 10 time-steps. Because it is sporadic in space, it can occur so irregularly and widely separated in place that one single emergency response team might find it struggle to quickly react to those successive but very distant outbreak spots. Thus, to deploy an effective dynamic recovery strategy in this spreading mode, a centralized control center that can put multiple emergency response units into in-time actions should be considered. In practice, it is true that many cities establish centralized epidemic control centers in their local authorities.

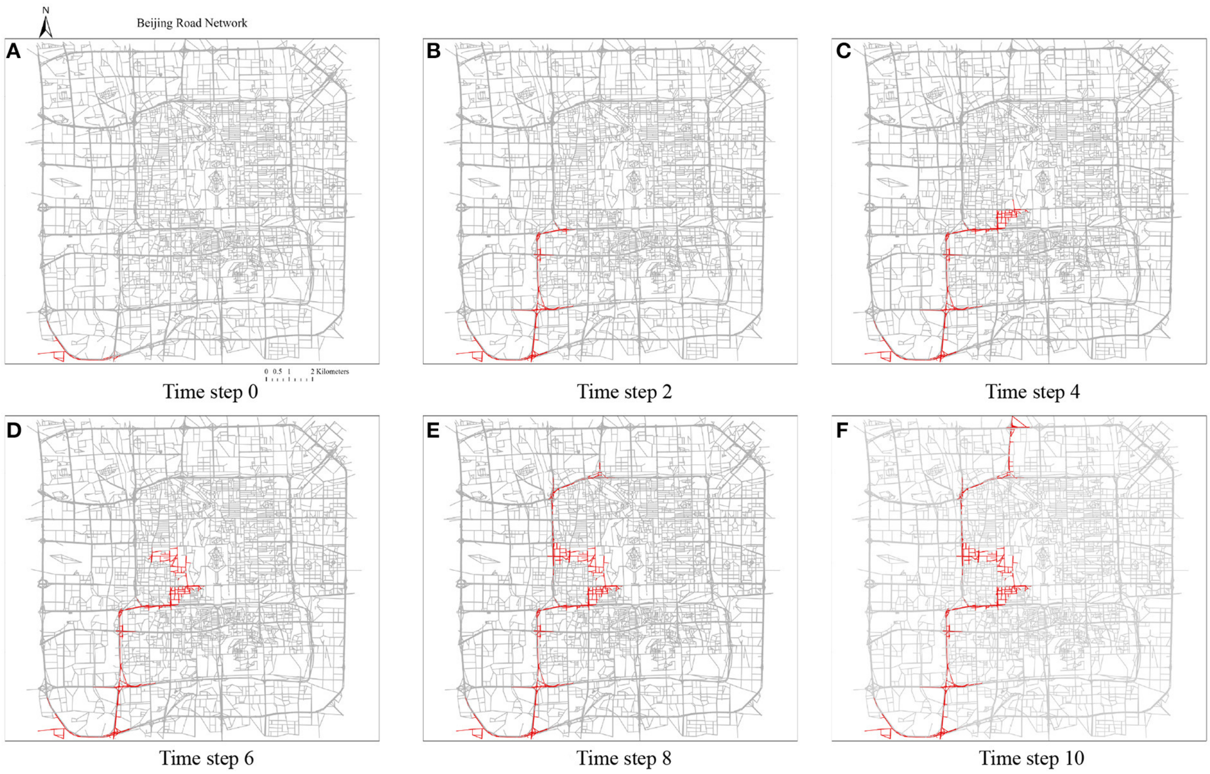

FIGURE 12
The trajectories of superspreader-based infections propagation. The traveling speed is set as 10 road segments/time step. The closest five segments adjacent to the traveler are assumed to be infected. The total moving time is 11 time steps. **(A)** Time step 0, **(B)** time step 2, **(C)** time step 0, **(D)** time step 6, **(E)** time step 8, **(F)** time step 10.

5.2. Trajectory-based spreading scenario

5.2.1. A simple non-commuting trip

Because there could be no typical symptoms, a superspreader very often does not have self-awareness of being a superspreader until the ones infected by him/her are positively confirmed, causing this mode of spreading to be extremely difficult to control. Figure 12 demonstrates the superspreader's traveling path and infected road edges. For this randomly selected OD trip, the superspreader starts from the southern left corner, which is close to the location of the Beijing south high-speed railway station (a very crowded place with numerous commuters on weekdays), to the north of the study area (a place where commercial offices and residential neighborhoods are clustered). In this demonstrative case, the superspreader would pass the center of the road network for the shortest path from his or her origin to the destination, which is intuitively not optimistic for epidemic control as it is highly populated and the road density is also high in the city center. Consequently, this leads to more road segments being infected in the center area in this spreading scenario than on the previous scenario.

Based on the demonstrative case in Figure 12, we set the recovery speed as 50 road segments/time step, and thus, the number of infected road segments at each time step (spreading speed) can also be inferred, which is shown in Figure 13. This curve demonstrates that the spreading speed is highly correlated with the road density in the network. The spreading speed increases when the superspreader travels from the southwest corner to the center of Beijing city. Around the 6th time step, the spreading speed decreases due to the shorter but denser road segments that are close to the center area. After that, the spreading speed increases again and eventually decreases after closing to the destination. A total of 1,477 road edges are infected during this spreading process.

Figure 14 shows the resilience curves of the network performance in this superspreader spreading scenario when implementing the proposed two recovery strategies. The total simulation time is longer than the travel time as the recovery process continues after the superspreader reaches the destination. Two similar-shaped performance drops can be observed in the first 10 time steps when using the FCFR recovery strategy and the dynamic recovery strategy, where a minor rebound occurred in the middle of the drop. One

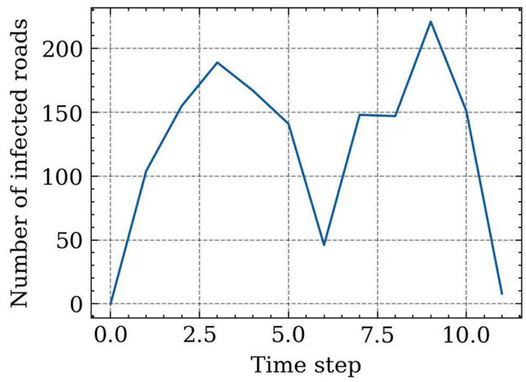

FIGURE 13
The number of infected roads at each time step of trajectory-based propagation.

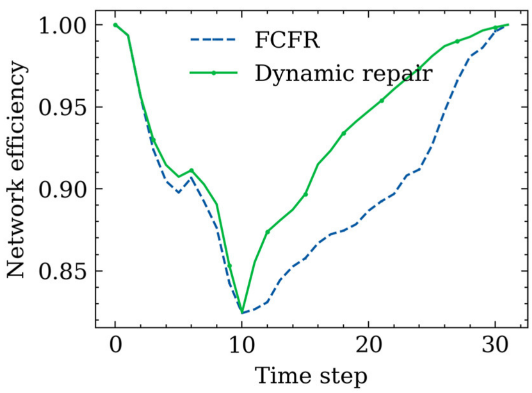

FIGURE 14
Trajectory-based recovery results.

possible explanation for this minor rebound could be due to the large recovery speed compared to the superspreader's traveling speed (the effects from various recovery speeds are discussed in the following). Once the trip is completed, the merits of implementing the dynamic recovery strategy become more significant; it can be seen that the dynamic recovery strategy reopens those critical road segments much faster than the FCFR does, which again leads to a more resilient recovery process. Quantitatively, the performance loss in FCFR is ∼3.98 (12.4%), whereas that figure in the dynamic recovery strategy is only 3.06 (9.6%), showing a 2.9% improvement for a single superspreader (Considering the large scale of the network in megacities, this improvement could already be pretty impressive). Furthermore, it only takes a second to realize that this single superspreader can cause almost the same level of damage as a series of sporadic spreads (as shown in Section 5.1).

5.2.2. Sensitivity to the changes of trip trajectory

To test the robustness of the merits of the dynamic recovery strategy, another four scenarios with heterogeneous trajectory paths and recovery speed are designed and simulated. An illustration of the four trajectory paths with different orientations in the city is shown in Figure 15A. The traveling speed is kept at 10 road segments/time step. The infection range is considered as 3 segment distances in this round of simulation. As shown in Figures 15B–E, the travel directions from south to north (SN), west to the east (WE), southwest to northeast (SW-NE), and southeast to northwest (SE-NW) are simulated. The recovery speeds are varied from 50 road segments/time step to 5 road segments/time step to facilitate the comparative analysis, where Figure 15B with recovery speed of 50 road segments/time step, Figures 15C,D has a recovery speed of 10 road segments/time step and Figure 15E with recovery speed of 5 road segments/time step. The appropriateness of this parameter setting can be explained as follows: (1) because there were no similar studies as references, in this study, we perform several sets of trials based on the simulation settings, and it was found that the parameters selected above are optimal in terms of simulation accuracy and computation time; (2) considering the virus propagation speed and realistic medical resource allocation, an excessively fast recovery speed may reduce the benefits of optimal decision-making, so this study set the recovery speed from 50 road segments/time step to 5 road segments/time step; and (3) this study may provide a reference for the setting of these types of parameters in future studies.

Comparing the performance curves from each orientation (Figure 16), the minimum impact to the road network scenario is when the superspreader travels from south to north with a recovery speed of 50 road segments/time step, which is an intuitive observation as the faster the response and reopening speed, the less the negative influence caused by the superspreader (regardless of which recovery strategy), i.e., performance loss of 1.59 (8.8%) in FCFR and 1.45 (8.1%) in dynamic. It can also be seen that the influence of superspreaders on network efficiency from southeast to northwest is more severe than that from south to north, i.e., performance loss of 12.85 (8.4%) in FCFR and 8.71 (5.7%) in dynamic. It is likely that this case affects more segments and many of the infected segments are in the central region. Graphically, we can see that the superiority of adopting a dynamic recovery strategy can be observed in all simulated scenarios. Comparing the scenarios with respect to different recovery speeds (Figures 16A,B,D, the corresponding performance loss indices are shown in Figure 17), which indicates that the superiority of the dynamic strategy is more obvious when the recovery speeds are slow.

This comparison also indicates that a slower recovery speed leads to a greater performance loss, and thus, less resilient network functionality (Figure 17), which further corroborates

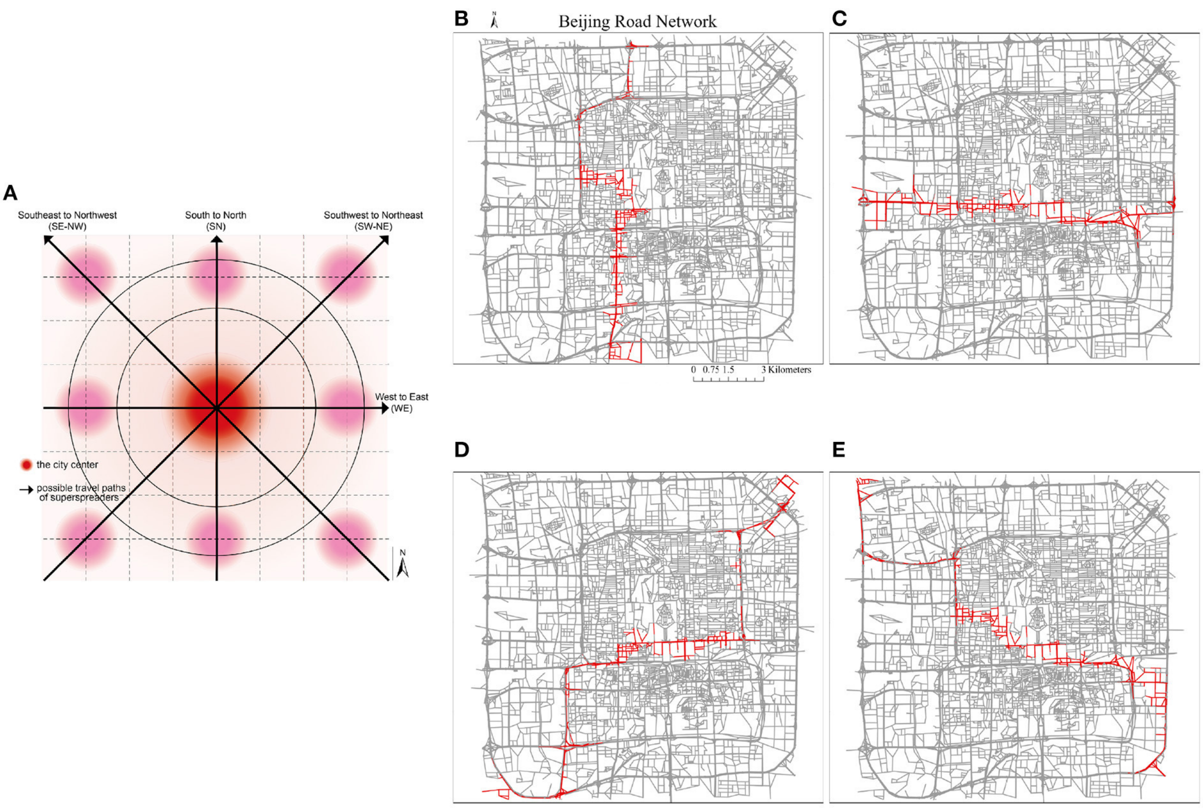

FIGURE 15
The trajectories with different orientations of a superspreader. **(A)** An illustration of possible traveling paths of superspreaders. **(B)** South to North. **(C)** West to East. **(D)** South-west to North-east. **(E)** South-east to North-west.

that the negative impact on the road network caused by superspreaders could be more severe than expected. Thus, this mode of virus spread is the one that most attention should be given to in airborne epidemic emergencies, such as COVID-19. Numerically, even superspreaders behave differently according to various orientations and road densities in the simulations, the averaged performance loss from the FCFR recovery is ∼6.98 (8.6%), while it is of only 5.25 (6.9%) from the dynamic recovery.

6. Discussion and implications

In terms of the comparison between the two recovery strategies, this study quantifies the considerable advantage of dynamic strategies over static FCFR strategies. Given that in many countries or regions it is not always possible for public health resources to be greatly reinforced in the short time of the spreading, thus, it is undeniably necessary to implement active, dynamic and strict epidemic prevention and control measures from early stage. This is intuitive, yet very often neglected in practice; observation again reiterates the importance of dynamically updating decision-making in fighting epidemics. In reality, this quick reaction often means a joined effort from different city authorities such as local public health authorities, land and transportation authorities, and emergency management authorities. Moreover, in the simulation, the dynamic recovery strategy has comparable advantages against trajectory-based spreading (the resilience of the dynamic recovery strategy is 3.6% higher than that of the FCFR recovery strategy). The same pattern observed in other testing cases indicates that this advantage of the dynamic recovery strategy is stable and generic. Meanwhile, we also found that the spreading speed of superspreaders is highly correlated with the road density (and orientations), which could imply that city managers should pay more attention to urban areas with denser roads from the perspective of epidemic prevention and design with extra care in urban street planning, especially in the post-pandemic era.

To reduce the risks of infection caused by super spreaders, it is effective to use smart and digital technologies for epidemic prevention and control, especially in tracking the trajectories of confirmed cases, analyzing crowded gathering hotspots and human mobility patterns, applying contactless transportation, etc. For example, using telecom technology

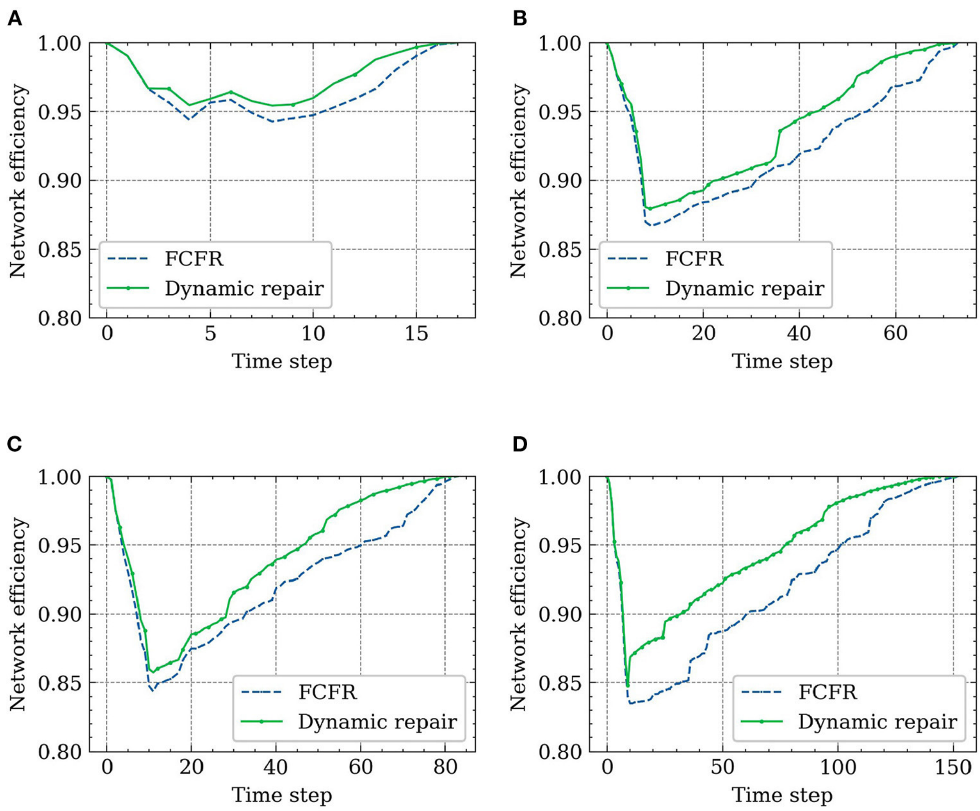

FIGURE 16
Final recovery results with different traveling paths and recovery speeds. **(A)** Recovery results of SN path (R = 50 roads/time step). **(B)** Recovery results of WE path (R = 10 roads/time step). **(C)** Recovery results of SW-NE path (R = 10 roads/time step). **(D)** Recovery results of SE-NW path (R = 5 roads/time step).

and data analytics, Vodafone, a telecoms and technology service provider, created heatmaps to help government in Lombardy, Italy learn about population movements (71). In China, AI-powered autonomous vehicles are used to deliver medical supplies and necessities to hospitals or isolated communities under remote video monitoring, which helps minimize direct contact between people (72). The Hyderabad state in India used an automatic license plate recognition system based on advanced learning algorithms to monitor travel speeds to help the government enforce the driving restriction order (i.e., citizens should not drive more than 3 km from their homes) (73). In addition to engaging technologies, policy measures are critical for dealing with superspreaders in urban transportation, such as initiating traffic-calming schemes (low-traffic neighborhood) (74). In fact, as part of the COVID-19 response, traffic-calming trials have been fast-tracked in many cities across the UK. However, due to multiple factors in personal travel behaviors, it remains challenging to deal with superspreading cases. In China, some optimistic examples of successfully controlling superspreaders exist, yet with appalling costs and sacrifices associated with the painstakingly strict control measures, such as in-depth epidemiological investigations and high-resolution tracing of contact trajectory.

To ensure a resilient and efficient urban road network, although many factors contribute to the spread of the virus, promoting proactive action plans with dynamic strategic measures should be taken as a bottom-line attitude regardless of the spreading mode. With the increasing emergence of various new variants of the new coronavirus, COVID-19, threats will continue, and the discussion of epidemic control will continue to emerge as well. For urban mobility, this might also continue triggering a growing number of relevant debates in public in the future. For example, the traffic-calming scheme mentioned above that was originally proposed to support social distancing and actively respond to COVID spreading by transforming dense-street residential areas has recently been heavily criticized due to critical cited concerns over congestion, emergency access issues and increasing inequity in local communities. Based on the findings and discussion

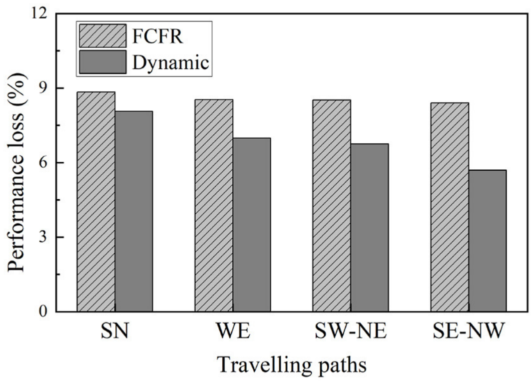

FIGURE 17
Performance loss with different traveling paths and recovery speeds.

in this paper, several policies and practical implications for improving the resilience of urban roads can be summarized as follows:

- In response to the spread of highly infectious epidemics, such as COVID-19, on urban roads, it will be more effective to combine dynamic recovery strategies with continuous preventive strategies rather than adopting one-size-fits-all static solutions, and this often requires a joint effort from multiple local authorities.
- To prevent and minimize the spreading risk caused by super-spreaders, city managers should consider even more proactive measures and seek diverse assistance from cutting-edge digital tools to achieve multiobjective epidemic control, such as tracking trajectories, monitoring real-time traffic, strengthening vehicle mobility management (e.g., congestion hotspot monitoring) and hierarchical control schemes for risk-prone areas.
- To maintain a more resilient urban road network during the pandemic time, if without an in-time response and a proper dynamic recovery strategy to ensure quick restoration, it is essential to acknowledge the following before implementing any epidemic control measures: The measure (such as road closure) could have negative impacts on road network resilience and might lead to severe consequences on accessibility and efficiency. In some cases, it could even exacerbate and provoke new issues, such as social inequity. For decision- and policy-makers, this is particularly noteworthy and should be borne in mind throughout the whole decision-making and policy-framing process.

7. Conclusion

This paper performs a simulation-based comparative investigation of the four different combinations of epidemic spread and recovery processes and quantitatively studies their impact on the resilience of Beijing's road network. We defined two modes of spreading mechanisms (i.e., sporadic occurrence and trajectory-based occurrence) and comparatively analyze the performance of urban road networks under two recovery strategies, namely, the "First-Close-First-Reopen" (FCFR) recovery strategy and the dynamic recovery strategy, to quantitatively benchmark their heterogeneous effectiveness, which provides several critical implications for practitioners.

The results show that (1) in terms of negative impact, the superspreader can cause much worse consequences for the overall accessibility of urban road networks. Given the real-world pandemic control cases, sporadic spreading and trajectory-based spreading could occur in tandem if no proper action is taken; (2) the road density and centrality order, as well as the network's regional geographical characteristics, can significantly affect the spreading speed of the virus and introduce heterogeneity into the recovery processes; and (3) In terms of better recovery strategy, we confirmed the superiority of the dynamic strategy; it considerably outperforms the common practice (i.e.,the static FCFR strategy). In the sporadic spreading scenario, the performance loss of the dynamic recovery strategy is only ∼4.63, which is of 9.1% of the total performance area, while that of the FCFR recovery strategy reaches 6.49 (12.7%). In the trajectory-based spreading scenario, the average performance loss from the FCFR recovery is ∼6.98 (8.6%), while it is of only 5.25 (6.9%) from the dynamic recovery.

This study provides insightful policy and managerial implications for city managers and policy-makers, which could inspire new strategies in managing public health emergencies during and even after the COVID-19 crisis. Like many other simulation-based analyses, we also acknowledge several limitations of this study as potential caveats for future roll-outs. First, our findings on the sporadic spreading mode rely on the basic assumptions and the parameter settings of the SIR model. Some assumptions of this paper might need to be further examined using more empirical data. For example, one of these assumptions is that the reopened road segments are assumed not to be infected and closed again. Urban roads, of course, could also be reclosed again due to the recurrence of the virus. This setting can be tested in future work. Another assumption, i.e., a 100% infection rate, was made to simplify the simulation process and to capture the worst spreading scenario. In the future, comparative studies based on various infection rates can be tested. Second, as the authors are writing this paper, new COVID variants have been periodically emerging. For instance, a SARS-CoV-2 variant named 'Omicron' has spread from South Africa and it was suggested that people who previously had

COVID-19 may be more likely to become reinfected with this variant (75). Thus, future work could consider simulating spreading with various levels of infection rates. Third, the travel paths of road users may not always be perfectly in line with the road topology. However, in megacities, such as Beijing, China, it is very common for pedestrians to walk on the streets and for drivers to park vehicles on roadside parking lots. Nevertheless, the uncertainty of human behaviors is not considered in our simulations and can be included in future explorations. Fourth, the betweenness centrality and network efficiency considered in this study are unweighted. However, pandemics can also occur in non-central areas. In future studies, we will consider assessing the resilience of road networks using weighted metrics, such as the weighted network efficiency mentioned in the paper by Zhou et al. (76). Finally, focusing on only one megacity case study from China could also be a shortcoming of this study. More cities with heterogeneous characteristics will be explored as additional case studies in future research.

Data availability statement

Publicly available datasets were analyzed in this study. This data can be found at: https://www.openstreetmap.org/.

Author contributions

Conceptualization, methodology, data curation, validation, and software: JT, XF, and QL. Writing—original draft, investigation, and writing—review and editing: JT, HL, XF, XY, and QL. Funding acquisition and supervision: XF and JT. All authors contributed to the article and approved the submitted version.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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Better future with better us: Exploring young people's energy-saving behavior based on norm activation theory

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Conserving energy use is a shared responsibility of all people, and it is essential for mitigating climate warming. The purpose of this study is to investigate energy-saving behaviors and the influencing factors of young people. We developed a new theoretical framework by adding self-efficacy and information publicity to norm activation theory. Partial least squares structural equation modeling was used to analyze 360 sample data from different regions in China. The findings show that attribution of responsibility and awareness of consequence are important prerequisites for personal norm. Personal norm positively influences energy-saving intention. Interestingly, information publicity has a significant positive effect on both intention and behavior to save energy, while self-efficacy only significantly affects energy-saving intention. This study focuses on the young group and enriches the research on factors influencing residents' energy-saving behaviors. The findings provide insightful ideas for governments and communities to guide individual energy conservation behaviors.

KEYWORDS

energy-saving behavior of young people, norm activation theory, PLS-SEM, self-efficacy, information publicity

Introduction

Since the 21st century, energy consumption has continued to grow all over the world (1). The global per capita energy consumption growth rate in 2018 is almost double that of 2010 (2), and CO_2 emissions have increased by 40% globally from 2000 to 2019 (3). Energy conservation remains a serious global challenge, and it is difficult to solve the problems of high energy consumption only by promoting energy-saving technologies and clean energy (1). Conserving energy use is a shared responsibility of all people, and changing people's energy consumption habits becomes a feasible solution to energy and environmental problems (4, 5).

It is of great meaning to foster a sense of environmental concern for young people (6). In recent years, the growth in population numbers and urbanization levels has brought an increase in energy consumption. The demand for domestic energy by urban residents, especially the younger age groups, is expanding (7). As high energy consumers and potential major energy consumers in the future, young people are an important target group for energy-saving interventions (8). Young people's high receptiveness to information, their higher awareness of environmental protection and consequences, and their new personal norms make their behavior and willingness to save energy different from those of other age groups. Therefore, the energy-saving behavior (EB) of young people is the focus of this study with a certain research value.

Current research on the influencing factors of EB focuses on the fields of sociology and applied psychology. For example, Hong et al. (9) used a sociological approach to analyze the macro policy perspective and suggested that government subsidies can promote EB among residents. Wang et al. (10) combined sociological and psychological research to investigate EB in terms of monetary incentives for electricity prices and moral suasion. Although research on environmentally friendly behaviors is relatively mature, as a potential energy-saving subject, few studies have focused on related behaviors among young people. By organizing the findings, we can classify these factors into external intervention factors and internal individual factors. This study uses the extended Norm Activation Model (NAM) to empirically analyze young residents' energy-saving willingness and behavior based on external intervention factors and individual internal factors. The two extended variables of self-efficacy (SFE) and information publicity (IP) are integrated into NAM to reveal the influence path of EB on young residents (7).

Literature review and hypothesis

Related research about NAM

Currently, Theory of Planned Behavior (TPB), NAM, and Structural Equation Modeling (SEM) is used to conduct research related to the factors influencing altruistic behavior (11–13). NAM is a theoretical model for investigating altruistic behavior based on the personal norm (PN) (14). Pro-environmental behavior is often associated with PN, and problem perception and attribution of responsibility (AR) in NAM have very strong explanatory power for pro-environmental intentions (15). Thus, NAM is widely used to explain altruistic behavior and altruistic intentions. Related research topics include energy saving (16), water saving (17), and electricity saving behaviors (18).

Young people are a typical pro-environmental altruistic behavior that applies to NAM. We collated relevant studies applying NAM and its extended models in recent years (Table 1). Zhang et al. (16) used 297 validated interviews in Jinan, China, and explored the mechanisms of individual subjective, external influences and willingness on EB. Fu et al. (19) identified that cognitive attitudes influence people's willingness to save electricity based on TPB and NAM. Hien and Chi (20) showed that primary factors (e.g., perceived behavioral control, subjective norms, attitudes, and personal ethics) and additional factors (perceived benefits) in TPB and NAM are important factors that influence residents' willingness to save electricity. In addition, electricity saving behavior is influenced by willingness, perceived benefits, policy guidance and social advocacy. Du and Pan (21) indicated that PN has a significant positive effect on the willingness to save energy. Yang et al. (23) found that SFE and perceived control showed a significant positive effect on the intention to engage in habitual EB. The existing literature provides the foundation for exploratory research on EB, but at the same time, there has been insufficient attention to specific groups, such as younger age groups. Therefore, this study focuses on young people, considering the importance of SFE and IP, we extend these two variables to the NAM to reveal the determinants that influence young people's energy saving behavior.

Research hypothesis

Extended NAM model

The original variable factors of NAM are Awareness of Consequence (AC), Attribution of Responsibility (AR), and Personal Norm (PN), of which PN is one of the core variables. PN affects behavioral intentions directly and has indirect effects through AC and AR. AC refers to whether individuals notice that pro-environmental behaviors can affect the person or object they are concerned about (24). In general, the stronger a person's perception of a particular outcome, then the stronger the moral obligation, and the more likely they are to activate their PN and display altruistic traits. AR refers to an individual's sense of responsibility for the results of performing pro-environmental behaviors (24). Cui et al. (25) found that awareness of the harmful outcomes of non-energy saving behaviors significantly influenced EB; AC and AR had a direct contribution to the formation of PN. Individuals realize that non-energy-saving behaviors can lead to serious environmental and social problems, thus promoting the formation of AR and PN, and thus adopting EB.

Abbreviations: AC, awareness of consequences; AR, attributing responsibility; AVE, average variance extracted; CA, Cronbach's alpha; CR, composite reliability; EB, energy-saving behavior; EI, energy-saving intention; IP, informational publicity; NAM, norm activation model; PLS, partial least squares; PN, personal norm; SEM, structural equation modeling; SFE, self-efficacy; VIF, variance inflation factor.

TABLE 1 Recent literature on NAM and other extended factors.

Literature	Context	Research subject	Theoretical basis	Expanded drivers	Significant results
Zhang et al. (16)	Household energy consumption	EB of household	SEM	Energy efficiency policy	Individual factors, external factors and intentions act on EB.
Fu et al. (19)	Conservative energy	EB of household	NAM& TPB	Policy awareness	Residents' willingness to save electricity positively correlated with perceived behavioral control and personal ethics.
Hien and Chi (20)	Increase in global electricity demand	EB of residents	NAM& TPB	Policy and social publicize	The perceived behavioral control, subjective norm, personal moral, policies, and social propaganda benefits affect household electricity saving behavior.
Du and Pan (21)	Carbon emissions	EB of students	TPB	Personal ethics	Personal ethics are found to enhance interpretability of TPB.
Li et al. (22)	Carbon neutral	EB of residents	NAM& TPB	Environmental habituation	Environmental problems indirectly affect residents' willingness to save energy.
Yang et al. (23)	Carbon neutral	EB of college students	TPB	Environmental concern	Perceived SFE and perceived control mediators between information intervention and Energy-saving intention.
Zhang et al. (18)	Energy consumption	EB of employee power	NAM	Energy-efficient climate	PN have a positive impact on employees' EB.

For pro-environmental behaviors with altruistic characteristics, PN continuously generates positive intentions, which are an important prerequisite for the performance of altruistic behaviors (26). Thus, the willingness to save energy directly influences the EB. Therefore, the more users perceive the consequences, the greater their sense of responsibility and the more likely they are to activate self-regulation and thus be more willing to engage in energy-saving activities. Therefore, NAM is applicable to young people's interpretation and prediction of EB and willingness to save energy (EI). Based on the above, we propose the following hypotheses.

For this study, AC can be interpreted as young people's perceptions of the consequences of non-energy-efficient behavior on the adverse effects of environmental pollution, climate warming, and increased carbon emissions. NAM notes that when young people believe that their non-energy-efficient behavior is causing negative environmental impacts, they are more likely to attribute these consequences to themselves and thus fulfill their moral obligations and responsibilities. Therefore, NAM is applicable to young people's interpretation and prediction of EB and energy-saving intention (EI). Based on the above, we propose the following hypotheses:

H1. Among young people, AC has a significant effect on PN.
H2. Among young people, AR has a significant effect on PN.
H3. Among young people, PN has a significant effect on EI.
H4. Among young people, EI has a significant effect on EB.

Self-efficacy

In NAM, SFE is used as the core variable to influence the willingness as well as the behavior to save energy. SFE is the confidence to accomplish a certain behavior, and the level of SFE affects an individual's behavioral decisions (27). Yang et al. (23) demonstrated that SFE and perceptual control had a significant positive effect on EI in the group of college students. Wang et al. (28) found that SFE directly influenced energy-saving-related behaviors in a study of office workers in the Netherlands. Allen and Marquart-Pyatt (29) reached similar conclusions in their study of the energy conservation behaviors of campus community members. In the case of residential EB, young individuals are directly influenced by SFE when making decisions about EB. SFE also influences EB through EI. It leads to the following hypothesis for this study:

H5. Among young people, SFE has a significant effect on EI.
H6. Among young people, SFE has a significant effect on EB.

Information publicity

Information publicity (IP) is usually defined as the process of transmitting information to individual units through specific policies, documents and other means of communication by governments, businesses, communities and specific organizations (30). In this study, we include IP as an extended variable in NAM. It is the process of government, organizations and communities promoting EB through online advertising and

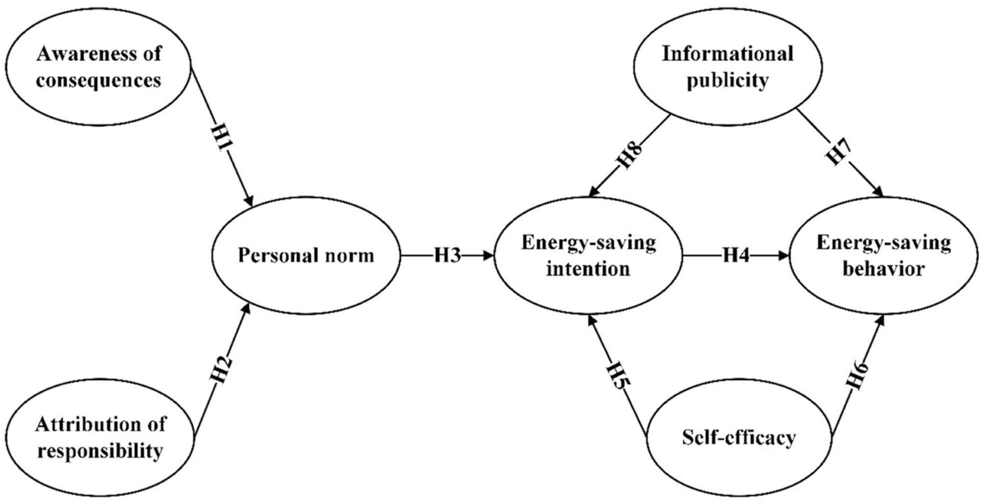

FIGURE 1
Energy-saving behavior model.

offline display boards. Yue et al. (30) found that policies and measures that promote the culture of energy conservation can help the public save energy more effectively. The correlation between EB and their influences suggests that motivation at the spiritual and material levels is equally important. Xu et al. (31) found from an analysis of questionnaire surveys conducted in four megacities (Beijing, Hangzhou, Guangzhou, and Guiyang) that energy conservation education should be enhanced to raise residents' awareness and thus promote EB. Wang et al. (32) found that IP has a strong influence on EB when they studied the daily behavior of Chinese urban residents. Among young groups, the intervention of external information influences individual decisions (32, 33). In specific scenarios, young people's decisions about EB are influenced by external information campaigns, which in turn influence their willingness and behavior to save energy. From this, we propose the following hypothesis.

H7. Among young people, IP has a significant effect on EB.
H8. Among young people, IP has a significant effect on EI.

The conceptual model of this study is shown in Figure 1.

Methodology

Partial least squares structural equation model

This study uses partial least squares structural equation modeling (PLS-SEM) for empirical analysis to explore the factors that influence the willingness and behavior to save energy among the younger age group of residents. An extended NAM is used to hypothesize the possible paths that influence the willingness and behavior to save energy. Unlike conventional SEM, which only constructs reflective structural models, PLS-SEM can construct both reflective and formative measurement models (13). PLS-SEM is a multivariate data processing tool that can verify or predict the relationship between variables without the data following a normal distribution (34). Thus, it applies to several fields, such as public transportation management (35), customer satisfaction and loyalty in sociology (36), vaccination intentions in psychology (37), and predictive model evaluation in engineering (38). In this study, a comprehensive analysis was conducted for internal and external factors of EB, and then the relationship between the predictor variables was verified to analyze the influencing factors that affect young people's EB and EI. In summary, PLS-SEM is feasible for this study.

Survey design

The questionnaire for this study consisted of three parts. The first part was a description, which included the survey purpose and the explanation of EB in this study. The second part investigated the socio-demographic characteristics of the participants, including gender, age, education level, income, and occupation. The third part included question items measuring eight latent variables.

The measurement items in this questionnaire mainly referred to previous studies and were modified according to the content of this study. The questionnaire design was pretested and insignificant measurement items were removed, and 29 valid measurement items were finally identified. The questionnaire was designed using a 7-point Likert scale, with

TABLE 2 Description of construct and measurement items.

Construct	Measurement item	Mean (standard deviation)	References
AC	The energy non-conservation behavior of residents may lead to damage to the ecosystem.	5.7005 (1.5890)	(18, 39)
	Inefficient energy use by residents may lead to global warming.		
	Residents' failure to save energy may lead to severe environmental pollution.		
	Residents' energy-saving behavior can reduce carbon emissions.		
AR	I am responsible for global warming caused by non-energy-saving behavior.	5.0612 (1.7368)	(18, 20)
	I am responsible for the damage to the ecological environment caused by the non-energy-saving behavior.		
	I am responsible for the severe environmental pollution caused by the non-energy saving behavior.		
	I am responsible for the increase in carbon emissions caused by non-energy saving behavior.		
SFE	I feel that my energy-saving behavior can set an example for others.	5.6047 (1.3893)	(23, 40)
	I feel that my energy-saving behavior can promote the sustainable development of the city to a certain extent.		
	I feel that my energy-saving behavior can help achieve carbon reduction.		
PN	When the residents' non-energy-saving behavior occurred, I felt guilty.	5.9193 (1.2807)	(19, 21)
	I think it is essential to save energy as a resident.		
	I will take the initiative to buy energy-saving products.		
EB	I will actively turn off the air conditioner or adjust to energy-saving mode.	5.7363 (1.4045)	(41, 42)
	I will take the initiative to avoid setting the electric water heater to low-power insulation for a long time.		
	I would turn off the electrical equipment before leaving the empty room.		
	I am willing to save energy in my daily life.		
EI	I intend to engage in energy-saving activities in my daily life.	5.9418 (1.2276)	(16, 43)
	I am willing to participate in some energy conservation and emission reduction activities.		
	I am willing to buy energy-saving products.		
	I am willing to respond to the energy-saving policy.		
	I think it is essential to disseminate information related to energy conservation.		
IP	Publishing information about the current state of energy will encourage me to conserve energy.	5.8440 (1.2903)	(30, 31)
	Spreading the word about energy conservation will motivate me to save energy.		
	I can see energy-saving advertisements through online channels such as the Internet, motivating me to save energy.		
	In reality, I will be inspired to save energy because of the energy-saving advertising display board.		
	The government and environmental protection departments will influence my electricity consumption behavior.		

one indicating complete disagreement and seven indicating complete agreement. The 7-point scale provided more options for the research respondents compared to the 5-point Likert scale, which improved the reliability of the data, and Table 2 shows the specific measurement questions for the latent variables in detail.

Data collection

The data for this study were collected through the Chinese questionnaire platform, Wenjuanxing. Wenjuanxing (44) is a professional online questionnaire platform that is widely used in the data collection phase of empirical studies. The questionnaire data were collected using a national scale sample database, and target populations from different regions of China were invited to complete the questionnaire. The division of the young group was referred to the United Nations World Health Organization, and people under 35 years old were taken as the target population of the survey (8). We collected a total of 477 online questionnaires. Twenty six invalid questionnaires were excluded based on trap items and preliminary screening, and 451 valid questionnaires were obtained, of which the sample size of the young group that fit the study population was 360. The detailed data screening process is shown in Figure 2, and the specific sociodemographic characteristics are shown in Table 3.

According to Table 3, among the 360 valid participants, most of those who completed the questionnaire were female (58.06%) and 41.94% were male. The age of the study sample after data screening was <35 years, which meets the criteria for young people set by the United Nations. In addition, the majority of the study respondents had education levels of college and above (88.06%), had a monthly income of <2,000 (CNY) (49.72%), and had students as their primary occupation (59.44%), which

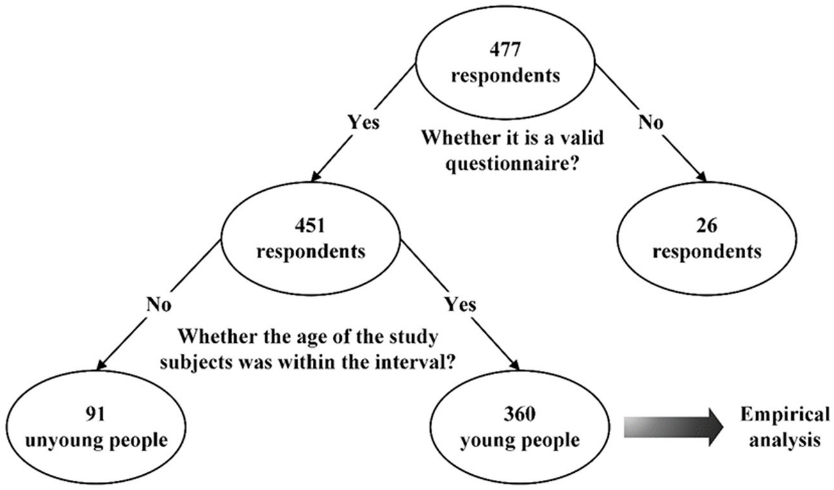

FIGURE 2
Data screening process.

TABLE 3 Socio-demographic information of respondents.

Characteristic	Demographic information	Frequency	%
Gender	Male	151	41.94
	Female	209	58.06
Age	Under 20	150	41.67
	21–25	80	22.22
	26–30	43	11.94
	31–35	86	23.89
Educational	High school or lower	43	11.94
level	Junior college	40	11.11
	Undergraduate university degree	251	69.72
	Postgraduate university degree	26	7.220
Monthly	<2,000	179	49.72
income (CNY)	2,000–4,000	55	15.28
	4,000–6,000	40	11.11
	6,000–8,000	39	10.83
	Over 8,000	47	13.06
Occupation	The staff of administrative bodies	13	3.610
	Public institution staff	26	7.220
	Employees of private enterprises	68	18.89
	Freelancer	38	10.56
	Farmer	1	0.280
	College students	214	59.44

is in line with the research objectives for the pro-environmental behavior of the younger group. The young college student population is influenced by multiple factors in their EB (45), and the causes are more complex (7). In summary, the sample fits the target group characteristics of our study.

Results analysis

Evaluation of the measurement model

We used Cronbach's Alpha (CA), Composite Reliability (CR) and Average Variance Extracted (AVE) to test the reliability of the survey data. The results of the reliability evaluation are shown in Table 4. The CA values of the survey data models in this study were all above 0.82, indicating good reliability (46). The CR values for each variable ranged from 0.898 to 0.978, which was greater than the critical value of 0.7 (47), indicating good internal consistency of the scales used for each variable. The AVE values of the data ranged from 0.733 to 0.918, which exceeded the criterion of 0.5 (46), indicating that the measurement model had sufficient convergent validity. The results of CA values and CR values indicate that the model has good internal consistency and high reliability, and the questionnaire data meet the needs of the study.

Table 5 shows the test results of discriminant validity based on the measurement model of the Fornell and Larcker (48), where the data values in the first vertical row (bold) indicate the square root of AVE and the remaining data values indicate the correlation coefficients of the different constructs. The model has good discriminant validity (48) when all square roots of AVE (all bolded data values) are greater than all other data values in the row and column where the value is located. Table 6 shows the factor loadings of the measured question items and the cross-loadings of the other latent variables. The bolded data values represent the latent variables. The factor distribution of all latent variables ranged from 0.760 to 0.964, which was greater than the standard value of 0.6 and exceeded the cross-loadings of the other constructs (49), and

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TABLE 4 Reliability and convergence validity testing results.

Item	Cronbach's alpha	Composite reliability	Average variance extracted
AC	0.899	0.931	0.773
AR	0.970	0.978	0.918
EB	0.878	0.916	0.733
IP	0.933	0.950	0.790
PN	0.945	0.956	0.783
SFE	0.829	0.898	0.746
EI	0.905	0.941	0.841

TABLE 5 Discriminant validity testing results.

	AC	AR	EB	EI	IP	PN	SFE
AC	**0.879**						
AR	0.456	**0.958**					
EB	0.407	0.405	**0.856**				
EI	0.472	0.432	0.787	**0.889**			
IP	0.495	0.474	0.754	0.868	**0.885**		
PN	0.565	0.610	0.609	0.704	0.723	**0.864**	
SFE	0.479	0.551	0.634	0.714	0.705	0.644	**0.917**

The bold values indicate the square root of AVE.

the discriminant validity of the model can be judged to meet the requirements.

In this study, the variance inflation factor (VIF) of the internal and external models was calculated by PLS. When the VIF is <10, it indicates that there is no covariance problem between the independent variables (34). The VIF values of all the observed factors in this study range from 1.262 to 8.377, all of which are <10, implying that the internal and external structures do not have multicollinearity.

Evaluation of the structural model

R^2 measures the fit degree of the predicted value to the true value (46). The R^2 of PN, EI, and EB in this study are the values in the circles in Figure 3. The R^2 of PN is 0.476, indicating that 47.6% of the variance in PN is explained jointly by AC and AR. the R^2 of EI is 0.781, indicating that 78.1% of the variance in EI is explained jointly by SFE, PN, and IP. The R^2 value for EB is 0.645, indicating that 64.5% of the variance in EB is explained by SFE, IP and EI together. In consumer-related studies, the value of R^2 above 0.20 is considered a higher adjudicated value that adequately explains the variance in the model (13). In summary, the theoretical model of this study has good explanatory power for PN, EI and EB of the younger group of residents.

The eight main effects tests were conducted to test the direct paths between AC, AR, IP, SFE, PN, EI, and EB in the model, as

TABLE 6 Factor loading (bold font) and cross-loading.

	AC	AR	EB	EI	IP	PN	SFE
AC1	**0.915**	0.430	0.381	0.442	0.450	0.521	0.417
AC2	**0.913**	0.405	0.360	0.378	0.400	0.470	0.412
AC3	**0.918**	0.419	0.393	0.443	0.472	0.498	0.434
AC4	**0.760**	0.343	0.290	0.389	0.413	0.490	0.416
AR1	0.464	**0.958**	0.413	0.434	0.468	0.600	0.550
AR2	0.430	**0.964**	0.402	0.429	0.465	0.572	0.520
AR3	0.412	**0.955**	0.380	0.414	0.453	0.576	0.522
AR4	0.440	**0.957**	0.357	0.380	0.431	0.589	0.517
EB1	0.407	0.395	**0.836**	0.754	0.680	0.580	0.566
EB2	0.345	0.391	**0.893**	0.698	0.650	0.507	0.611
EB3	0.305	0.349	**0.891**	0.651	0.639	0.499	0.537
EB4	0.327	0.232	**0.800**	0.572	0.608	0.492	0.439
EI1	0.439	0.342	0.763	**0.864**	0.751	0.671	0.604
EI2	0.386	0.394	0.712	**0.917**	0.789	0.621	0.711
EI3	0.382	0.395	0.650	**0.882**	0.776	0.571	0.662
EI4	0.416	0.411	0.716	**0.901**	0.769	0.625	0.628
EI5	0.476	0.380	0.650	**0.880**	0.773	0.640	0.564
IP1	0.436	0.384	0.709	0.810	**0.879**	0.676	0.613
IP2	0.503	0.411	0.699	0.820	**0.904**	0.671	0.617
IP3	0.450	0.400	0.681	0.800	**0.911**	0.668	0.630
IP4	0.371	0.441	0.614	0.689	**0.863**	0.593	0.628
IP5	0.403	0.427	0.625	0.695	**0.870**	0.593	0.616
IP6	0.457	0.460	0.667	0.780	**0.883**	0.630	0.643
PN1	0.442	0.536	0.472	0.549	0.518	**0.809**	0.522
PN2	0.499	0.540	0.575	0.650	0.683	**0.883**	0.567
PN3	0.519	0.506	0.527	0.621	0.665	**0.897**	0.577
SFE1	0.408	0.482	0.584	0.652	0.646	0.587	**0.896**
SFE2	0.448	0.504	0.586	0.653	0.647	0.564	**0.937**
SFE3	0.461	0.529	0.573	0.659	0.648	0.620	**0.918**

The bold values indicate the factors of the latent variables.

shown in Figure 4 and Table 7. The model results showed that all the hypotheses were verified except H6. And the results of the confidence intervals of the eight paths in this study are consistent with the above findings, and it can be concluded that the model shows good statistical significance.

Discussion

Results discussion

The survey results reflect the current status of EB among young people in China. According to the results of PLS-SEM, the original hypothesis of NAM is supported and consistent with the results of previous studies on EB of urban residents. First, AC positively affects PN, a finding identical to that obtained in Zhang et al. (18) study of employees' EB. AR has a significant positive effect on PN, which is consistent with the original

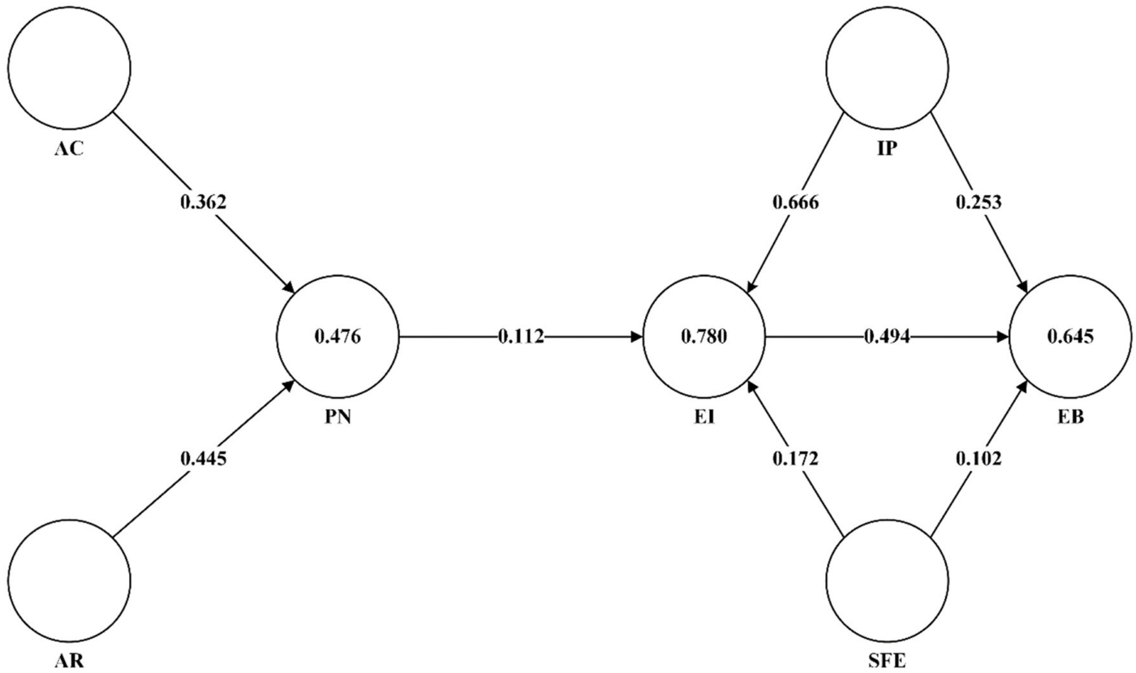

FIGURE 3
Model path coefficients, R^2 (inside the circle) values.

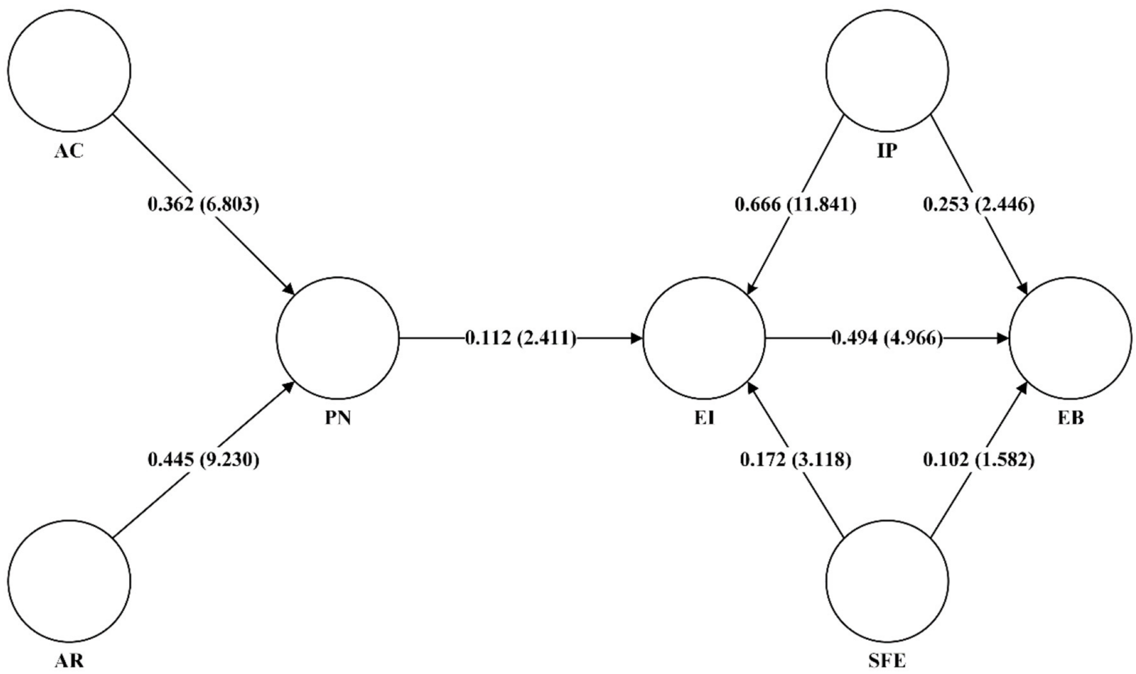

FIGURE 4
Model path coefficients and T values (in parentheses).

TABLE 7 Empirical results of hypotheses.

	Path	Standardized Path coefficient	T Statistics	*P*-values	Confidence interval 2.50%	Confidence interval 97.50%	Hypothesis Test
H1	AC -> PN	0.362	6.803	0.000	0.257	0.470	Supported
H2	AR -> PN	0.445	9.230	0.000	0.352	0.535	Supported
H3	PN -> EI	0.112	2.411	0.016	0.02	0.203	Supported
H4	EI -> EB	0.494	4.966	0.000	0.306	0.707	Supported
H5	SFE -> EI	0.172	3.118	0.002	0.057	0.268	Supported
H6	SFE -> EB	0.102	1.582	0.114	−0.024	0.231	Not supported
H7	IP -> EB	0.253	2.446	0.015	0.039	0.426	Supported
H8	IP -> EI	0.666	11.841	0.000	0.546	0.773	Supported

hypothesis of NAM (24). As Hong et al. (9) mentioned in their study, urban residents' sense of environmental responsibility has a significant positive effect on PN, i.e., AC has a significant effect on PN, while Han and Cudjoe (41) argued that AC indirectly affects PN. In our study, this finding that AC affects PN was again validated in the younger age group. In addition, many studies have concluded that PN has a significant positive effect on EI and EB. For example, Li et al. (22) found that PN affects the willingness of residents to engage in habitual EB in a study on environmental issues. This result remains consistent with the results of this study. That is, in EB of the young group, the sense of responsibility for the environment and the awareness of the consequences of non-energy-saving behavior activate the individual's PN, which in turn promotes EB. In summary, the hypotheses of the original model of NAM were all validated in this study, reasonably explaining the factors influencing EB of young people, and validating the reasonableness of the prior variables of the original model of NAM.

In addition, another variable that was extended in this study was SFE. The findings of this study showed a significant effect of SFE on EI. The present results are consistent with the results of previous studies. For example, Yang et al. (23) suggested that perceived SFE and perceived control have a significant positive effect on habitual energy-saving behavioral intentions in urban residents, i.e., the effect of SFE on EI. But surprisingly, the hypothesis that SFE has a significant effect on EB in this study did not hold, which was not consistent with previous studies, where Yang et al. (23) concluded that SFE affected EB in urban residents. By analyzing the behavioral characteristics of young people, we learned that young people have a weaker sense of SFE compared to other age groups and that their EB is more influenced by, for example, IP or financial benefits. So it may cause that the direct effect of SFB on EB here is not significant. Fatmawati et al. (7) also concluded in a study of EB among young people in Indonesia that the participants showed good attitudes, willingness, and behavioral SFE toward electricity-saving behavior. However, the findings of this study are consistent with the findings of Foster et al. (40) on the pro-environmental behavior of 150 public officials in an organization in Terengganu. The possible reason for the inconsistent results is that the study respondents did not pay enough attention to EB itself, while the reason for the consistency with the results of Foster et al. (40) study may be that more of their respondents were young people. According to Fatmawati et al. (7), the younger group belonged to those with the lowest energy consumption rate and low attention to EB. Moreover, this group was influenced by life experiences and maybe positively motivated to save energy when they had a sufficiently high SFE, but not enough to support the implementation of EB. The above results suggest that SFE, as an individual's confidence to accomplish a certain behavior, can directly and positively influence EI, but does not directly influence EB. In summary, the extended variables in this study can also have a significant positive effect on EB, further enriching the variables of NAM. However, we also found that SFE did not directly affect EB significantly. The results of the study provide some references for the development of related policies. And IP had a positive impact on EB in this study. This finding is consistent with previous studies, e.g., Fatmawati et al. (7) found that IP was of research value in a study of EB among young people, and Wang et al. (33) found that community campaigns can improve electricity savings in a study of community EB. These findings fit with the behavioral characteristics of young people. Young people receive a wider range of information and are more receptive. In addition, the measurement questions in this study also demonstrate that increased information dissemination on EB by government, community, and social organizations, both online and offline, can help promote EB among residents. In summary, IP can positively influence young people's EI and EB. The findings of this study further enrich the factors that influence young people's EB.

The contributions of this study are as follows. First, this study extends the NAM's explanation of adolescents' EB. The subjects of this study are young people, and as adolescents are important potential targets for implementing EB, conducting a study on youth is strategically important for implementing carbon reduction, and it is conducive to further promoting the implementation of EB among residents on a larger scale. Second, this study further strengthens the explanatory ability of the NAM and expands its use boundaries. The validity of the expanded model was verified by integrating two extended variables, SFE and IP, into the NAM, confirming the application of the NAM in the field of altruistic behavior. In addition, the results provide feasible policy suggestions for governments, communities, and relevant organizations, and serve as a reference for the research of EB in other countries and regions.

Policy implications

This study used the young group of residents as the study population and concluded that IP, PN, and SFE played a significant and positive role in influencing the young group's willingness and behavior to save energy. Corresponding policy implications include that descriptive norms and prohibitions of EB should be strengthened first. On the one hand, government, community and other social organizations can conduct education related to energy conservation to promote awareness of energy efficiency policies among younger groups. The government can use exemplary energy-saving communities as examples and call on other communities to follow suit. On the other hand, the government can further motivate SFE of the research subjects by encouraging and recognizing EB in young people, so that the young people will have a stronger desire to save energy and thus promote EB.

More awareness campaigns should be developed to promote the willingness and behavior of young residents to save energy. Given that young people are more receptive to information on the Internet, they can use online resources and online channels to promote EB. Self-media channels such as short videos can be used to promote EB and related policies. Collaborate with public figures or Vloggers to call on city residents to join in energy-saving initiatives. At the same time, we should also focus on offline publicity and the function of public display boards to expand the coverage of EB. At the same time, we can also organize energy-saving activities on university campuses, and have the government and schools organize public welfare activities, so that young people such as college students can actively participate in EB and maximize the positive results of EB for the whole society and the environment.

Conclusions and limitations

Conclusions

The purpose of this study was to examine the factors influencing EB among the younger age group of the residents. Using data from 360 questionnaires obtained in China, an extended NAM was obtained by expanding SFE and IP into NAM. The results of this study also verify the applicability of this extended model. Based on PLS-SEM, it is verified that the extended NAM has strong explanatory power for EI and EB of the study subjects. The empirical results show that AR and AC in young people's EB are important prerequisites for PN. Both PN and IP have significant positive effects on the study subjects' EI and EB. SFE has a significant direct effect on EI, but SFE does not have a significant direct effect on EB. Overall, external intervention factors in the younger group have a greater impact on EI than internal psychological factors (these factors were IP, SFE, and PN, in descending order of importance). That was, external intervention factors play an important role in EB of the young group. Based on these findings, we provide policy recommendations for the government, communities, and related organizations to further promote EB among young people.

Limitations and future research directions

Although we have new findings, several limitations of this study should still be noted. First, although we used an extended NAM, the influencing factors that affect people's EB in life are more complex. Subsequent studies can continuously extend the model to add more influencing factors. For example, subjective norms, attitudes, perceived behavioral control, social norms, and energy-saving climate. Second, this study used a questionnaire survey. Future studies should expand the sample size and further improve the representativeness of the sample. Also, this study should refine the socio-demographic characteristics and conduct a more detailed multi-group analysis. For instance, comparisons between different age groups, different genders, and different education levels of the study subjects could be added. Finally, future studies may be conducted in other parts of the world, taking into account differences in global energy environments, cultures, and economic levels.

Data availability statement

The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding author/s.

Author contributions

HS: conceptualization, methodology, and supervision. ZY: writing—original draft, data curation, validation, and formal analysis. QJ: methodology, editing, and supervision. YS: data curation, validation, and investigation. WH: writing—reviewing and editing, language enhancement, and supervision. XL: conceptualization, data curation, and writing—reviewing and editing. All authors contributed to the article and approved the submitted version.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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Tourist risk assessment of pollen allergy in tourism attractions: A case study in the Summer Palace, Beijing, China

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Pollen allergy has already been an increasingly prominent ecosystem disservice in tourism attractions. However, few studies have assessed the tourist risk of pollen allergy through integrating multidisciplinary knowledge of ecology, medicine, phenology, and risk management. Basing on the conceptual framework of risk assessment proposed by UNISDR, we first established an index system of pollen-allergy risk for tourists in attractions and outlined assessment methods 18 available indexes were put forward to cover three aspects: hazard of plant allergen, tourist vulnerability, and resilience of assessment units. Subsequently, taking the Summer Palace as the case study area, we conducted a tourist risk assessment of pollen allergy. Values of nine available indexes were obtained *via* ecological investigation, phenological observation, and data mining of visitors' logs on Sina Weibo. Risk levels of spring pollen allergy for tourists in different assessment units were revealed by combining the green zone allergenicity index model and three-dimensional risk assessment matrix. The results showed that: (1) There were seven primary pollen-allergenic plants in the Summer Palace, including *Platycladus orientalis*, *Sabina chinensis*, *Salix babylonica*, *Pinus tabulaeformis*, *Populus tomentosa Carr*, *Morus alba L.* and *Fraxinus chinesis*, among which *Platycladus orientalis* and *Salix babylonica* were the highest allergenic. (2) Among 18 spots, tourists faced the highest risk level of pollen allergy in spring at three spots, namely the Hall of Serenity, Hall of Benevolence and Longevity, and Gallery of Literary and Prosperity. (3) The two routes of the Long Corridor and Longevity Hill scored high on the risk level. (4) Among four areas, risk levels of the Front-hill and Rear-hill areas were high. Given the increasing spatial-temporal uncertainty of pollen allergy and tourist behaviors under global warming and urbanization, the related monitoring should be strengthened in the future. Furthermore, the dynamic and improved assessment of pollen-allergy risk should be institutionalized and be integrated into the evaluation of tourism experience quality. Tourism administration should make full use of relevant assessment results and conduct more effective risk communication.

KEYWORDS

tourism attractions, pollen allergy, tourist risk assessment, green zone allergenicity index model, data mining, risk matrix, Summer Palace, climate change

Introduction

Pollinosis is a "national disease" around the world. It can cause allergic rhinitis, conjunctivitis, hay fever or asthma, urticaria, and allergic dermatitis, etc. Patients may suffer from shock and have a risk of sudden death, when correlated symptoms are severe. In developed countries, 20–30% of the population is allergic to pollen (1), while the prevalence rate in China is about 14.16%[1]. Moreover, there are many people in China who developed pollinosis symptoms but did not know that their symptoms belong to the pollinosis. The economic burden of pollinosis is enormous. An analysis estimated that the annual global expenditure was about 7.9 billion dollars, including direct medical expenses and indirect economic losses (2). Besides direct and indirect economic losses, intangible costs (social costs, loss of life quality) carried by pollinosis are also enormous. Therefore, pollen allergy has already attracted worldwide attention. In 1997, the WHO pointed out that pollinosis would be a prevalent disease in the twenty first century, whose treatment and prevention should be given a high priority (2).

Studies on pollen allergy came from medicine, ecology, phenology, and some other disciplines. Among them, medicine focused on the difference in the allergenicity and emissions of various pollens, the association between its incidence and the demographic characteristics of patients, and seasonality changes of airborne pollen (3). Ecology focused on the effect of the urban environment on pollen emissions (4), the allergenic species composition in different green spaces (5, 6), the allergenic potential of parks and campuses (6, 7), and interventionist approaches for allergenic environment improvement (8). The allergenic hazard of green spaces has already been assessed by using a green zone allergenicity index model, which combined multiple indexes, such as canopy height, canopy cover, allergenic potential, pollen emission and pollination duration (6, 7). Phenology paid more attention to multi-timescale variation of the allergenic flowering duration and pollen season, and relationships between these phenological indexes and different climatic factors (9, 10). In general, most studies were on a spatial scale larger than city, and allergen studies have not yet been linked to spatial-temporal behaviors of people. Moreover, few studies on pollen allergy have integrated multidisciplinary knowledge to guide the sustainable development of tourism. From the prospective of tourism, the pollen allergy risk has not been taken into account by previous studies on the tourist safety in China (11, 12), and was ignored by the existing evaluation of experience quality in tourism attractions (13, 14).

Tourism attractions play a key role in tourism and have become more and more important with the continuous enhancement of Chinese travel desire and payment capability. In 2021, the number of National A—5A level tourism attractions in China reached 14196, and their tourism revenue increased to 2.92 trillion yuan, up 31.0% over 2020 (15). Compared with the rapid increase of number and production value, the ecosystem services and functions of tourism attractions still need to be improved. The increasingly prominent pollen allergy risk is such a typical ecosystem disservice in tourism attractions. Many common woody and herbaceous plants in tourism attractions have allergenicity. The former includes *Sabina chinensis*, *Populus tomentosa*, *Fraxinus chinensis*, *Rhus Typhina*, *Syringa reticulata*, and the latter includes *Chrysanthemum morifolium* and *Brassica rapa*. Despite their undeniably benefits of the adaptability to local climatic conditions, the ease of management, and the ability to enhance the landscape, allergenic plants make tourism attractions uncomfortable seasonally for the human respiratory system. Under the background of nature tourism and outdoor education becoming more and more popular, people' exposure to the allergenic environment is increasing.

Climate change have posed unprecedented challenges to human health (16–18). As for the pollen allergy, the flowering dates of *Morus*, *Robinia* and *Cerasus yedoensis* across many regions have already advanced (19, 20), the pollen seasons of *Tilia sp. L.*, *Quercus* and *Platanus* have prolonged (21–23), and the allergenicities of *Betula* and *Juniperus* have increased (22, 23). How to properly handle the pollen allergy risk, has become more and more important. A study has pointed out that the countermeasure of health risk caused by climate change contains at least two aspects: the establishment of a comprehensive assessment index system and the clarification of high-risk areas and periods (24). "*The 2021 China report of The Lancet Countdown on health and climate change: seizing the window of opportunity*" highlighted that the exposure and vulnerability of humans should be clarified, and the mapping of health risks should be conducted (25). At present, the risk assessment of pollen allergy serving the tourism industry is still blank in China. Consequently, this paper integrates multidiscipline knowledge to establish a comprehensive assessment index system of pollen-allergy risk for tourists and outlines preliminary approaches to estimate this risk. To illustrate the practical application of the assessment indexes and methods, a case study was carried out in the Summer Palace, Beijing, China. The index system of pollen-allergy risk described here can be used to guide related green-space plans of tourism attractions, to promote the tourist management, and to help pollen allergy patients to avoid environmental triggers in attractions during the allergenic pollen season.

Materials and methods

Conceptual framework of pollen-allergy risk assessment

Risk is defined as the possibility of a hazardous outcome or expected loss caused by the interaction between a natural

1 http://henan.china.com.cn/m/2021-03/29/content_41511485.html

or man-made disaster and it suffers (26). The United Nations International Strategy for Disaster Reduction (UNISDR) argued that risk assessment can be conducted by use of the conceptual framework of "Risk (R) = Hazard (H) × Vulnerability (V)" (27). Under this framework, the safety of landscapes and tourists in attractions has been assessed effectively (11, 28). After considering the general applicability of this framework, we used it to assess the pollen-allergy risk of tourists in tourism attractions. The assessment was conducted at three spatial hierarchies (scenic spot, route, and area), taking account of the space structure and functional partition of tourism attractions.

Construction of index system

The index system was made of four layers: target (A), factor (B), category index (C) and bottom index (D). The pollen-allergy risk of tourists in attractions was defined as the target (A). According to the risk conception and the pollen-allergy formation mechanism, the target was determined by three factors on the B layer, including the hazard of plant allergen, tourist vulnerability, and resilience of assessment units. As for the hazard of plant allergen, its category indexes and bottom indexes were selected considering both the biological and ecological characteristics of allergenic species. With reference to the meanings of risk exposure and the resistibility of human body in the assessment theory of natural disaster risks (29, 30), category indexes and bottom indexes of tourists vulnerability were constructed. The resilience of assessment units was designed to have no category index and the selection of its bottom indexes also referenced indexes of risk resistance capacity used in disaster-risk assessments (29, 30).

As shown in Figure 1, 18 bottom indexes were selected to describe different category indexes and factors. As for the first category index—community characters and distribution of allergenic plants, we selected five bottom indexes which were often used in previous ecological studies (5–7), namely the species composition and quantity, canopy height, canopy cover, crown breadth, and vegetation coverage. The values of relevant indexes can be obtained by combining the ecological investigation and remote-sensing image interpretation. There are also five commonly used indexes which can describe the second category index—comprehensive allergenicity of species: pollen emission, allergenic potential (AP), airborne pollen concentration, pollen season duration, and flowering duration (31). Their values are documented in medical and phenological reports and databases, or available *via* phenological observations and airborne allergen monitoring. Concerning the third category index of tourist exposure, we selected two basic indexes (tourist amounts and dwell time) used in most studies on tourist behaviors. More tourist amounts and dwell time mean greater tourist exposure. According to previous studies, tourist amounts can be obtained *via* the sampling survey, GPS tracking survey (32), Weibo data mining (33). Dwell time of tourists in assess units can be roughly graded into different scales through evaluating the landscape value and environmental capacity of tourism resources, or be precisely calculated by using an Agent-Based Model (ABM) (34). Regarding the fourth category index—human resistance, it is closely related to the age, education level, treatment and protection cost, income level (35, 36). If the four values can be obtained through survey questionnaire, the human resistance will be measured well. Finally, as for the resilience of assessment units, we recommended two bottom indexes (medical rescue ability and emergency vehicle equipment) with reference to disaster-risk studies. The medical rescue ability can be measured *via* calculating the shortest distance between the assessed unit and the nearest medical center on the ArcGIS platform. The numbers of equipped emergency vehicles can be obtained from the attraction's administration.

Quantification and coupling of assessment indexes

To eliminate the effect on data comparability imposed by dimensions and attributes, data normalization and criterion classification should be handled. There are multiple normalization techniques, such as Min-Max normalization, Z-score normalization, and Mean normalization. As for the classification criteria of indexes, most statistical values can be arranged into different "natural" classes by using the Jenks optimization method. Previous studies also provided classification criteria of some specific indexes (Table 1).

Referring to the assessment experience of disaster risks (29, 30), there are two applicable techniques for the coupling of pollen-allergy risk indexes, namely the multi-factor model and risk matrix. As for the former, there are several approaches to determine the weight of each index, which can be divided into subjective, or objective, or combined approaches. Common subjective approaches include the Delphi method, analytic hierarchy process (AHP) and so on, which is simple but greatly affected by the subjective preferences of assessors. Objective weighting approaches without decision-maker involvement include equal weighting method, standard deviation weighting method, entropy weighting method, principal component analysis (PCA), etc. The popular Green Zone Allergenicity Index (I_{GZA}) model (7, 31) (Equation 1) is essentially an equal weight method for assessing the hazard of plant allergen. Although these objective weighting approaches have a sound mathematical basis, the application of them are restricted by the amount of data and specific problem domains. Sometimes their weights did not conform to the importance of corresponding indexes. Combined approaches have the advantages of both the subjective and the objective weighting, however, their calculation process is complicated.

$$I_{GZA} = \frac{1}{378 \times S_T} \sum_{i=1}^{k} N_i \times AP \times PE \times FD \times S \times H \quad (1)$$

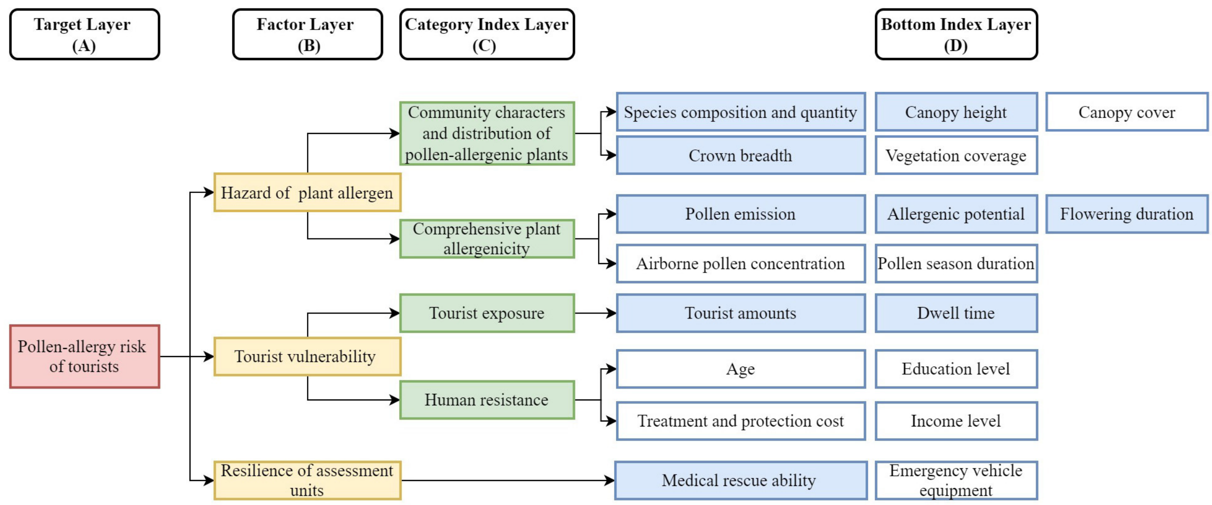

FIGURE 1
The construction of index system for tourist pollen-allergy risk in attractions (Blue indexes were used in the case study of the Summer Palace).

Where k = number of pollen allergenic species, N_i = number of individuals belonging to the i-species, AP = allergenic potential, PE = pollen emission, FD = flowering duration (d), S = vertical crown projection area covered (m^2), H = canopy height (m), S_T = total surface area of the assessment unit (m^2).

Risk level matrix is another convenient fundamental tool used to assess risk (29, 30, 38). Traditionally, the two-dimensional matrix (Figure 2A) was the most widely used. In the assessment process, a scale of 1–4 was often used, with one indicating the lowest and four indicating the highest. However, more and more experts contended that this method failed to adequately account for human factors affecting risk, and they recommended adding some human factors as a third dimension to gain a fuller picture of the true risk involved in an operation (39, 40). Therefore, according to the above-mentioned index system, we can define the three-dimensional matrix of pollen-allergy risk as a matrix between hazard, vulnerability, and resilience (Figure 2B).

Data collection and applied model for the study area

Study area

Beijing, in the northwest of the North China Plain, is a typical continental monsoon region, with a semi-humid climate and deciduous broad-leaved forests. The superior geographical environment and neo-urbanization oriented by "ecological civilization" have promoted green spaces development. The present urban green space in Beijing covers an area of 926.83 km^2, in which 357.20 km^2 are parks (41). However, many common landscaping species in green space can cause pollinosis, including *Juniperus chinensis, Populus tomentosa, Salix babylonica, Platycladus orientalis, Pinus tabuliformis, Styphnolobium japonicum, Salix matsudana, Pinus bungeana* (5). To date, the prevalence rate of pollinosis in Beijing reached 47.02%, higher than that in other high prevalence areas in China (42).

The Summer Palace in the northwest of Beijing, covered an area of 290.8 hectares, in which the land area is 75.30 hectares (Figure 3). There are 22,803 pollen-allergenic trees in the park, such as *Platycladus orientalis*, *Sabina chinensis, and Salix babylonica*, which belong to 33 species, 11 families, and 20 genera (43). As the largest existing royal garden in China and a National 5A level tourism attraction, the average daily tourist amount of the Summer Palace exceeded 50,000 in the past decade[2]. In 2018, the park visits reached 120,000 per day during the National Day[3], far exceeding the daily visitor capacity of 6.1 million (44). Therefore, from the perspective of plant allergen and allergen contact, the Summer Palace is a potentially high-risk area for pollen allergies.

Data collection

The research data used in this paper include three main categories: the first is the type and quantity data of allergenic species obtained from ecological investigation, used for addressing the distribution differences in the pollen allergen. The second is the flowering data of allergenic plants obtained through phenological observation in the Summer Palace, which was used to comprehensively analyze the hazard of pollen

2 https://www.bjnews.com.cn/detail/162356847914694.html
3 https://www.sohu.com/a/257639840_267106

TABLE 1 Classification criteria of specific indexes for pollen allergy risk.

Assessment indexes	Scale class	Classification criteria
Pollen emission[a]	1	Only a few visible pollen granules on the plant are released when gently shaken or blown into the palm of the observer onto a dark surface.
	2	Many granules are released.
	3	A layer of pollen covers the palm, or a cloud of pollen can be seen in the air when the wind blows.
Allergenic potential (70)	1	Less than three sneezes per time.
	2	Intermittent nasal itching, 3–9 sneezes per time, having a running nose less than four times per day, occasional nasal congestion, intermittent eye itching.
	3	Having a tolerable sense of ant movement in the nose, continuous 10–14 sneezes per time, having a running nose 5–9 times per day, constant nasal congestion, and obvious and tolerable itching of eyes.
	4	Having an intolerable sense of ant movement in the nose, more than 15 sneezes per time, having a running nose more than 10 times per day, continuous nasal congestion, and intolerable itching of eyes.
Pollen duration or flowering duration (6)	1	Less than 1 week
	2	1–3 weeks
	3	4–6 weeks
	4	More than 6 weeks
Airborne pollen concentration (granule/1000mm^2) (37)	1	Woody pollen: ≤100; herbal pollen: ≤50
	2	Woody pollen: 101∼250; herbal pollen: 51∼100
	3	Woody pollen: 251∼400; herbal pollen: 101∼150
	4	Woody pollen: 401∼800; herbal pollen: 151∼300
	5	Woody pollen: >800; herbal pollen: >300
Human Age (35, 36)	1	The elder (≥65 years old)
	2	Adolescence (≤17 years old) and the middle-aged (46–64 years old)
	3	Youth (18–45 years old)

[a]https://usanpn.org/files/npn/reports/USA-NPN_Plant_and_Animal_Phenophase_Definitions_v2.0.pdf.

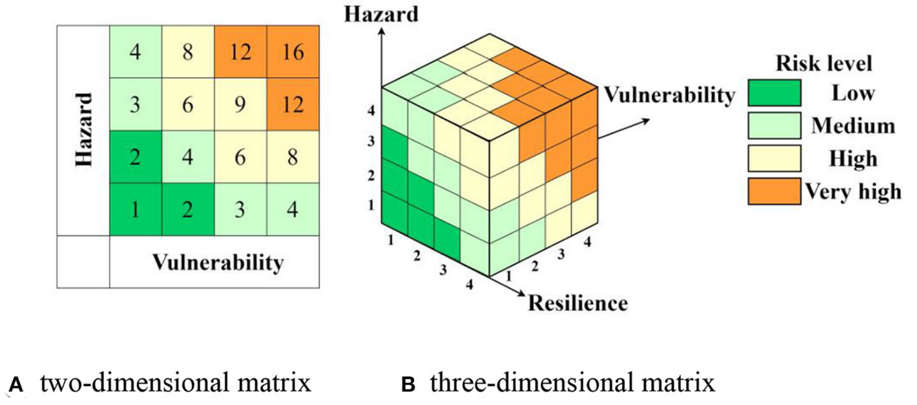

FIGURE 2
Assessment matrixes of pollen-allergy risk. **(A)** Two-dimensional matrix. **(B)** Three-dimensional matrix.

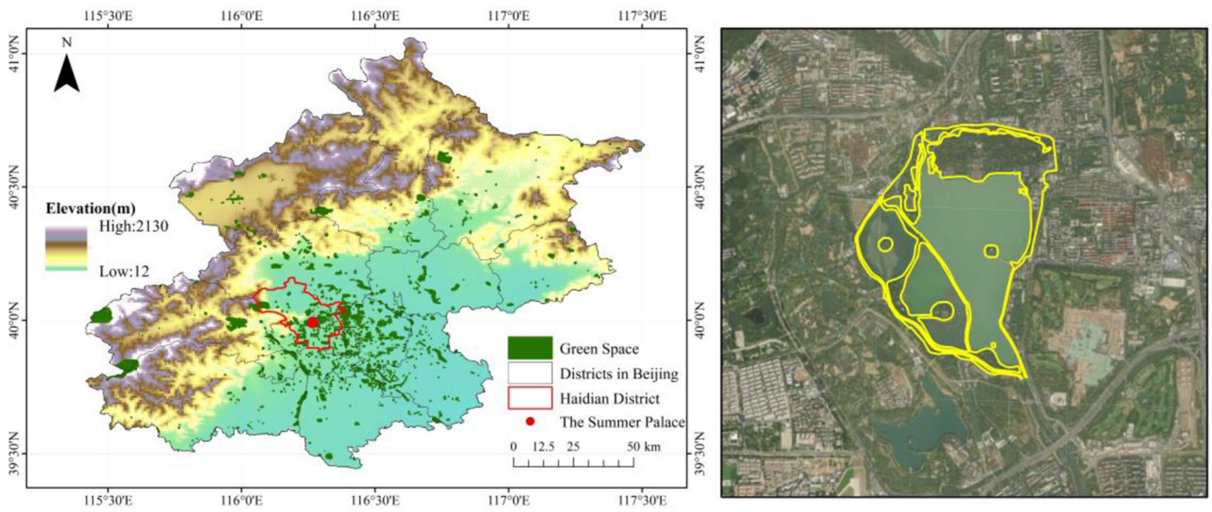

FIGURE 3
The geographical location of the Summer Palace.

allergen. The third is visitors' logs data obtained by data mining of Sina Weibo, used for analyzing the difference in tourists amounts among different spots, routes and areas in the park.

Ecological investigation data

The ecological investigation was carried out by means of a sample plot survey in April 2021. This period was chosen because trees in April have more branches, blossoms, and stamens per unit of surface area than in other months of spring. We divided the land area in the Summer Place into different grids with a resolution of 150 × 150 m. In each grid, at least one 10 × 10 m quadrat was set. The exact geographical locations of allergenic plants within the quadrat were marked by use of the GPS. The diameter at breast height (DBH), canopy breadth and canopy height of every allergenic plant were measured by DBH ruler, tape measure, and laser rangefinder, respectively. During the investigation course, The DBH was measured at the height of 1.3 m, and the canopy breadth was calculated as described by Liu et al. (45).

Phenological observation data

There are seven main allergenic woody species in the Summer Place, including *Platycladus orientalis*, *Sabina chinensis*, *Salix babylonica*, *Pinus tabulaeformis*, *Populus tomentosa Carr*, *Morus alba L*, and *Fraxinus chinesis*. Their phenological observation data were obtained from the Chinese Phenological Observation Network (CPON, http://www.cpon.ac.cn/). Records of first flowering dates (FFD), full blooming dates (FBD) and end of flowering dates (EFD) of them in 2021 were extracted from the dataset, whose observation process conformed to the traditional criteria in China (46). According to these criteria, the FFD is the date when at least three flowers came out on the plant individual. The FBD is the date when more than half of the flowers on the tree bloomed. The EFD is the date when only 5% of the flowers remained on the plant.

Visitors' logs data retrieved from Sina Weibo

According to the flowering observation data in the Summer Place over the past years, there is a spring peak of local pollen amount persisting from March to May. Consequently, the index of tourist amounts was also analyzed during the same period. Social media check-in data is considered as an important data which can reflect the spatiotemporal characteristics of tourist amounts (47, 48). In light of this, between 1 March and 31 May 2021, the sign-in logs of tourists to the Summer Palace were retrieved from Sina Weibo (https://weibo.com/). By use of a search engine developed by Sichuan University (33) and the application programming interface (API) provided by Sina Weibo, we conducted the data retrieval. The settings of retrieval environment were shown in Table 2. There were 72,137 valid records after data cleansing, whose useful information included names, locations, coordinates, check-in times, tourist activities and so on. We identified 19 main points of interest (POI) in the Summer Palace. Among them, the West Causeway was treated as a scenic route because of its spatial form, and the other points were treated as scenic spots.

Applied model

According to the overall tourism planning for the Summer Palace (44) and its tourism introduction on the official website, the risk assessment units in the park were ascertained as 18 scenic spots, five scenic routes and four scenic areas. Because of the limited data accessibility, we only selected nine

TABLE 2 The search settings and results of Sina Weibo.

Search settings			Raw results	Filter settings		Filtered results
Semantics recognition	Year	Month		White words	Black words	
Tourist behaviors	2021	March to May	75857	e.g., take photos, make videos, sightsee, and hike.	e.g., work, patrol, serve, and take a boat.	72137

TABLE 3 Factor portfolios of the three-dimensional risk matrix (39, 40).

Risk level	Factor portfolios										
Very high	444	443	442	434	433	424	344	343	334	333	244
High	441	432	431	423	422	414	413	342	341	332	324
	323	314	243	242	234	233	224	144	143	134	
Medium	421	412	411	331	322	321	313	312	241	232	231
	223	214	213	142	141	133	132	124	123	114	
Low	311	222	221	212	211	131	122	121	113	112	111

bottom indexes to assess the tourist risk of pollen allergy in attractions, including species composition and quantity, canopy height, crown breadth, pollen emission, allergenic potential, flowering duration, tourist amounts, dwell time, and medical rescue ability.

When coupling these indexes, we firstly assessed the hazards of plant allergen in different units by use of the above-mentioned I_{GZA} model. Secondly, the tourist vulnerabilities were assessed by combination of tourist amounts and dwell time. Subsequently, the medical rescue abilities of different units were measured *via* calculating their shortest distances to the six service centers located at North Ruyi Gate, North Palace Gate, East Palace Gate, New Built Gate, South Ruyi Gate, and West Palace Gate. Values of the three risk factors were all classified into four levels *via* the natural break classification method. Finally, pollen allergy risks in different scenic spots, routes and areas were revealed by using the three-dimensional assessment matrix whose factor portfolios were shown in Table 3.

Results analysis

Hazard of plant allergen in spring

Based on the phenological observation, ecological investigation and literature review, the distribution and community characteristics of seven primary pollen-allergenic trees in the Summer Palace were revealed effectively. These plants can be found throughout the park, which are densely distributed on the Longevity Mountain. According to Table 4, the numbers of *Platycladus orientalis, Sabina chinensis* and *Salix babylonica* ranks the top three. Based on the AP scale classes for different trees (7, 31, 49–51), *Fraxinus chinesis* was identified as the species with the highest allergenic potential in the Summer Palace, followed by *Platycladus orientalis* and *Sabina chinensis*. As for the pollen emissions, *Platycladus orientalis*, *Sabina chinensis* and *Fraxinus chinesis* were identified as the top three. The flowering durations of *Platycladus orientalis*, *Populus tomentosa Carr* and *Morus alba L.* all reached 20 days in 2021, while that of *Pinus tabulaeformis* was only 11 days. Overall, the allergenic hazards of *Platycladus orientalis* and *Salix babylonica* were the top two in the spring of 2021, according to the calculation results of the I_{GZA} model.

Among the 18 scenic spots in the Summer Palace, the Hall of Serenity, Garden of Harmonious Interests, Hall of Benevolence and Longevity, and Gallery of Literary Prosperity had the highest pollen-allergenic hazard in the spring of 2021. The allergenic hazards on the scenic routes of Long Corridor and Longevity Hill were higher than those on the three others. Among the four scenic areas, tourists faced higher allergenic hazard in the East-lake and Rear-hill areas (Table 4). In general, the high hazard of spring allergen in the Summer Palace was mainly distributed within the range of Longevity Mountain in 2021.

Tourist vulnerability and unit resilience

Tourist vulnerability (namely tourist exposure in the case study) was revealed by combining the data mining of visitors' check-in on Sina Weibo and the dwell-time analysis. Among the 18 scenic spots, the Hall of Benevolence and Longevity, East Palace Gate, Gallery of Literary Prosperity and North Palace Gate were most visited in the spring of 2021. Therefore, tourist vulnerabilities of them were the highest. In contrast, the scenic spots of the Marble Boat, Chamber of Cultivation, Hall of Happiness and Longevity, Chamber of Clearness, and West Palace Gate had low tourist vulnerabilities. Among the five scenic routes, the tourist vulnerabilities of the Long Corridor route and the Longevity Hill route were very high and high, respectively, while those of the West and East Causeway routes were both low. As for the scenic areas, the tourist vulnerability of the Front-hill area was very high, while that of the East-lake

TABLE 4 List of pollen-allergenic species in the Summer Palace and their parameters.

Specie	Number (N)	Allergenic potential (AP)	Pollen emission (PE)	Flowering duration (FD) (Unit: d)	Mean vertical projected area of crown (S) (Unit:m^2)	Mean canopy height (H) (Unit: m)	Hazard level
Platycladus orientalis	9446	3	3	21	13.72	9.6	4
Sabina chinensis	4062	3	3	16	15.20	10.1	2
Salix babylonica	3536	2	2	16	44.40	16.1	3
Pinus tabulaeformis	3205	1	2	11	95.03	13.4	2
Populus tomentosa Carr	682	2	2	20	94.99	17.8	2
Morus alba L.	196	2	1	20	67.02	14.2	1
Fraxinus chinesis	114	4	3	16	94.99	11.8	1

area was the lowest (Table 5). Overall, tourist vulnerabilities in the north and east of the Summer Palace were higher than those in the south and west.

Because all the six medical centers are located near the gates of the park, the distances from the assessment unit to the nearest gate have great influence on their resilience. Among the 18 scenic spots, four scenic spots had the poorest resilience, namely the Garden of Farming and Weaving, Chamber of Clearness, Marble Boat, and Hall of Serenity (Table 5). According to the comparisons among the five scenic routes, the resilience of the West Causeway route was the poorest, while the route of the Rear-hill and back-lake was the best. The resilience of the West-lake area, Rear-hill area, the East-lake area, and Rear-hill area was decreased in turn.

Risk difference of pollen allergy for different assessment units

According to the assessment results of the three-dimensional risk matrix, tourists in three scenic spots (namely the Hall of Serenity, Hall of Benevolence and Longevity, and Gallery of Literary and Prosperity) had a very high risk of pollen allergy, whose governance should be given the top priority (Table 5). In the 15 other spots, the number of high-risk, medium-risk, and low-risk spots were five, six, four, respectively. Among the five scenic routes, tourist risks on the two routes of the Long Corridor and Longevity Hill reached a very high or high level, while the two routes of the Rear-hill and back-lake, and East Causeway had low risks. Among the four scenic areas, both the Rear-hill and Front-hill were assessed as the high-risk area, while the risks of East-lake and West-lake areas were labeled as moderate. Basing on the above results, we drew a tourist-risk map of pollen allergy in the Summer Palace (Figure 4).

Discussion

Uncertainty of pollen-allergy risk under global warming and urbanization

Climate change has already brought about significant impacts on both the plant allergen and the tourist behaviors. As for the hazard of plant allergen, due to the global warming observed over the past 70 years, there have been significant changes in regional species composition (52), phenological dates (20), and ecological functions (53). These changes have subsequently affected the start, duration, and intensity of regional pollen season (21–23). A recent study estimated that under a warming scenario of SSP5 8.5, the increasing concentration of atmospheric CO_2 would increase the likelihood of seasonal allergies throughout the continental USA, with end-of-century emissions being increased up to 200% (54). Another study from Brussels, Belgium showed that the allergy hazard in urban green spaces might increase by 11–27% in the increased allergenic potential scenarios, and by 44% in the increased pollen season duration scenario (51). In addition, precipitation and near-surface wind speed will exhibit greater regional variability in the future (55), thereby increasing the hazard uncertainty of plant allergens. When continuous precipitation occurred, it can not only affect the plant flowering, but also have a scouring effect on pollen grains, resulting in a rapid decrease in pollen concentration (56). The increase of wind speed is conductive to the pollen spread. When the wind speed reaches 4–6 m/s, the pollen quickly spreads to the downwind, resulting in more extensive pollinosis (57). Besides the above climate factors, weather and climate extremes have also shown significant regional differences (55). For example, late-spring frost risk between 1959 and 2017 increased significantly in Europe and East Asia but decreased in North America (58), indicating that differences in spring pollen emissions and duration across

TABLE 5 Assessment results of pollen-allergy risk for tourists in the Summer Palace.

	No.	Name	Hazard	Vulnerability	Resilience	Element portfolio	Risk level
Scenic spot	A1	North Palace Gate	1	4	1	141	Medium
	A2	Suzhou Street	3	2	1	321	Medium
	A3	Hall of Serenity	4	2	4	424	Very high
	A4	Chamber of Clearness	3	1	4	314	High
	A5	Garden of Harmonious Interests	4	2	3	423	High
	A6	Chamber of Cultivation	2	1	3	213	Medium
	A7	Purple Cloud Gate Tower	2	3	2	232	Medium
	A8	Hall of Celebrating Virtues	3	3	2	332	High
	A9	Hall of Happiness and Longevity	2	1	2	212	Low
	A10	Hall of Jade Ripples	1	2	2	122	Low
	A11	Hall of Benevolence and Longevity	4	4	2	442	Very high
	A12	East Palace Gate	3	4	1	341	High
	A13	Gallery of Literary Prosperity	4	4	3	443	Very high
	A14	Marble Boat	2	1	4	214	Medium
	A15	Garden of Farming and Weaving	2	3	4	234	High
	A16	West Palace Gate	1	1	1	111	Low
	A17	South Ruyi Gate	1	2	1	121	Low
	A18	South Lake Island	1	3	3	133	Medium
Scenic route	B1	Rear-hill and back-lake route	1	2	1	121	Low
	B2	Longevity Hill route	3	3	2	332	High
	B3	Long Corridor route	4	4	3	443	Very high
	B4	East Causeway route	2	1	2	212	Low
	B5	West Causeway route	1	1	4	114	Medium
Scenic area	C1	Rear-hill area	3	3	2	332	High
	C2	Front-hill area	2	4	3	243	High
	C3	East-lake area	4	1	2	412	Medium
	C4	West-lake area	1	2	4	124	Medium

regions is rising. In the future, projected climate changes will still manifest differently for different weather regimes and may lead to contrasting changes in average and extreme conditions.

In regard to tourist behaviors, climate change can have a potential impact on travel decision. The Sixth IPCC Assessment Report (AR6) shows that heat waves will significantly increase the risk of morbidity and mortality, and have a profound impact on population behavior patterns and transportation choices for travel (55). David Maddison found that the number of British tourists decreased significantly with the increase of temperature (59). Another study in China suggests that the improvement on the climate comfort in high latitude and high altitude areas will be beneficial to the development of outdoor sports (60). In conclusion, as described by Robert Steiger (61), when planned excursions cannot be carried out due to climate change, travelers may make three substitutive decisions, namely alterations of the travel time, destination and activity type.

The acceleration of urbanization may not only lead to the heterogeneity warmth of inner-city areas, but also promote the intensification of air pollution and the change of local wind environment. All these potential changes are influential in uncertainties of pollen-allergy hazard. Firstly, a large temperature gradient between urban and rural will occur when the heat island effect is remarkable (62), thereby urging the flowering period and pollen season of urban allergenic plants to be earlier than those in suburbs (63). Secondly, it has been found that urban land area was significantly positively correlated with $PM_{2.5}$ concentration (64), while the $PM_{2.5}$ concentration can promote the increase of pollen concentration (56). Moreover, the rapid change of urban underlying surface morphology can cause the urban ventilation corridors to change (65), and changes will occur in the range and direction of pollen diffusion thereby.

To sum up, the uncertainty of pollen allergy risk in the future scenarios of global warming and urbanization may increase and subsequently pose complicated impacts on people's routine outings and leisure activities. At present, the knowledge about the impact of future climate change on the pollen allergy and tourist behaviors is very limited in China. So, it is of great significance to develop parallel observation of flowering and pollen seasons, and to do further researches on the tourist's

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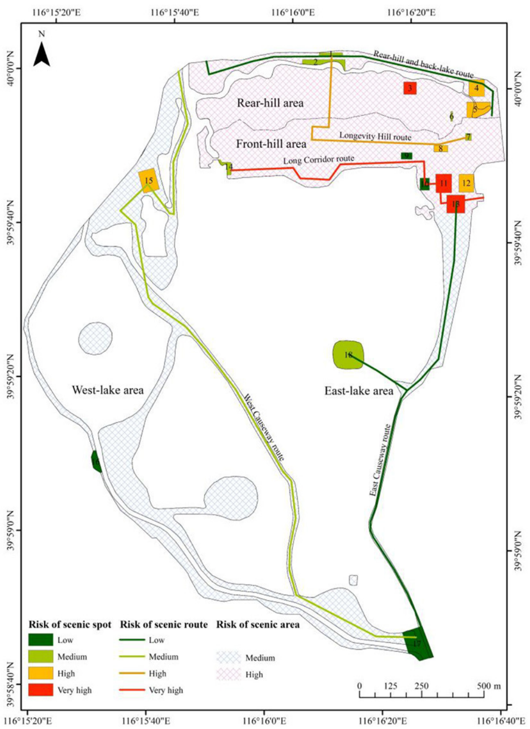

FIGURE 4
Distribution of pollen allergy risks for tourists in the Summer Palace.

behavior. Systematic observations and the improvement of prediction models will help us to better understand the spatial-temporal uncertainty of pollen allergy risk in the future.

Improvement of pollen allergy risk assessment

Because of difficulties with data acquisition, we only selected nine from 18 bottom indexes in the conceptual model and utilized the easiest risk matrix to conduct the case assessment. In the future, the relevant evaluation indexes and methods can be further improved based on enriching data. On the one hand, the installation of pollen monitors and the interpretation of high-resolution remote sensing images will greatly contribute to the assessment of the comprehensive allergenicity in green spaces. In this paper, flowering duration of native allergenic plants was used as an alternative index of airborne pollen seasons. However, there are some differences between them due to the influence of atmospheric circulation (9). Therefore, the index of airborne pollen duration should be added into the follow-up assessment. Furthermore, the segment of pollen season with consideration of allergenicity difference among species is better to describe the hazard of pollen allergy than the total pollen season frequently used in previous studies (66). The calculation of a vegetation index based on high-resolution RS was proved to effectively reflect the pollen concentration at a micro scale (67), and this method should also be tried.

On the other hand, the optimization of tourist behavior investigation can make the vulnerability assessment for the pollen allergy risk more accurate. In the case study, visitors' logs data retrieved from Sina Weibo essentially reflects the activity of online tourists and is only an effective data supplement when the field monitoring data of tourists is lacking. Subsequent studies based on the mobile phone location data will better reveal the tourist exposure to the plant allergen. In fact, a case-crossover study in Belgium has already utilized uploading records from mobile medical health software to analyze the relationship between the patients' exposure to green space and their pollen allergy symptom severity (68). In addition, previous analysis showed that the prevalence of pollinosis is closely related to the age, education level and income level (35, 36). Therefore, conducting a sample survey of tourists in tourism attractions is helpful to accurately assess their human resistance to this disease.

After taking possession of more and better indexes values in the future, subjective and objective integrated weighting methods should also be tried.

Conclusion and outlook

Climate change has already affected human health directly and indirectly in China. From the perspective of tourism management, it is imperative to assess the pollen-allergy risk of tourists and visualize it by risk mapping. For this purpose, we established an assessment index system consisting of 18 available bottom indexes, which covered three aspects of allergen hazard, tourist vulnerability and resilience of assessment units. The quantification and coupling of assessment indexes were also outlined. Taking the Summer Palace as the case study area, we obtained the values of nine representative indexes *via* phenological observation, ecological investigation, and data mining of visitors' logs on Sina Weibo. Then, we combined the I_{GZA} (Green Zone Allergenicity Index) model and three-dimensional risk assessment matrix to assess and map the risk levels of spring pollen allergy in 18 scenic spots, five scenic routes and four scenic areas. The results showed that: (1) There were 7 primary pollen-allergenic plants in the park, among which *Platycladus orientalis* and *Salix babylonica* had the highest allergenic hazard. (2) Among 18 spots, tourists faced the highest risk level of spring pollen allergy in three spots, namely the Hall of Serenity, Hall of Benevolence and Longevity, and Gallery of Literary Prosperity. (3) The two routes of the Long Corridor and Longevity Hill scored high on the pollen-allergenic risk level. (4) Among four areas, the Front-hill and Rear-hill areas were high risky for tourists.

In global warming scenarios, the allergenicity of pollen-allergy plants will be driven by the changes of climate factors, such as temperature, precipitation, wind speed, CO_2 concentration, and extreme events. Urbanization will also affect the local climate, thermal environment and $PM_{2.5}$ concentration. As a result of these two driving forces, greater uncertainty of pollen allergy risk may occur subsequently in the future. Therefore, under the policy background that Chinese government has placed increasing emphasis on the construction of ecological civilization and the improvement of human wellbeing and public health, the high-quality development of tourism attractions should attach importance to the risk impact of local thermal environment, climate comfort and air pollution (64, 69). The dynamic assessment of pollen-allergy risk should be institutionalized and be integrated into the evaluation of tourism experience quality. Researchers should further clarify the spatial-temporal distribution characteristics of pollen allergen and tourists in China and improve the reliability of risk assessment by optimizing the index system and assessment method. Relevant government departments should also apply the assessment results to guide decisions of green spaces planning and publish sufficient information to help pollen allergy tourists to avoid environmental triggers during the airborne pollen season.

Data availability statement

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

Author contributions

YZ processed data, constructed assessment model, and wrote the original draft. JD provided guidance for phenological observation and field survey. XL edited the draft and visualized research results. HL built the workflow framework, clarified methodology, reviewed the writing, and provided fund support. All authors have read and agreed to the published version of the manuscript.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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Measuring spatial accessibility and supply-demand deviation of urban green space: A mobile phone signaling data perspective

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The reasonable distribution of urban green space (UGS) is a topic that urban researchers have been exploring for a long time. Solving the imbalance between the supply and demand of UGS plays an important role in improving the health level of a city. This study examines the central urban area of Hefei as an example. We developed a modified Gaussian two-step floating catchment area method and used the path planning model of Gaode Map to evaluate the accessibility of UGS under different transportation modes and different time thresholds while integrating mobile phone signaling data. Additionally, a fine-scale analysis of the actual supply and demand relationship of UGS was conducted by integrating the accessibility evaluation results with the recreational situation of UGS to analyze the deviation of supply and demand to further discuss the spatial distribution equilibrium of UGS. The main conclusions are as follows. (1) The spatial distribution of UGSs in the central urban area of Hefei is uneven. Different time thresholds and different transportation modes have a significant impact on the UGS accessibility evaluation results. (2) With the increase in the time threshold or travel distance, the number of grids above the moderate accessibility level generally increases. The spatial distribution of the grids with moderate, high and highest accessibility level present different patterns of contiguous, clusters, and spots distribution. (3) After combining these results with the actual recreational situation of UGS, we found that the overall demand in the central urban area exceeds the supply at the 15-min threshold, while the overall supply exceeds the demand at the 30-min threshold. The grids with balanced supply and demand or more supply than demand have comprehensive parks with a moderate population density and strong road connectivity in the neighborhood. This study strengthens the data granularity and improves the accuracy of accessibility evaluation by integrating mobile phone signaling data with the path planning model of Gaode Map. Also, we evaluate the accessibility with multi-transport modes and different time thresholds, which can bring more practical guidance for optimizing the distribution of UGS.

KEYWORDS

urban green space, mobile phone signaling data, spatial accessibility, supply-demand, Ga2SFCA method

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Introduction

With the acceleration of urbanization in China, residents' demand for urban green space (UGS) is growing (1). Meanwhile, as an important component of urban ecosystems (2), UGS can reduce the negative impact of environmental factors such as space pollution (3), noise (4), and high temperatures (5). Prolonged exposure to UGS helps promote the physical and mental health of residents (6) and reduces stress as well as the risk of obesity, stroke, and other diseases (7). Due to that the traditional evaluation of UGS is based on the traditional indicators of urban park area per capita, the greening rate and green coverage rate, it can be difficult to reflect the spatial distribution, quality, and fairness of the service function of UGS (8). In the context of limited urban construction land, it is of great theoretical and practical significance to evaluate the spatial distribution quality of the existing UGS.

Accessibility is an important index to measure the fairness of UGS spatial distribution. Accessibility refers to the potential of overcoming resistance, such as time and distance, to reach a certain place (9). In recent years, an increasing number of studies have introduced the concept of accessibility into the evaluation of UGS. Researchers often measure the accessibility of UGS by setting statistical indicators (10) and using the cost-weighted distance method (11) or the gravity model method (12). The statistical index method evaluates accessibility by counting the number of places and area of UGS in the region, or by counting the number of places and area of UGS within a certain buffer zone from the living area (13). This method is also known as the cumulative opportunities method (14) or the covering method (15). The disadvantage is that it does not take into account the resistance that residents encounter on their way to UGS, and it is difficult to reflect the accessibility within the UGS' actual service area. Based on remote sensing data, the cost-weighted distance method assigns different crossing resistances to different urban landscape types, and the accessibility is evaluated by calculating the cumulative resistance encountered by residents on their way to the UGS (8). The advantage is that this method takes into account the impact of resistance on accessibility, but the disadvantage is that it does not consider the attractiveness of UGS of different qualities and levels; hence, the accessibility calculation results cannot accurately reflect the actual recreational situation (16). In the calculation of accessibility, the gravity model (17) adopts the distance decay function and considers the service capacity and potential of UGS, so that the results can better reflect the impact of UGS' attraction on accessibility. However, the relationship between residents' demand and accessibility remains to be further explored (18). The two-step floating catchment area (2SFCA) method was first proposed by Radke in 2000 (19) and was further improved by Luo and Qi (20) in 2009. Accessibility decreases with the increase of the resistance encountered by the residents on their way to the UGS and increases with the increase of the area and quality of the UGS. Based on the 2SFCA, the accessibility of UGS can be calculated comprehensively and simply from the perspective of the interaction between the park supply and residential demand, which makes up for the shortcomings of the gravity model (21). Due to its advantages, this method has been widely used in accessibility evaluation (21–24), and many studies have tried to improve this method to promote the accuracy of the evaluation results (Table 1).

Some studies revealed the competition effect between supply facilities and proposed the 3SFCA model to address the fact that 2SFCA cannot reflect the actual supply and demand situation. Based on the traditional 2SFCA model, 3SFCA calculates the option value between each pair of demand points and supply facility points and measures the competitive effect of multiple supply points within the same demand point search radius (25). However, Delamater showed that 3SFCA overestimates the competitive effect among supply points while ignoring the availability of the facility resources (26). Therefore, a simpler Modified 2SFCA model was proposed, which introduced the attenuation function in the selection weight to reflect whether facility resources are fully utilized, simplifying the quantification process of competition effect between supply facilities. Luo et al. (27) introduced the Huff model to reflect the selection weights, and on this basis, proposed the Huff 2SFCA model, which quantified the probability of people choosing supply facilities with continuous weight functions, further improving the applicability of the 2SFCA model. In the original form of 2SFCA, distance decay is treated dichotomically (28): the accessibility within the search radius is the same, and the accessibility outside the search radius is 0. This method ignores the influence of the spatial distance on accessibility. Some studies used different distance decay functions to solve this problem. For example, Luo and Qi (20) proposed the optimized 2SFCA to segment the distance within the search radius. However, the segmentation of distance is greatly influenced by subjectivity to a certain extent, and the segmentation weight given to the distance will lead to discontinuous results at the segmentation boundary. Therefore, 2SFCA applies continuous functions such as the gravity model (29), kernel density function (30), and Gaussian function (31) to solve the above problems. The Gaussian function is an s-shaped attenuation, and the attenuation rate of accessibility with distance is slower in the near and far stages than in the middle, which is more consistent with the actual situation than the 2SFCA method. Therefore, it is widely used in the optimization of accessibility evaluation methods (32). The 2SFCA model also fails to consider multiple traffic modes comprehensively. Yang et al. (23) proposed the multi-mode 2SFCA model to solve this problem. This model uses the weighted average time of multiple transportation modes to replace the time of a single transportation mode, which can better reflect the heterogeneity of accessibility under different transportation modes. Taking the central urban area of Hefei as an example, this study optimized the 2SFCA model for the

TABLE 1 Main extensions of the Gaussian two-step floating catchment area (2SFCA) method.

Type	Form	Content	Document
Improvement based on supply and demand factors	Three-step floating catchment area (3SFCA) method	The choice weight between the demand point and supply point is used to represent the competition effect between facilities.	Wan et al. (25)
	Modified 2SFCA method	The primary attenuation function is reused considering the suboptimal space configuration of facilities.	Delamater (26)
	Huff 2SFCA method	The Huff model is used to quantify the probability of people choosing facilities when considering the influence of facility supply factors on facility selection behavior.	Luo (27)
Improvement based on the search distance	Dynamic 2SFCA method	Different search distances are set by considering different demand points for facility supply.	Mcgrail and Humphreys (33)
	Variable 2SFCA method	The search radius of variable supply and demand elements is set to balance the supply and demand within the search radius.	Luo and Whippo (34)
	Multi-catchment sizes 2SFCA method	The search radius is set according to the size and quality of the supply factors.	Tong et al. (22)
Improvement based on the distance attenuation function	Enhanced 2SFCA method	The distance is segmented within the search radius.	Luo and Qi (20)
	Gravity 2SFCA method	The distance attenuation function of the gravity model is added within the search radius, such as the power function, exponential function, and logarithmic function.	Wang and Tang (29)
	Gaussian 2SFCA method	The Gaussian function-type distance attenuation function is added within the search radius.	Dai and Wang (30)
	Kernel density 2SFCA method	The kernel density function-type distance attenuation function is added within the search radius.	Dai (31)
Improvement based on the travel mode	Multi-mode 2SFCA method	The weighted average time of multiple transportation modes is used to replace the time of the single transportation mode.	Yang et al. (23)

purpose of comparing the accessibility differences of UGS under various transportation modes. Mobile phone signaling data were used in the study and combined with the Gaode map path planning model to improve the shortcomings of poor timeliness and low accuracy of the evaluation results caused by the use of statistical data for evaluation in traditional research. The UGS recreational situation extracted from the mobile phone signaling data and accessibility evaluation results was used to calculate the UGS supply and demand deviation to further elucidate the fairness of UGS spatial distribution and optimization strategies.

Materials and methods

Research area

Hefei, located in east China, is a sub-center city of urban agglomeration and a national science center, with a total area of 11,445 km^2 and a population of 9.36 million (China National Bureau of Statistics, 2020). The government of Hefei has made considerable efforts in ecological construction. After the 1956 edition of the urban master plan, a ring-city park system and a fan-shaped urban structure were formed. Hefei was selected as one of the first national garden cities of China in 1992. By the end of 2020, Hefei city's forest coverage rate reached 28.36% of the total area, with a forest volume of 10.6 million m^3, while the urban built-up area green coverage rate reached 46%. The green area per capita was 13 m^2, far more than the minimum UGS requirement of 9 m^2 per capita recommended by the World Health Organization. Although the greening level of Hefei is higher than that of other surrounding cities, more in-depth UGS accessibility evaluation research is needed for the future optimization of UGS.

This study takes the central urban area of Hefei as the research area (Figure 1) and the public parks in the central urban area of Hefei as the UGS research objects (Figure 2). The central urban area of Hefei has a total area of about 486 km^2, according to the definition of the central urban area of Hefei City Master Plan (2011–2020).

Data source and processing

UGS data

The UGS data used in this paper were derived from the Gaode Map. Using the Hefei Green Space System Planning (2007–2020) and Hefei City Master Plan (2011–2020), combined

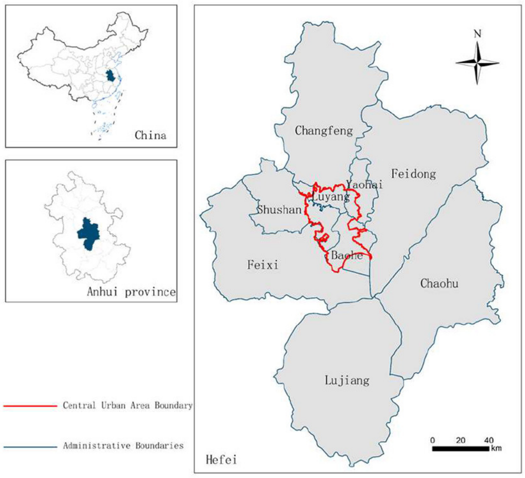

FIGURE 1
Central urban area of Hefei.

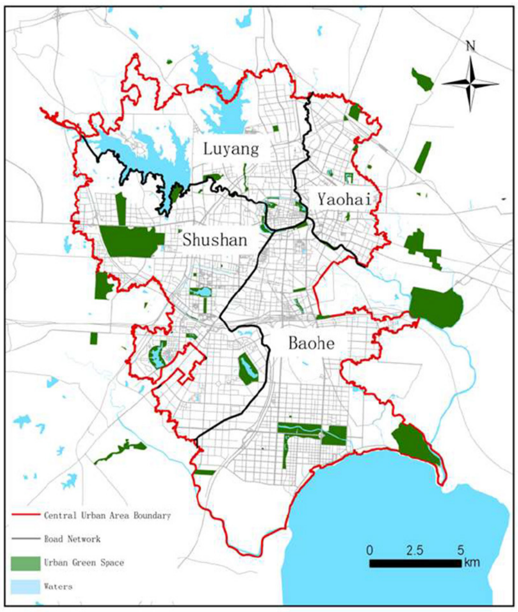

FIGURE 2
Distribution of UGS in central urban area of Hefei.

with the map and field survey, the spatial location, area, and quantity of the UGS in the central urban area and its surrounding area within a distance of 15,000 m were further verified. A total of 75 parks were obtained and considered to be UGS (Table 2).

We converted UGS surface elements to point elements in ArcGIS 10.2. The centroid of the park with an area of <100 hm^2 was taken as the supply point, and the coordinates of the entrances and exits of UGS equal to or >100 hm^2 were considered as supply points for the accessibility evaluation (35). To avoid the repeated calculation of the area, UGS equal to or >100 hm^2 were also decomposed accordingly when the entrance and exit coordinates were taken as its supply points, which can reduce the error of accessibility calculation. Finally, 80 supply points of the UGS were obtained.

Residential population and visitor data

The precision of the population statistics has a direct impact on the evaluation results of UGS accessibility (36). It is difficult to use traditional statistical data, such as census data, to analyze the behavioral patterns of different populations at a fine scale due to a large scale of statistical units (37). Compared with traditional statistical data, mobile phone signaling data have a higher accuracy and can reflect massive and real-time population activities, and these data have been widely used in urban population activity research, such as work-housing commuting behavior, urban dynamic space identification, and traffic efficiency evaluation (38). We used the mobile signaling data of China Unicom users in May 2021 to identify the residents in the central urban area by screening the users who have stayed in Hefei for over 10 days. Finally, we identified 929,916 residents from the China Unicom mobile phone signaling database, accounting for 18.17% of the total population of central urban residents.

When the user's mobile phone communicates with the mobile phone signaling base station of China Unicom, the base station will locate the user and record the user interaction information, including user ID, interaction time, base station code, and territory code (Table 3). There are about 13,000 China Unicom mobile phone signaling base stations in Hefei's central urban area, with distance intervals of 250–1,000 m.

In relevant studies, a regular hexagon, which has the same distance from point to centroid in six directions, can reduce the sample deviation caused by the boundary effect of grid shape and is suitable for spatial analysis (39, 40). Therefore, we used a regular hexagon grid with a lateral length of 500 m to establish the honeycomb grid network in ArcGIS10.2 and aggregated the areas falling within the regular hexagon into the centroid of the grid. On this basis, the spatial analysis honeycomb network was formed, and 827 hexagon grids were obtained. We assigned the corresponding attribute information to the grid according to the land use category in the grid and identified the residential grids and the UGS grids. The identification standard of the residential grid was that there is a residential population within the grid range, and the identification standard of the UGS grid was that the centroid of the grid falls in the UGS area. The same grid can be identified as both a residential grid and a UGS grid at the same time. While the UGS grids are used for UGS recreational visitor identification, the centroids of the residential grids are used as the demand points in the accessibility evaluation. The residential

TABLE 2 Summary of UGS in the central urban area of Hefei.

District	Comprehensive park /hm^2	Theme park /hm^2	Community park /hm^2	Garden /hm^2	Total area of the park /hm^2
Luyang	92.39	37.89	58.73	5.33	194.34
Shushan	1,106.54	263.23	65.69	18.77	1,454.23
Yaohai	69.98	12.19	34.34	5.06	121.57
Baohe	966.57	45.64	57.7	3.01	1,072.92
Total	2,235.48	358.95	216.46	32.17	2,843.06
Proportion	(78%)	(13%)	(8%)	(1%)	(100%)

TABLE 3 Sample data of interaction information collected by mobile phone signaling base station.

User ID	Interaction time 1 (the beginning of an event)	Interaction time 2 (the end of an event)	Base station code	Territory code
773068*****3505730	2021-5-1 0:15	2021-5-1 9:56	7007403516115268	340104
777258*****8329382	2021-5-1 7:56	2021-5-1 18:38	70071403728115696	340104
772948*****5537730	2021-5-1 11:42	2021-5-1 15:29	7007403420115260	340104
…	…	…	…	…

grids are used as the basic units for both accessibility evaluation and supply-demand deviation evaluation. By collecting data on the places where the residents were at from 21:00 P.M. to 08:00 A.M. the next day and marking the places with the longest stay as the places of residence, the population of each place was included in the residential grid that each of the places was in. The distribution map of the residential population density in the central urban area of Hefei is shown in Figure 3.

To acquire the deviation between the theoretical accessibility and actual recreational activities in the UGS, we first needed to identify UGS visitors who visited UGSs in the month and were in the UGS grids for 30 min or more from 8:00 A.M. to 21:00 P.M. Then, the number of residents who have been to a UGS once or more than once in each grid was counted for the supply and demand deviation calculation.

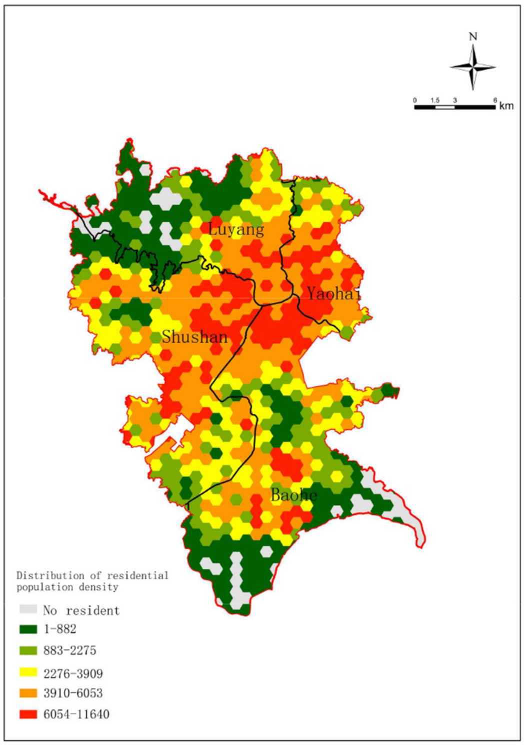

FIGURE 3
Distribution of the residential population density in the central urban area of Hefei.

Travel mode and travel distance data

If the speed of UGS visitors was 0–5 km/h, then they were considered to be in walking mode. Visitors with speeds of 5–15 km/h and 15–60 km/h were considered to be in riding mode and driving mode, respectively. There were 244,017 residents who went to UGS in May 2021 and made 801,311 trips to UGS, including 72,622 walking trips, 147,530 cycling trips, and 581,159 driving trips, accounting for 9.06, 18.41, and 72.53% of the total trips, respectively. The proportion data of the different travel modes to UGS were used as the weight basis for the accessibility evaluation.

The shortest travel path from each demand point to the supply point of the UGS was obtained through the path planning interface in the Gaode API (application programming interface). First, by using the coordinate conversion interface, the GPS coordinates of the supply point and the demand point were

TABLE 4 Sample data of the travel distance between UGS and residential areas.

UGS number	Residential grid number	Walking distance	Cycling distance	Driving distance
001	001	2,653 m	3,055 m	3,070 m
001	002	8,662 m	9,633 m	9,656 m
001	003	7,552 m	8,873 m	8,900 m
......	......	......	......	......

transformed into the Goethe coordinates. Then, by using the path planning interface and taking the coordinates of the origin and destination (OD) points as parameters, the path planning requests of walking, cycling, and driving were initiated to obtain the distance data under different travel modes as the actual distance from each supply point to the demand point (Table 4).

Methodology

Implementation of Ga2SFCA

In this study, the commonly used 2SFCA method is improved in terms of the data source and OD cost calculation rules. The Gaussian function decays slowly when approaching the search threshold, which is more in line with the actual travel situation of residents (41). Therefore, we used the Gaussian two-step floating catchment area (Ga2SFCA) method to calculate UGS accessibility, which includes the following steps:

Step 1: For each supply point j of the UGS, all residents' demand points k with j as the center and d_0 as the threshold range are searched. For the population of these demand points, the Gaussian function is used for the attenuation calculation, and then, the sum is obtained. Finally, the area of the supply point is divided by the sum of the population of the demand point to obtain the supply-demand ratio R_j of the UGS j, which is the service capacity value of the supply point of the UGS. The calculation formula is as follows:

$$R_j = \frac{S_j}{\sum_{k \in \{d_{kj} \le d_0\}} G(d_{kj}, d_0) \times P_k} \tag{1}$$

where S_j represents the supply scale of UGS j, measured by its area; d_{kj} represents the travel time from residential area k to park green space j; and P_k is the scale of demand for residential area k in the search range, measured by population.

G (d_{kj}, d_0) is a Gaussian function, and the calculation formula is as follows:

$$G\left(d_{kj}, d_0\right) = \begin{cases} e^{-\frac{1}{2}\times\left(\frac{d_{kj}}{d_0}\right)^2} - e^{-\frac{1}{2}}, d_{kj} \le d_0 \\ 0^{1-e^{-\frac{1}{2}}}, \\ d_{kj} > d_0 \end{cases} \tag{2}$$

Step 2: For each residential grid i, all UGS j values with i as the center and d_0 as the threshold range are searched. Similarly, the supply-demand ratio R_j of each UGS is calculated and summed by Gaussian function attenuation. Finally, the accessibility index A_i of each residential area i is obtained. The calculation formula is as follows:

$$A_i = \sum_{i \in \{d_{ij} \le d_0\}} G(d_{ij}, d_0) \times R_j \tag{3}$$

where R_j is the supply and demand ratio of park green space j in the threshold range; and d_{ij} is the walking time between residential area i and UGS j. A_i represents the accessibility index of UGS of residential area i, and the larger the value, the higher the accessibility of UGS.

Step 3: The accessibility index of UGS under different traffic modes is calculated for each residential area i. The accessibility index is overlayed according to the proportion of various traffic modes used by permanent residents in the central urban area in May 2021 to obtain the comprehensive accessibility C_i of each residential area i. The larger the calculated C_i, the better the comprehensive accessibility of residential area i. The calculation formula is as follows:

$$C_i = \sum_{n \in \{1,2,3\}} W_n \times A_{in} \tag{4}$$

where W_n is the proportion of traffic mode n used by permanent residents in the central urban area in May 2021, and A_{in} represents the accessibility index of UGS in the traffic mode n of residential area i.

Considering that residents have different traffic modes to go to the UGS and are willing to bear different travel time costs, we divided the search thresholds into six categories, namely, the walking comfort threshold, cycling comfort threshold, driving comfort threshold, walking limit threshold, cycling limit threshold, and driving limit threshold. Combined with the average speed of various traffic modes, the final search threshold was determined, as shown in Table 5.

Overlay analysis of accessibility and UGS recreational characteristics

We obtained the UGS visitor data from the mobile phone signaling data and analyzed the coupling matching degree

TABLE 5 Summary of accessibility search thresholds for UGS.

Travel mode / Time	Walking	Cycling	Driving
15 min	1,250 m	3,750 m	7,500 m
30 min	2,500 m	7,500 m	15,000 m

between the number of UGS visitors and the accessibility level results to explore the actual situation of the UGS supply and demand relationship. We used the normalized value of the number of residents who have visited UGS between May 9th and 15th and lived in residence i as the demand for UGS and the accessibility level as the supply of UGS. Then, the two were overlayed to calculate the supply and demand ratio. The spatial distribution of the measured results was visualized to visually examine the spatial difference between the UGS supply and demand in the central urban area of Hefei. The calculation formula is as follows:

$$Z_i = \frac{A_i/A}{P_i/P} \quad (5)$$

where A represents the sum of the accessibility levels of all grids in the central urban area, P_i is the number of visitors who have visited UGS between May 9th and 15th and lived in residential area i, and P denotes the total population of all UGS visitors in the central urban area. Z_i represents the deviation between the supply and demand of UGS. The calculation results between 0 and 0.8 were considered as "low supply–high demand" areas; 0.8–1.2 were considered "supply–demand balance" areas; and above 1.2 were considered "high supply–low demand" areas.

Results

Accessibility analysis

In this study we used the Ga2SFCA model to calculate the accessibility of the three travel modes under different time thresholds; then, the accessibility results of three travel modes were overlayed according to the weight values obtained from the proportion data of the different travel modes. Based on the results of the above analysis, the comprehensive comfort accessibility and comprehensive limit accessibility were obtained. The standardized results were visualized in ArcGIS10.2 and divided into five grades according to the geometric interval, representing the lowest, low, moderate, high, and highest accessibility scores (Figures 4, 5).

Figures 4, 5 shows that there is an obvious uneven distribution of UGS resources in the central urban area of Hefei. In general, with the increase in the time threshold or travel distance, the number of grids above the moderate accessibility level generally increases, and the spatial distribution of the grids with moderate, high and highest accessibility level present different patterns of contiguous, clusters, and spots distribution, respectively. Specifically, the accessibility of the surrounding areas of the Four Seasons Flower Sea City Garden, the Emerald Lake Park, the Nanyan Lake Park, and the Jindou Park at different time thresholds and different travel modes is much higher. The accessibility of UGSs in the western Yaohai District, the southeastern Luyang District, the northeastern Shushan District, and the northern Baohe District is poor, mainly because these areas are old urban areas with a relatively dense population and a large demand for UGS.

The accessibility of UGS under different thresholds was analyzed based on the residential grid scale. (1) At the 15-min threshold, the areas with a moderate or higher walking comfort accessibility level are small, accounting for about 11.85% of all the grids, and are mainly distributed in spot patterns along the periphery of the UGSs. The areas with a moderate or higher cycling comfort accessibility level are slightly more than those with walking comfort accessibility, accounting for about 13.06% of all the grid units, and show a cluster distribution pattern. The areas with a moderate or higher driving comfort accessibility level are far larger than those with walking and cycling comfort accessibility, accounting for about 48.25% of all the grid units, among which the moderate-level areas are regularly distributed all around the central urban area, and the high-level areas are mainly distributed in the west of the central urban area, showing a contiguous distribution pattern along the Four Seasons Flower Sea City Garden, the Shushan National Forest Park, the Swan Lake Park, the Ring City Park, the Green Axis Park, the Emerald Lake Park, and the Nanyan Lake Park. (2) At the 30-min threshold, there are relatively fewer areas with a moderate or higher level of walking comfort accessibility, accounting for about 11.97% of all the grids, mainly distributed in linear patterns along the periphery of the UGSs. The areas with moderate or higher cycling accessibility were far greater than the former, accounting for about 48.25% all the grid units, mainly distributed regularly around the west part of the central urban area. The areas with a moderate or higher level of driving accessibility are fewer than those with a moderate or higher level of cycling accessibility, accounting for about 45.22% of all the grid units, and the moderate-level areas are distributed regularly, while the high-level areas have fewer numbers and mainly distributed in the northwest part of the central urban area. The high level of comprehensive comfort accessibility with the 15-min threshold is distributed around the Four Seasons Flower Sea City Garden, the Xiaoyao Jin Park, the Swan Lake Park, the Taochong Lake Park, the Emerald Lake Park, the Jindou Park, and the Nanyan Lake Park, accounting for about 1.45% of all the grid units. The Four Seasons Flower

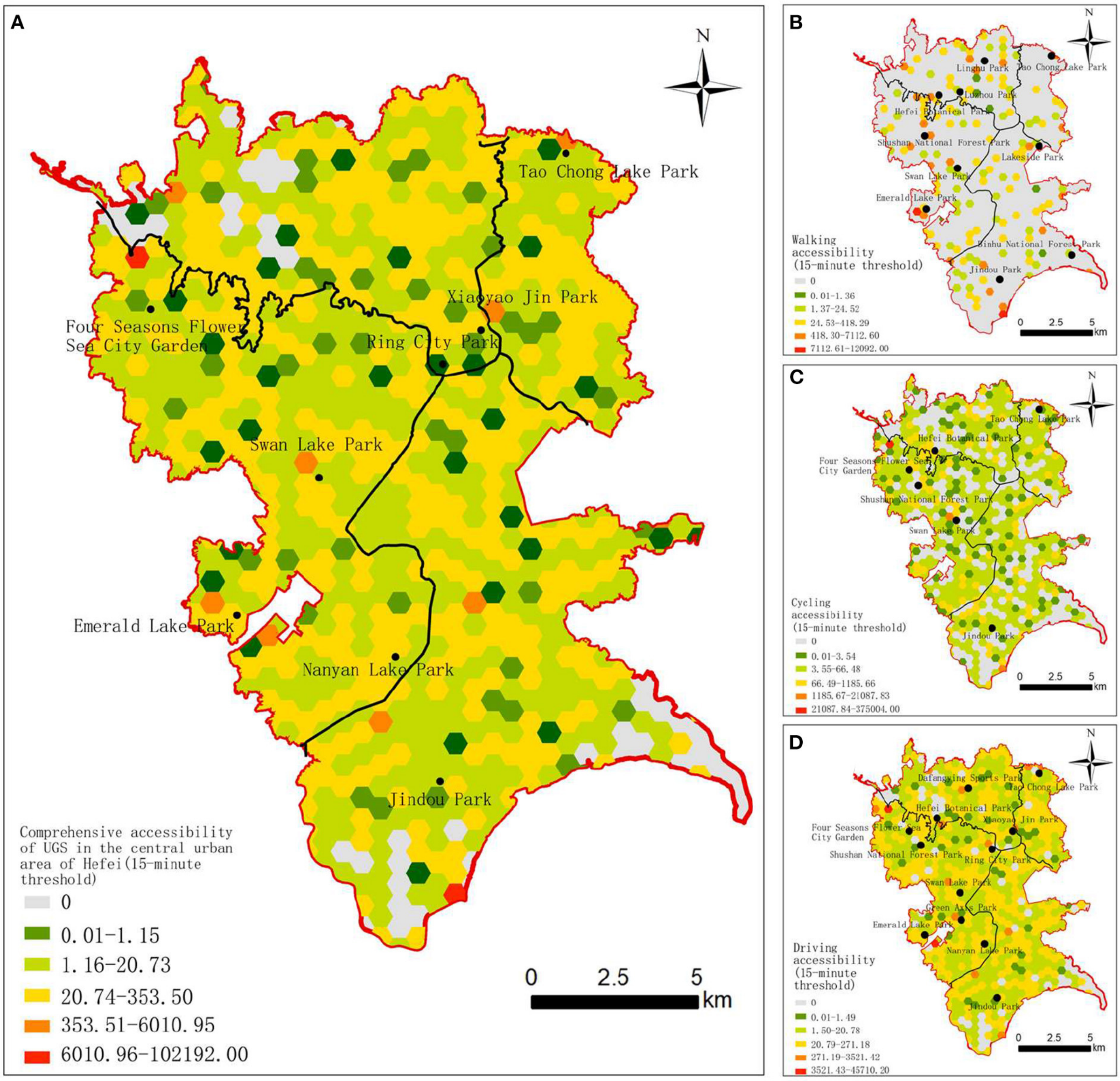

FIGURE 4
Accessibility of UGS in the central urban area of Hefei at the 15-min threshold. **(A)** Comprehensive accessibility. **(B)** Walking accessibility. **(C)** Cycling accessibility. **(D)** Driving accessibility.

Sea City Garden is located in the western suburbs of Hefei, about 10 km from the center of the old urban area. The road network around the Four Seasons Flower Sea City Garden is relatively developed, and the living density of the surrounding population is moderate; so, the comprehensive accessibility is high. The Jindou Park, the Emerald Lake Park, and the Tao Chong Lake Park are surrounded by other UGSs, with a lower residential population. Although the Xiaoyao Jin Park and the Swan Lake Park are surrounded by high-density residential population, their better green space construction and road system planning make up for the accessibility level. The low comprehensive comfort accessibility areas are distributed in the west part of the Yaohai District, the south part of the Luyang District, the northeast part of the Baohe District, and the north of the Shushan District. There are few UGSs but a large number of residential areas in the above regions, and the road network connectivity is poor, all leading to low comprehensive comfort accessibility.

The high and highest comprehensive limit accessibility levels with the 30-min threshold are distributed around the Four Seasons Flower Sea City Garden, the Emerald Lake Park, the Nanyan Lake Park, and the Jindou Park, accounting

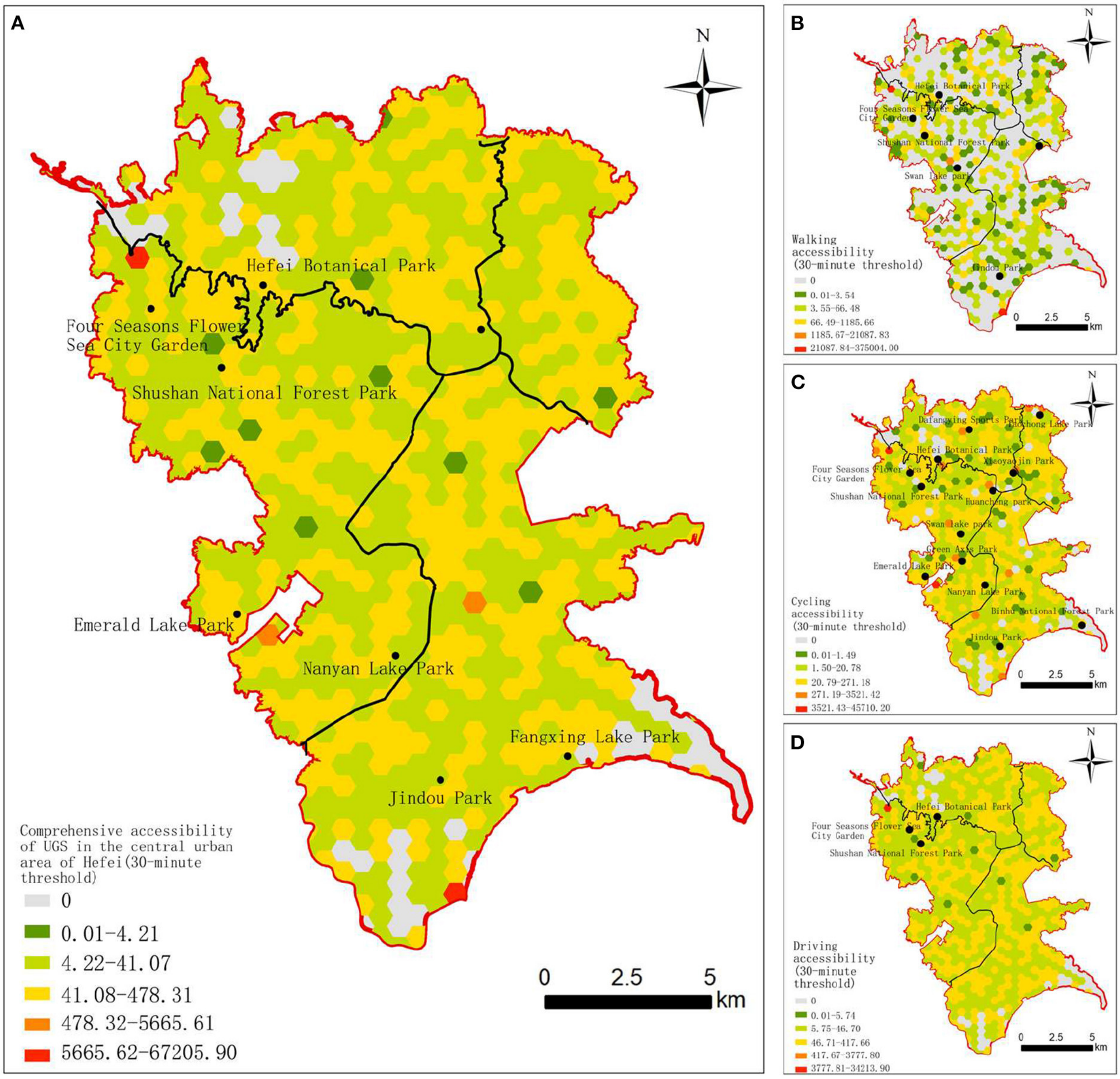

FIGURE 5
Accessibility of UGS in the central urban area of Hefei at the 30-min threshold. **(A)** Comprehensive accessibility. **(B)** Walking accessibility. **(C)** Cycling accessibility. **(D)** Driving accessibility.

for about 0.48% all the grid units, which is slightly less than the comprehensive comfort accessibility with the 15-min threshold. The areas with a low comprehensive limit accessibility are distributed in the west part of the Yaohai District, the southeast part of the Luyang District, the northeast part of the Shushan District, and the north part of the Baohe District. With the increase in the general travel distance of users in the central urban area, the comprehensive limit accessibility shows a significant regular distributed phenomenon, and the number of areas with the highest and lowest grades decreased significantly.

Analysis of supply and demand deviation

According to the distribution of the UGS recreational population density in the central urban area of Hefei (Figure 6), it can be concluded that there are 10 parks favored by the central urban population for UGS recreational activities, namely the Swan Lake Park, the Taochong Lake Park, the Shushan National Forest Park, the Four Seasons Flower Sea City Garden, the Ring City Park, the Xiaoyao Jin Park, the Yaohai Park, the Binhu Lakeshore National Park, the Leijie Park, and the Huiyuan Garden.

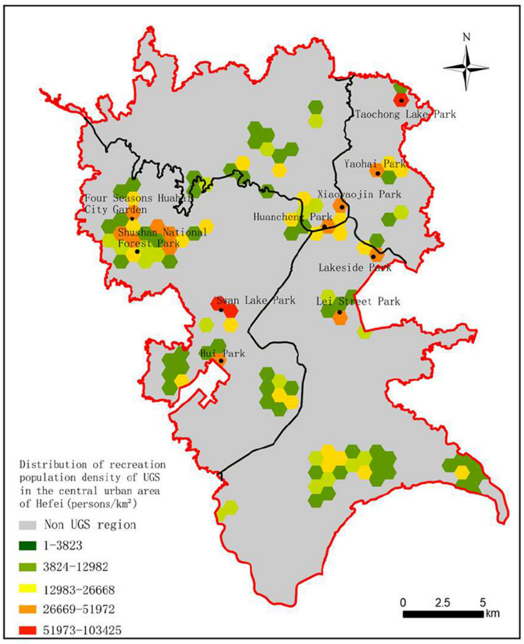

FIGURE 6
Distribution of the UGS recreational population density in the central urban area of Hefei.

Using Formula 5, the hexagonal grid was used as the statistical unit to calculate the deviation between supply and demand of UGS at different time thresholds (Figure 7). In the grid, the China Unicom users without UGS recreational demand in May 2021 were not included in the consideration of the deviation of supply and demand of UGS, and this result appears as the blank area.

According to results, for the 15-min threshold, the overall demand of the central urban area is greater than the supply, and the proportion of grid units where demand exceeds supply accounts for about 63.97% of all the grid units. The number of grids with a balanced supply and demand of UGS is small and scattered, accounting for about 3.75% of all the grid units. The grid units where supply exceeds demand account for about 32.29%, and these are mainly distributed in the north and south part on the edge of the central city near the suburbs. For the 30-min threshold, the central urban area shows a pattern of supply being greater than demand, but the proportion of areas with balanced supply and demand decreased, accounting for 1.09% of all the grid units.

Further analysis was carried out based on the distribution of the recreational population density of UGS in the central urban area of Hefei. First, the old urban area is the center of the city, which has a high residential population density and low per capita green space, which are the main reasons for the deviation of the supply and demand of the UGS. Second, compared with the old urban area, the northern Shushan District and southern Baohe District are both newly built and have better UGS construction, better road infrastructure, and low population density, which leads to a lower demand than the old urban area, resulting in the supply exceeding demand. Third, there are many comprehensive parks near the periphery of the old urban area, and residents are generally more inclined to use these comprehensive green spaces. The abovementioned comprehensive effects lead to the contradiction between the supply and demand of accessibility of UGS in the urban area.

Discussion

In this study, mobile phone signaling data were used instead of traditional statistical data to obtain accurate population positioning data. The distance between supply and demand points was represented by the actual distance of the Gaode Map path planning tool, which strengthened the data granularity and improved the accuracy of the evaluation results. The optimized Ga2SFCA method was used to measure the accessibility level under different transportation modes, and the actual traffic mode proportion data were used to calculate the comprehensive accessibility level. In addition, two different search distances for the time threshold were set based on residents' comfort and limited travel time. The accessibility differences under different travel modes and time thresholds were discussed. Finally, we combined the results of the UGS accessibility evaluation with the actual use of UGS to analyze the difference between supply and demand. In this study, we focused on the application of mobile phone signaling data in measuring the actual usage of UGS. Based on mobile signaling data, we acquired the precise resident positioning data in the residential area and the actual recreational activities in the UGS. Combined with the path planning interface in the Gaode API, with the support of refined travel data, we can analyze the coupling matching degree between the number of UGS visitors and the accessibility level results to explore the actual situation of the UGS supply and demand relationship. The use of fine-grained data and the improvement of the 2FSCA method are the most important contributions of this study.

In general, the grids with high accessibility to the UGSs in the central urban area of Hefei tend to be distributed near large urban parks, and this phenomenon is more obvious in the evaluation results of walking and cycling accessibility at the 15-min time threshold. However, with the increase in the time threshold and travel distance, the accessibility evaluation results gradually show a regular distributed pattern. In addition, the accessibility level of the driving mode at the 15-min time threshold and the walking and cycling mode at the 30-min time threshold shows that the number of grids above the moderate level increases significantly. For some socially vulnerable groups,

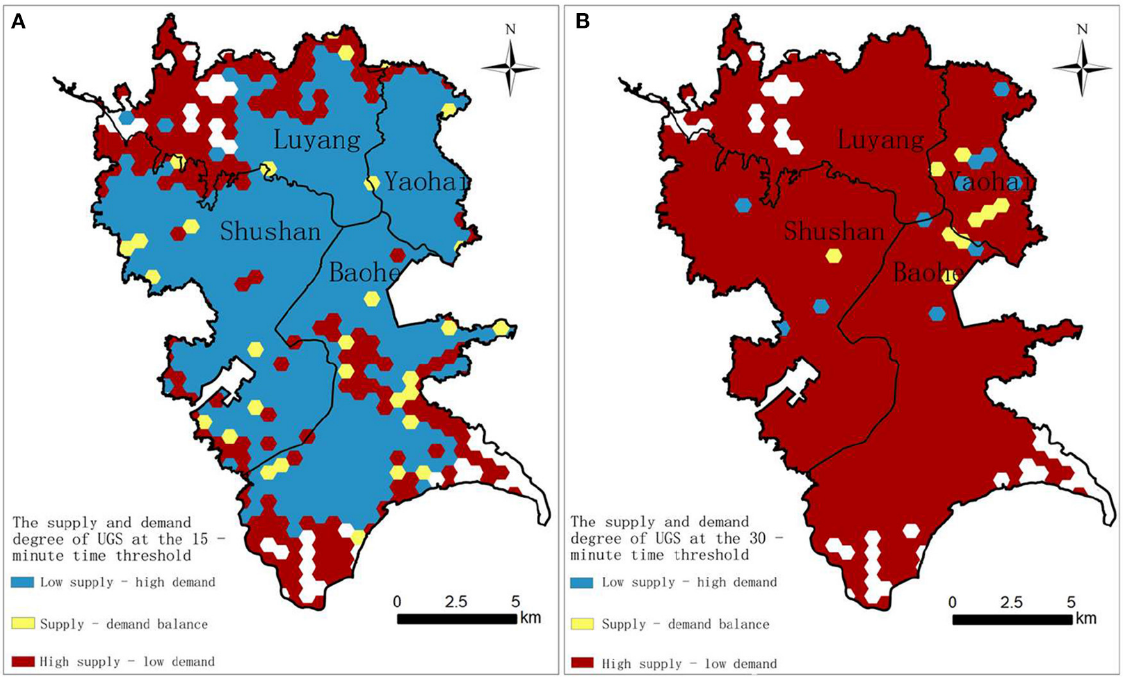

FIGURE 7
Deviation between supply and demand of UGS at different time thresholds. **(A)** At the 15-min time threshold; **(B)** At the 30-min time threshold.

especially low-income groups and the elderly, the ownership of a private car and the ability to undertake long-distance travel are clearly unfair conditions for access to more UGSs (42, 43). Therefore, it is still necessary to increase the area of UGSs to increase the opportunities for urban residents to obtain green space resources and ensure fairness of access to UGS for socially vulnerable groups. When urban land resources are limited and incremental expansion of old urban areas is difficult, decision-making departments should first consider improving the quality of existing UGSs. In densely populated areas with limited vacant land, smaller street gardens, pocket parks, and rooftop gardens should be considered to improve the accessibility of the UGS. Decision-makers should increase the number of large park entrances and strengthen the construction of roads around comprehensive parks.

In addition, China's government recommends that residents stick to low-carbon travel modes, which means giving priority to walking, cycling, and public transportation. For the old urban area, where there is limited urban construction land, it is undoubtedly a better choice to further develop the low-carbon transportation system than to increase the green area of the park. The construction of pedestrian and cycling networks, as well as the public transportation system, should be strengthened to improve the connectivity between residential areas and UGSs. According to the specific situation, decision-making departments should consider increasing the residential land area around UGSs to improve the utilization rate of UGSs in the new urban area, where the resources are sufficient.

Conclusion

The fairness of the UGS layout is the basic guarantee of urban residents' quality of life. Based on the optimized Ga2SFCA method, we evaluated the spatial accessibility of the existing UGS in the central urban area of Hefei under different travel modes and analyzed the supply and demand deviation of the UGS combined with the actual recreational population. The results show the following:

(1) Setting different travel modes and different time thresholds significantly affects the evaluation results of the UGS accessibility level. At the 15-min threshold, the areas with a moderate or higher walking comfort accessibility level are small, and the areas with a moderate or higher driving comfort accessibility level are far larger than those with walking and cycling comfort accessibility. At the 30-min threshold, there are relatively fewer areas with a moderate or higher level of walking comfort accessibility, while the areas with moderate or higher cycling accessibility were far greater than the former. The spatial distribution of UGSs in the central urban area of Hefei is uneven. In general, with the increase in the time threshold, the number of grids above the moderate accessibility

level generally increases, and the spatial distribution of the grids with moderate, high and highest accessibility level present different patterns of contiguous, clusters, and spots distribution respectively. The accessibility of UGSs in old urban areas is poor, mainly because these areas have a relatively dense population and a large demand for UGS. Due to the shortage of construction land, it is difficult to add new UGS, even if the problem of the relatively small number of UGSs becomes more severe.

(2) The characteristics of supply-demand deviation of UGSs are revealed by analyzing the coupling matching degree between the number of UGS visitors and the accessibility level results. At the 15-min threshold, the demand of UGSs in the central urban area is greater than the supply, but at the 30-min threshold, the supply exceeds the demand. In addition, at the two different time thresholds, the number of grids with balanced supply and demand is small and the grids are scattered, mostly distributed around large comprehensive parks. Such areas usually have moderate residential density and good road connectivity. The grids with balanced supply and demand or more UGS supply than demand are mainly concentrated in the southern area and the edge of the central city near the suburbs. All these areas have large, comprehensive parks. The population density of the surrounding communities is moderate, and the road connectivity is better, with a higher level of transportation infrastructure than that in the old urban area. The southern area is the new urban area established by Hefei City, which has more capital and land for the construction of UGSs and various urban infrastructure, and the construction level of living environment is relatively high. At the same time, an increasing number of people choose to live in the new urban area, which further brings capital and population vitality and reduces the supply-demand deviation. Due to the increasing urban population, the population density of the old urban area is not decreased, which makes UGS resources scarce. The government should pay attention to improving the existing quality of UGSs, as well as alleviating UGS inequality by using small vacant lands and inefficiently developed lands to increase the area of UGSs.

Refined and scientific evaluation of UGS accessibility is an important foundation for the accurate restoration of urban green space fairness. Based on the refined mobile phone signaling data, we can obtain the precise accessibility evaluation results and actual supply and demand situation, which can certainly help the government to understand the status of the actual park usage. For the area with imbalanced supply and demand, the government should carry out thematic studies and further explore the reasons. This study can provide guidance for the government to formulate fair green space policies, advocate to guarantee access to green space resources for the socially vulnerable groups, and finally promote the healthy and sustainable development of cities. This study also had some limitations, largely due to the availability of data. When calculating the supply capacity of UGS, we did not consider the internal facilities, service quality, and service facilities of UGS. In the calculation of UGS demand, only the population number of the statistical unit was considered, without an in-depth consideration of the needs of people with different social attributes, which can be significant (44). A discussion on the causes of the discrepancy between the supply and demand of accessibility is needed and will be further explored in future research.

Data availability statement

The data analyzed in this study is subject to the following licenses/restrictions: The urban green space data were derived from the Gaode API (application programming interface) (https://lbs.amap.com/), which is publicly available. The travel mode and travel distance data was also obtained through the path planning interface in the Gaode API. Additionally, the residential population and recreational visitor data were extracted from the China Unicom mobile phone signaling database (http://daas.smartsteps.com), which is not publicly available, and, after logging into the database system, the data can be retrieved and statistically analyzed by using structured query language. Requests to access these datasets should be directed to Gaode API (application programming interface) (https://lbs.amap.com/); China Unicom mobile phone signaling database (http://daas.smartsteps.com).

Author contributions

JC and CW contributed to the conception and design of the study. CW performed the statistical analysis and wrote the first draft of the manuscript. JC wrote sections of the manuscript. YZ and DL contributed to funding acquisition. All authors contributed to manuscript revision, read, and approved the submitted version.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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Assessment of walkability and walkable routes of a 15-min city for heat adaptation: Development of a dynamic attenuation model of heat stress

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Actively addressing urban heat challenges is an urgent task for numerous cities. Existing studies have primarily developed heat mitigation strategies and analyzed their cooling performance, while the adaptation strategies are far from comprehensive to protect citizens from heat-related illnesses and deaths. To address this research gap, this paper aims to enhance people's adaptation capacity by investigating walkability within fifteen-minute cities (FMC). Taking cognizance of thermal comfort, health, and safety, this paper developed a dynamic attenuation model (DAM) of heat stress, along with heat stress aggravation, continuance, and alleviation. An indicator of remaining tolerant heat discomfort (R_t) was proposed with the integration of the Universal Thermal Climate Index (UTCI) to assess heat-related walkability. Following an empirical study among 128 residents in Mianyang, China, and assessing four levels of heat stress, the maximum tolerant heat discomfort was determined to be 60 min. Furthermore, the DAM was applied to an FMC with 12 neighborhoods in Fucheng, Mianyang, China. The results indicate that for each neighborhood, the street was generally walkable with an R_t ranging between 15 and 30 min, after walking for 900 m. A population-based FMC walkability was further determined, finding that the core area of the FMC was favorable for walking with an $R_t$of 45–46 min, and the perpetual areas were also walkable with an $R_t$of 15–30 min. Based on these results, suggestions on the frequency of public services (frequently used, often used, and occasionally used) planning were presented. Overall, this paper provides a theoretical model for analyzing walkability and outlines meaningful implications for planning heat adaptation in resilient, safe, comfortable, and livable FMCs.

KEYWORDS

extreme heat, 15-min city, thermal comfort, dynamic attenuation model, UTCI, ENVI-met

Introduction

Cities are now the main human settlement and urbanization will remain mainstream in the coming decades, especially in Asian and African nations (1). Whilst urban living infrastructure is getting better and living quality is improving, the upward trend of urbanization is accompanied by various challenges such as climate change, environmental deterioration, traffic congestion, housing shortage, urban noise, rapid economic development, and inadequate health facilities (2–4). To address such challenges, the UN Sustainable Development Goals (SDGs), particularly Goal 11, suggested the creation of sustainable cities and communities to ensure cities are inclusive, safe, resilient, and sustainable. Goal 11 is interconnected with other goals such as Goal 13 on climate action, where changing climate is a macro driver of various disasters such as urban flooding, extreme heat, and air pollution. Problems such as urban flooding and air pollution have already been widely recognized, and various interventions and actions in aspects of policy, finance, programs, and initiatives have been implemented to address them. However, urban heat challenges have not received enough attention from society and limited measures have been adopted in practice (5).

Urban heat is the combined effect of heat waves and urban heat islands (UHIs) associated with climate change and urbanization (6). Numerous climate-related research among urban physicists and meteorologists have revealed the formation, aggravation, and drivers of urban heat (7–9). Their significant impact on environmental, economic, social, and health aspects has also been widely reported (10). However, urban heat has not been widely recognized as an emergent disaster, although it has caused excessive deaths (11–13). The extreme heat event in August 2003 killed more than 70,000 Europeans (14). In 2015, about 3,000 French lost their lives because of extreme heat events (15). In 2019 and 2020, the extreme heat killed 2,000 people each year in England (16). Urban heat has now emerged as a silent killer, causing higher mortality than any other climate-related disaster (17). In the coming decades, heat waves are projected to be more frequent, intense, and longer. While at the same time, contiguous modifications of natural environments during urbanization will further aggravate UHIs in dense and prominent areas associated with heat-absorption and storage material use, nature-based infrastructure reduction, anthropogenic heat release, and increased urban density (18). Synergies between heat waves and UHIs can possibly further aggravate heat-induced impacts (19). In general, addressing the urban heat challenge is an urgent task, not only for the current situation but also in the context of constant climate change.

To address heat-related challenges, He et al. (20) developed a comprehensive heat-resilient framework consisting of heat preparation, heat mitigation, heat adaptation, and a co-benefits approach (20). Heat preparation refers to the development of heat monitoring, impact assessment, heat health information transfer, and education system to improve heat impact prediction capability and to increase people's awareness and knowledge of what heat impacts are and how to address them. Heat mitigation is focused on heating source dissipation and cooling source enhancement through green and blue infrastructure (21, 22), innovative materials (reflective, retro-reflective, and permeable) (23, 24), urban ventilation (25, 26), and shading structures (27, 28) (Figure 1). Although heat adaptation does not alleviate heat severity from the source, it is currently the most effective approach to protecting people from heat-related illnesses and deaths through the adoption of air-conditioning facilities, behavioral and operational change, and activity rescheduling. The co-benefits approach has been thought of as a win-win strategy in tackling climate change issues by employing the additional benefits of other projects and initiatives for heat preparation, mitigation, and adaptation (29).

Heat adaptation is complex depending on individuals' body heat tolerance, personal behaviors, enterprise operation, and governmental department adaptation. First, the body can resist heat stresses to an extent, which is also known as body thermoregulation. The heat resistance capacity varies with demographic characteristics (such as gender, health, and age), where children and older adults are weak in resisting heat stresses (30). Second, people can change their daily functions such as outdoor activities, work/study, transportation, sleep/rest, and diet in types, time, and duration to adapt to heat (31). In particular, laborers and farmers who need to work outdoors can take their breaks in air-conditioned places or cooling centers during extremely hot temperatures (32). People can select heat-resilient walking routes if outdoor activities are necessary (33). Third, enterprises could upgrade service or operation patterns to ensure emergency systems and public facilities work well under extreme conditions (34). For instance, electricity suppliers could improve production and upgrade the grid to meet increasing energy demands associated with the increase in air-conditioning systems for cooling and overcome grid failure due to extreme heat (34). Fourth, governmental departments could improve their responses for dealing with urban heat by recognizing challenges, formulating policies, setting up financial schemes, and supporting pilot projects and initiatives, to overcome the lack of policies and formal governance (35). However, knowledge of how to improve heat resilience capacity in these four aspects is still a big research gap.

Many global cities are exploring 15-minute city (FMC) models aiming to promote the creation of sustainable and livable communities, neighborhoods, and 15-minute community-life circles with three primary goals of inclusion, health, and safety (36). The FMC initiative is an active response to SDG 11 on sustainable cities and communities to make cities and communities inclusive, safe, resilient, and sustainable. Various

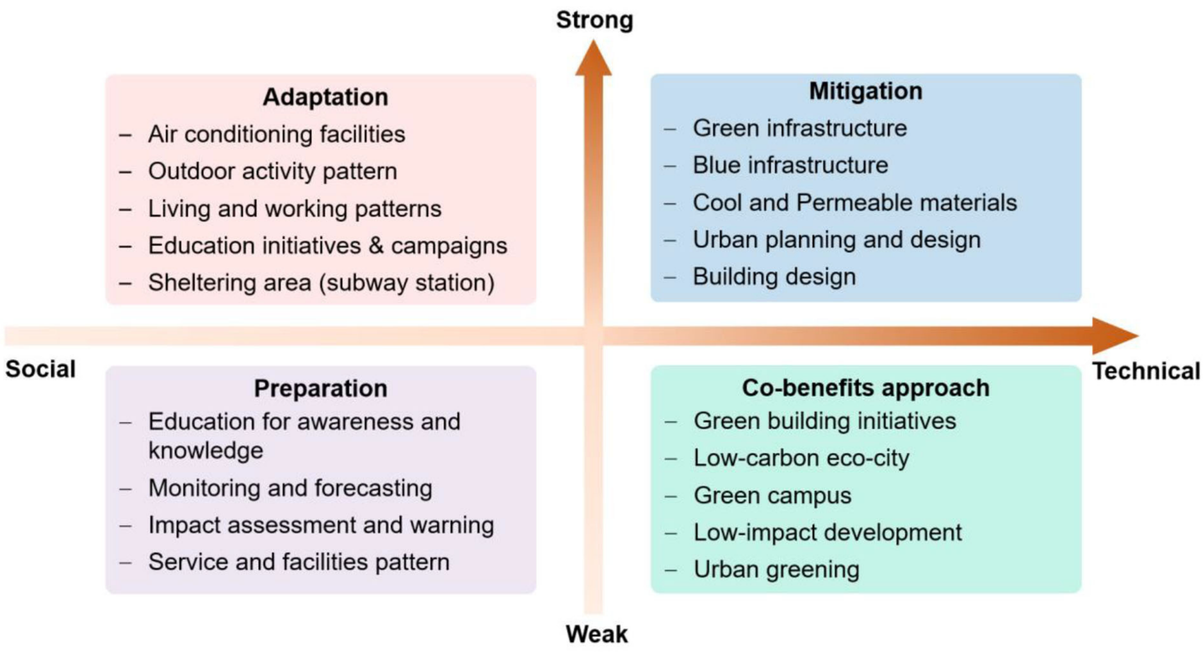

FIGURE 1
Social-technical solutions to urban heat challenges (20).

FMC frameworks have been piloted in cities across the world including Australia, China, Colombia, France, Italy, and the United States (36). Whilst such frameworks consider factors such as residence, job opportunities, transport, services, and entertainment, the improvement of heat resilience capacity has not been considered, or at least the interlinkage between FMC and extreme heat, a macro background of numerous cities, has not been well considered. It is essential to integrate heat resilience into FMC planning. Until now, the only work on the integration of heat resilience and FMC has been conducted by Chen and He (37) by developing a framework to integrate heat adaptation into FMC through the identification of heat impacts, recognition of heat-induced impact, documentation of influential factors, the suggestion of heat adaptation strategies, and optimization of adaptation (37).

To overcome the research gap relevant to heat resilience and its integration into FMC, this paper aims to investigate the heat-related walkability within the FMC. The consideration of heat impacts on walkability adds new knowledge to people's understanding of neighborhood walkability based on facilities, public services, and demographic characteristics (38, 39). In particular, this paper developed a dynamic attenuation model (DAM) of heat stress to assess heat tolerance when people are walking along specific routes. The model was further applied to an FMC in Fucheng District, Mianyang, China, to identify the heat stresses and the most walkable paths. Overall, this paper can better support stakeholders to integrate heat resilience into FMC and improves the understanding of walkability amid heat stresses.

Heat-related adaptation and heat tolerance

Based on the three primary goals of inclusion, health, and safety in the FMC, the targets of heat resilience improvement are expected to be inclusion, health, and safety. Namely, the fundamental target of integrating heat resilience into FMC is to improve all possible individuals' capacity of avoiding heat-related impacts on thermal comfort, heat stresses, illnesses, and deaths through heat preparation, mitigation, and adaptation. Beyond this, the integration can further enhance economic growth and social equality by improving thermal environments. There have been numerous indicators to assess the thermal conditions of outdoor environments, such as air temperature, surface temperature, heat stress, and thermal comfort. Among them, thermal comfort, which refers to individuals' subjective feelings of thermal environments, has been widely accepted to assess if the environment is suitable for activities such as working, walking, and standing.

Thermal comfort and assessment indicators

Subjective feelings are the combination of physical, physiological, and psychological responses to thermal environments (40). The psychological response is associated with people's experience and expectations during the perception and reaction toward heat senses. The physiological response is assessed by the thermo-adaptive approach and governed by the human heat balance, under the change of physical heat exposure. The physiological responses can be measured by the body core temperature, sweat rate, and skin temperature (41). The physical response is relevant to the built form and microclimatic environments which can affect the individuals' physiological responses. Many recent studies have linked physical environments in terms of sound and visual landscape with psychological responses (41). In addition, thermal comfort can be regulated by social and behavioral characteristics (42, 43).

Studies on thermal comfort have been conducted for over 100 years, and the PMV-PPD was the first thermal comfort evaluation indicator developed by Fanger to define comfort, by considering heat-balance equations and empirical studies about skin temperature. It presents a simple method of a seven-point scale from cold (−3) to hot (+3) to survey respondents' feelings (44). Following Fanger, more than 160 thermal comfort assessment indicators have been proposed (45). The WetBulb Globe Temperature (WBGT) is a comprehensive temperature index to evaluate the impacts of temperature, humidity, and solar radiation on people (45). In general, the larger the WBGT value, the harder it is for the human sweat to evaporate, and the lower the body's ability to dissipate heat. This indicator has been used to inform industrial hygienists, athletes, sporting events, and the military of suitable situations for exercise. For instance, during hot climates in the US, when the WBGT is below 22°C, individuals can conduct normal activities, and when the WBGT increases to 28.8°C, there should be limited intense exercises and total daily exposure to heat and humidity. When the WBGT increases to 31.0°C, all exercises should be canceled (46).

The physiological equivalent temperature (PET) and the Universal Thermal Climate Index (UTCI) are found to be the most accurate indicators of outdoor thermal comfort assessment. Both PET and UTCI are a function of environmental parameters (e.g., air temperature, relative humidity, wind speed, solar radiation) and personal behaviors (e.g., clothing, metabolic rate). Both have been classified into different grades of heat stress according to different values (Table 1). For instance, a PET value ranging between 35 and 41°C indicates strong heat stress for western/middle European countries (47). However, there are some differences in people's feelings toward heat stresses after long-term adaptation, where a PET ranging between 38 and 42°C indicates strong heat stress for people from subtropical areas (48). In comparison, the UTCI has different levels of heat stress, where a UTCI value ranging from 38 to 46°C indicates a very strong heat stress (49). Both PET and UTCI have a significant correlation with extreme heat-induced mortality. For example, Matzarakis et al. (47) analyzed the relationship between heat stress and mortality from 1970 to 2007, finding that in Vienna, at 14:00 central Europe time, the mortality at a PET value of 41°C increased to 8.9% on the first day and reached the maximum value of 27.4% on the fourth day, about 3.42 and 10.53 times, respectively of the average mortality level (2.6%) (47). Furthermore, by analyzing the relationship between daily mortality and heat stress in eight Polish cities between 1975 and 2014, Kuchcik found that the risk of death increased to 10–20% in most cities when the UTCI exceeded 32°C, and to 25–30% when the UTCI crossed 38°C (50).

Spatiotemporal heterogeneity of thermal environments

Heat intensity of outdoor environments is determined by heat sinks and sources which are always highly heterogeneous spatially and temporally. Open spaces such as streets, squares, plazas, grassland, and park for people's outdoor activities, generally exhibit differences in land cover (e.g., pavement, vegetation, water bodies) (51, 52), and surface structure (such as building height, street width, orientation, and density) (53, 54), resulting in the heterogeneity of microclimatic conditions and human thermal comfort. For instance, a square paved with cool materials could be 12°C cooler in surface temperature and 1.9°C cooler in peak air temperature (55). A study in Taipei indicated that parks could generate an average airborne cooling effect of 0.81°C in summer noon, and a cooling effect of 0.29 °C in summer night (56). Water bodies could be strong cooling sinks, compared with many other land use types (e.g. vegetation, road, building, bare land) (57). Overall, the heterogeneity of thermal environments generates significant implications for outdoor activities, transport, and heat health issues (58).

Existing studies have extensively reported the spatial heterogeneity of microclimates and outdoor thermal comfort. For instance, at the building scale, a study in Tianjin, China, indicated that daily maximum temperature decreased with building height at an average rate of 0.05°C for every 10 meters (59). However, the daily minimum temperature increased with building height at an average rate of 0.08°C for every 10 m. At the street scale, street orientation, aspect ratio, length-width ratio, sky view factor, enclosure degree, and building elevation can regulate aerodynamic and radiation properties and thereby the variation of thermal characteristics. A study conducted by Emmanuel et al. (60) in Colombo, Sri Lanka, found that air temperature reduced proportionally with the street aspect ratio and the distance from the sea, and the wind speed increased with the street aspect ratio (60). Street orientation affects solar

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TABLE 1 Heat stress and thermal comfort indicators of PET and UTCI (47–49).

Stress category	PET range for Western/Middle European countries (°C)	PET range for subtropical regions (°C)	UTCI range (°C)
Extreme cold stress	<-4	<14	<-40
Very strong cold stress	–	–	−40 to −27
Strong cold stress	4–8	14–18	−27 to−13
Moderate cold stress	8–13	14–22	−13 to−0
Slight cold stress	13–18	22–26	0–9
No thermal stress	18–23	26–30	9–26
Slight heat stress	23–29	30–34	–
Moderate heat stress	29–35	34–38	26–32
Strong heat stress	35–41	38–42	32–38
Very strong heat stress	–	–	38–46
Extreme heat stress	>41	>42	>46

radiation incidence. Ali Toudert and Mayer found that east-west streets were exposed to direct solar radiation much longer than other streets so thermal environments and thermal comfort in east-west streets were much worse (61). Taleghani et al. (62) analyzed summertime street thermal environments of a Netherland neighborhood, finding that east-west streets could receive solar radiation for 12.5 h, much longer than north-south streets (4.5 h). Moreover, the higher the sky view factor, the higher the mean radiant temperature (62). At the precinct scale, the thermal environments could be more complex due to the combined effects of building height, street structure, and building density. According to the local climate zone studies, the industrial and compact high-rise precincts could be much warmer than all other types. According to the precinct ventilation zone, open low-rise precincts in Sydney were the worst in PET, followed by open midrise and compact high-rise precincts (26).

Shading structures or tree shade could also result in strong cooling performance in the mean radiant temperature reduction (63, 64). Trees, in particular, could generate shades and evapotranspiration effects for better cooling performance. Existing studies indicate that though different tree species could have different cooling effects, the ambient temperature could still reduce by 0.5–1.0°C, and the reduction of mean radiant temperature was more prominent by 10°C (65). Local adoption of tree cooling strategies could increase the heterogeneity of street thermal environments since trees are not planted evenly in numerous precincts. In addition, waste heat or cold sources released from air-conditioning systems, traffic systems, and open doors and windows in and surrounding public spaces can also cause significant changes in local microclimate and thermal comfort (9). Overall, in heterogeneous neighborhoods, it is particularly important to predict and present microclimate and thermal comfort characteristics in a precise and real-time manner and to identify and determine areas with good microclimate and thermal comfort that are suitable for outdoor activities and daily travel for the analysis of FMC walkability.

Transient and cumulative variation of thermal comfort

Since thermal comfort is the combined result of physical, physiological, and psychological responses, it exhibits spatial-temporal variations associated with a transient change of physical environment (40). Individuals can endure different levels of heat stress, due to the variation of mean radiant temperature, when walking in streets with sparse trees. During such a period, individuals may undergo a mix of conditions of heat stress aggravation, continuance, and alleviation (Figure 2), depending on the exceedance of the neutral heat stress threshold. If a thermal comfort value exceeds the neutral thermal comfort threshold, individuals will suffer from heat stress (Table 1), generating negative impacts on street walkability. Heat stress cumulates if individuals are walking in heat-positive environments continuously. In comparison, if a thermal comfort value is within or below the "no thermal stress" level, individuals will not endure heat-induced thermal stresses. The heat-stress-free level can be further divided into two sub-levels: (i) the heat stress alleviation zone, which alleviates cumulative heat stress, and (ii) the heat stress continuance zone, which neither alleviates nor strengthens the cumulative heat stress (Figure 2). Heat stress alleviation depends on the exceedance of optimal thermal comfort value.

Accordingly, individuals' bodies endure the alternation of stress aggravation, continuance, and alleviation when they conduct activities. Heat tolerance, namely the cumulative heat stress that reaches the maximum body adaptation capacity,

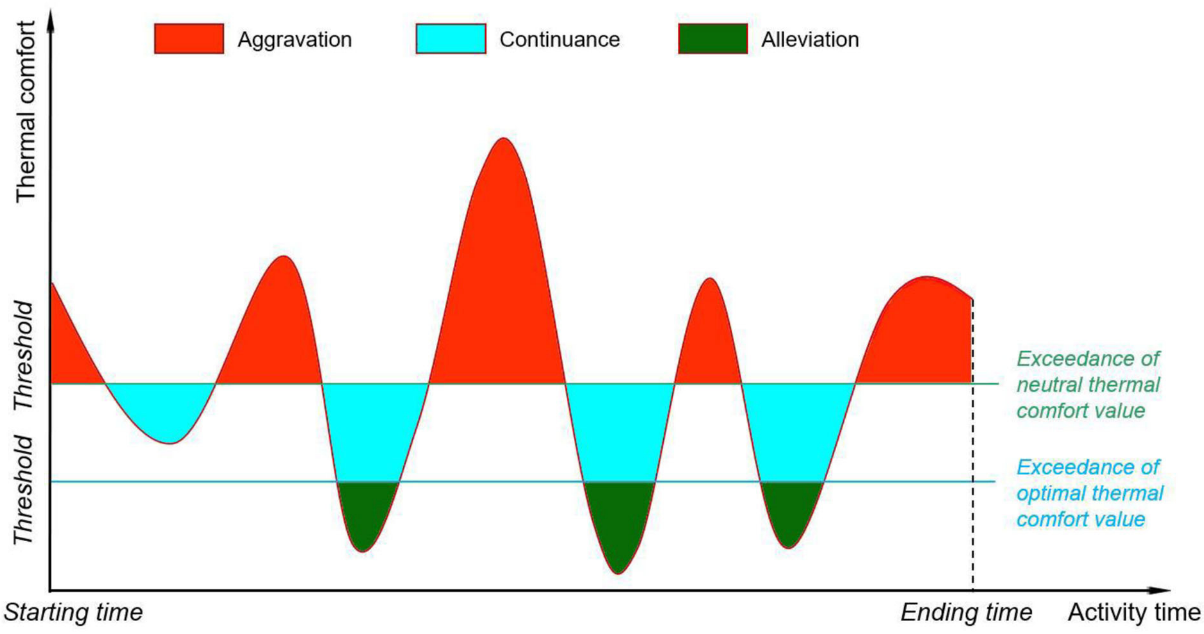


FIGURE 2
Heat stress aggravation, continuance, and alleviation with activity duration.

is a function of aggravation, continuance, and alleviation (Equation 1).

$$F(x) = f(\text{aggravation}) + f(\text{continuance}) + f(\text{alleviation}) \quad (1)$$

Heat tolerance is also dependent on the socio-economic features of individuals (physiological response), their activity type and the alternation (behavioral feature), the clothing-related adaptive behaviors (behavioral and physical adaptation), their attention to thermal environments (psychological response), and the distance from the destination (social property). For instance, when individuals undergo severe heat stress and feel unwell during strenuous exercise, there is a high level of possibility of stopping exercising, meaning a change in heat stress aggravation to continuance or alleviation. Likewise, people may wear sun protection clothes or hold up an umbrella to shelter themselves from direct solar radiation, at which time the significant reduction of mean radiant temperature could indicate the transition from aggravation to continuance or alleviation. Limited time for commuting toward destinations (e.g., railway station, office, hospital), or visual and sound landscapes could divert their attention to thermal environments, resulting in increasing heat tolerance. Hiding in an attractive destination could potentially be an intervention of heat tolerance. Within an FMC, therefore, it is critical to consider associations between heat tolerance and social, economic, environmental, and behavioral characteristics for specific adaptation measures such as type and intensity, time and duration, route optimization, and clothing behaviors (Figure 3).

Case study and method

Case study area

This study was conducted in Fucheng District, Mianyang, Sichuan, China. Mianyang (30°42′-33°03′N, 103°45′-105°43′E) is the second largest prefecture-level city of Sichuan province (Figure 4), with a total area of 20,267.46 km^2 and a population of 4,868,243 according to the 2020 Population Census. Mianyang has an urban area of 2,755.4 km^2 and an urban population size of 2,232,865. It has a monsoon-influenced humid subtropical climate (Köppen Cwa) with four distinct seasons. The annual average temperature ranges between 14.7 and 17.3°C. Its summer is hot and humid, whereas July and August are the two hottest months throughout the year, with average high temperatures of 30.1 and 30.5°C, respectively.

Mianyang city is undergoing rapid urbanization, where living quality and well-being have been important concerns given the urbanization experience and lessons from various highly urbanized cities. The 15-min city concept has been integrated into urban sprawl and urban renewal to meet residents' requirements for various public service facilities relevant to daily life, leisure, and entertainment. Furthermore, the FMC underlines the proximity of fundamental public

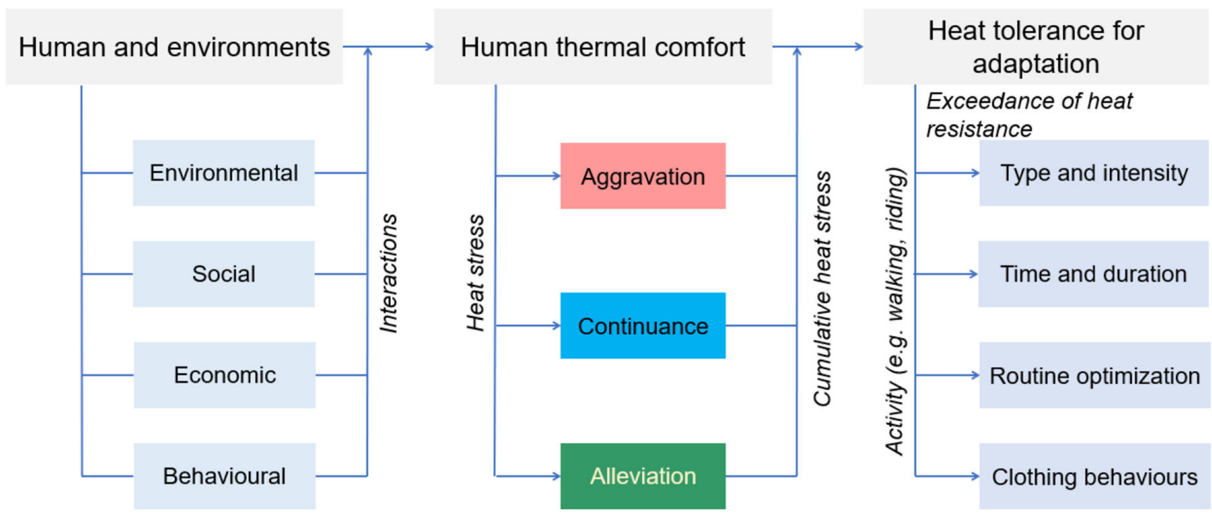


FIGURE 3
Association between heat tolerance and human-environmental characteristics.

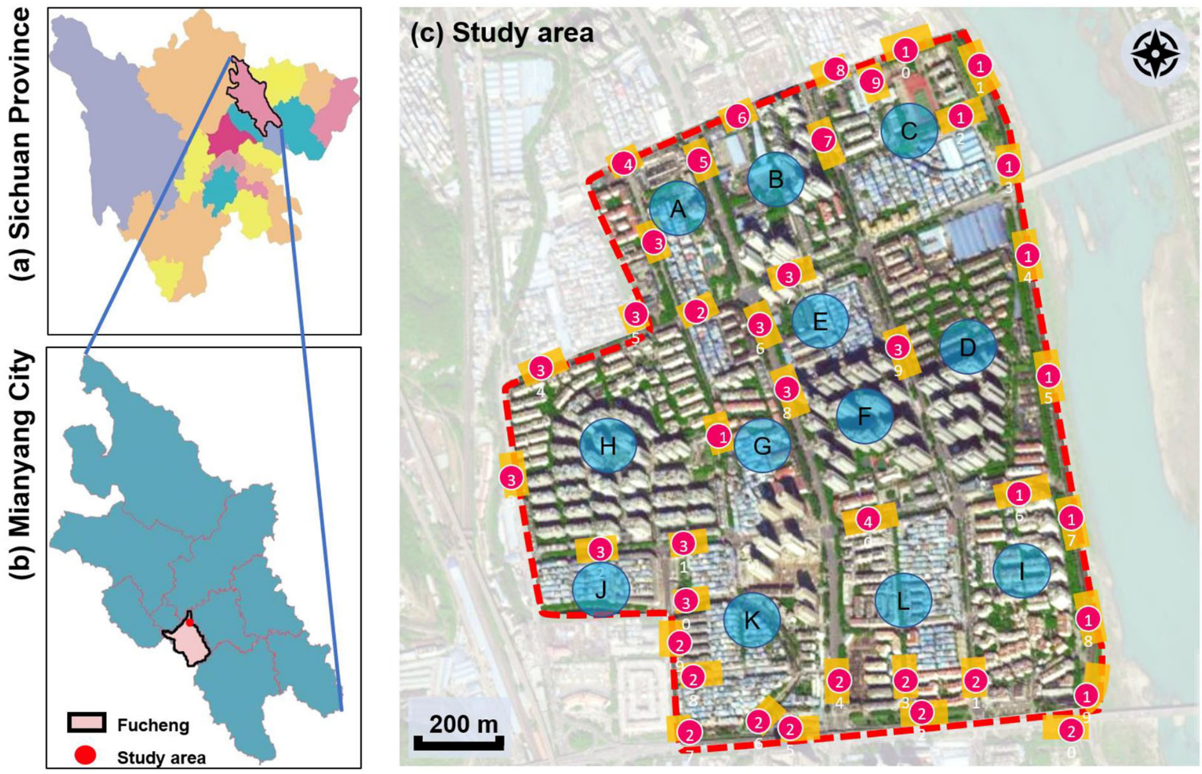


FIGURE 4
Location of study area and its streets and neighborhoods. **(a)** Sichuan province, **(b)** Mianyang city, and **(c)** Study area.

services in the place. Such a principle requires not only the availability of public services but also the accessibility to them within FMC walkable areas. Therefore, the Gaoshui FMC in the Fucheng district was selected to analyze the walkability. This FMC consists of 12 neighborhoods (A–L, Figure 4), within which the buildings have various ages and streets exhibit different kinds of typology. On function type, the FMC is mainly used for residential purposes and is home to about 73,000 citizens. It also includes commercial, food, accommodation, and maintenance facilities for daily life. In particular, the flat terrain enables people to walk or ride in daily transportation functions, whereas the outdoor thermal environment is a precondition of walkability, especially in summer.

The spatial environments of the FMC exhibit a high level of heterogeneity, indicating the spatial variations of thermal environments (e.g. air temperature, wind speed, thermal comfort), and variations of walkability. Table 2 details the morphological information of 40 street scenarios presented in Figure 4c. For instance, Street 1 is well structured with mid-rise buildings, and it is almost covered by tree canopies and offers ample shade from trees and evapotranspiration cooling. Street 2 is equally well structured with dense high-rise buildings on one side and dense low-rise buildings on the other; however, there are no street trees and people can find relief only from narrow building shades. Street 11 is a riverside road with trees on both sides of the street, and the road is surrounded by a large patch of lawn. Street 24 is the main road of the city with high vehicular traffic, and trees on the street offer good and sheltered walkways protecting people from direct solar radiation. Street 26 is a pathway along with a city river and is covered by trees and an awning. The spatial variation of urban morphological characteristics is always coupled with temporal variations of thermal environments given the complex combination of time-based heat sources/sinks with morphological characteristics. Therefore, people can hardly have an intuitive assessment of street heat stress. This necessitates an accurate assessment of heat stress and associated walkability in this community.

Thermal comfort assessment indicator and dynamic attenuation model

This study adopted the UTCI as the thermal comfort assessment indicator for it presents a multi-node model of human heat transfer and temperature regulation with the consideration of clothing adaptation. Furthermore, UTCI is more sensitive to the spatial variation of thermal environments, which is capable of simulating unsteady or transient conditions. Therefore, UTCI can well respond to the frequent spatial-temporal variations of the microclimates when walking and thereby reflect the dynamic psychological responses. The UTCI is also linked with different levels of thermal sensations (Figure 5), where a heat stress level (L_{HS}) of 4 indicates an extreme heat stress level when UTCI is above 46°C.

To assess the dynamic variation of thermal comfort during walking, this study proposes a DAM of heat stress. The model defines the remaining tolerable heat discomfort (R_t) during walking with the cumulation of heat stress. In a specific duration, the cumulation of thermal stress is defined as a function of time and heat stress level (Equation 2).

$$S_t = \sum\nolimits_0^i L_{HS_i} \bullet t_i \tag{2}$$

where S_t is the cumulative heat stress with a time duration of t (Unit: min$'$); L_{HS_i} is the *ith* heat stress level, and i can be 0, 1, 2, 3, and 4; t_i is the time duration of the *ith* heat stress level (Unit: min).

Therefore, the remaining tolerant heat discomfort (R_t) can be expressed as:

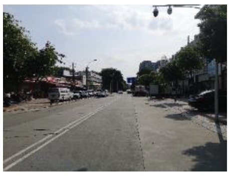
$$R_t = H - S_t \tag{3}$$

where H is the maximum tolerant heat discomfort (Unit: min$'$), at which value the remaining tolerant heat discomfort R_t equals to 0, indicating that people have to stop walking to relax. Moreover, it is suggested the higher the remaining tolerant heat discomfort, the higher the walkability of the street. In an FMC, citizens are expected to be informed of the route with the highest walkability.

To determine the maximum tolerant heat discomfort H, a 15-min walkability experiment was conducted in Fucheng District, Mianyang. During the experiment, the microclimatic parameters including air temperature, wind speed, relative humidity, and mean radiant temperature were recorded for analyzing the UTCI and weighting heat stress level. A total of 128 residents attended the experiment, where they were requested to walk for 15 min at four levels of heat stress (1, 2, 3, and 4). Their perceived heat stress levels (slightly uncomfortable, uncomfortable, very uncomfortable, extremely uncomfortable) were asked and recorded at an interval of 1 min. After the experiment, the reliability analysis was carried out using SPSS 22.0. The result shows a Cronbach's α coefficient of 0.929. The Cronbach's α coefficient of each variable was above 0.8, indicating the survey results were highly reliable.

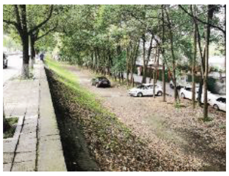
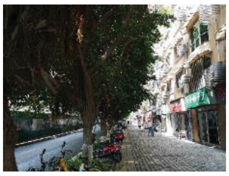
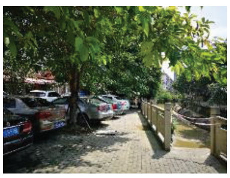
Figure 6 presents the walkable duration and respondents' discomfort level at different levels of heat stress. Respondents felt just slightly uncomfortable during their 15-min walking activity under moderate heat stress, and there were no uncomfortable, very uncomfortable, or extremely uncomfortable responses. In comparison, when respondents were under strong heat stress, they felt slightly uncomfortable in 0–8 min, while they expressed uncomfortable feelings in 9–15 min. Nevertheless, their feelings did not upscale to very uncomfortable and extremely uncomfortable levels. Under very strong heat stress, people felt slightly uncomfortable and uncomfortable in 0–5 min and 6–11 min, respectively. However, the cumulative heat stress made respondents feel very uncomfortable within 12–15 min. Under extreme heat stress, in comparison, people felt slightly uncomfortable in 0-4 min, uncomfortable in 5–7 min, very uncomfortable in 8–12 min, and extremely uncomfortable

TABLE 2 Morphological characteristics of 40 street sections.

NO	Imagery information	Details	NO	Imagery information	Details
1		Four driveway lanes, no non-motorized lane, wide walkways, street tree canopy (∼0.20 m in truck diameter), dense midrise buildings on both sides	2		Six driveway lanes, two non-motorized lanes, narrow walkways, no street tree canopy, dense low-rise or midrise buildings on both sides
3		Four driveway lanes, no non-motorized lane, wide walkways, street tree canopy (∼0.30 m in truck diameter), dense midrise buildings on both sides	4		Four driveway lanes, no non-motorized lane, wide walkways, street tree canopy (∼0.15 m in truck diameter), dense low-rise buildings on both sides
5		Eight driveway lanes, two non-motorized lanes, wide walkways, street tree canopy (∼0.25 m in truck diameter), dense midrise buildings on both sides	6		Four driveway lanes, no non-motorized lane, wide walkways, street tree canopy (∼0.25 m in truck diameter), dense low-rise buildings on both sides
7		Four driveway lanes, one non-motorized lane, wide walkways, street tree canopy (∼0.15 m in truck diameter), dense low-rise buildings on one side and dense high-rise on the other side	8		Four driveway lanes, wide riding or walkways, street tree canopy (∼0.15 m in truck diameter), dense low-rise buildings on one side and dense high-rise on the other side
9		Six driveway lanes, wide riding or walkways, sparse street tree canopy (∼0.15 m in truck diameter), dense low-rise buildings on one side and dense high-rise buildings on the other side	10		Four driveway lanes, wide riding or walkways, sparse street tree canopy (∼0.15 m in truck diameter), sparse low-rise buildings and lawns on both sides
11		Two driveway lanes, street tree canopy (∼0.20 m in truck diameter), lawns and a narrow walkway on one side and a wide riverside walkway on the other side	12		Two driveway lanes, street tree canopy (∼0.20 m in truck diameter), lawns and a wide walkway on one side, and a wide walkway and paved square on the other side
13		Two driveway lanes, street tree canopy (∼0.20 m in truck diameter) on one side, lawns and a narrow walkway on one side and a wide riverside walkway on the other side	14		Two driveway lanes, street tree canopy (∼0.20 m in truck diameter), lawns and a narrow walkway on one side and a wide riverside walkway on the other side

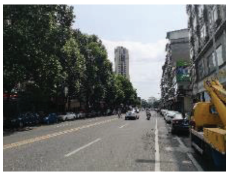
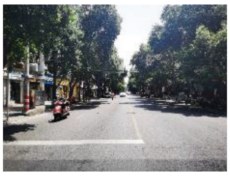
(Continued)

TABLE 2 (Continued)

NO	Imagery information	Details	NO	Imagery information	Details
15		Two driveway lanes, street tree canopy (~0.20 m in truck diameter), sunken lawns and a narrow walkway on one side and a wide riverside walkway on the other side	16		Four driveway lanes, wide walkways, street tree canopy (~0.20 m in truck diameter), dense midrise buildings on both sides
17		Two driveway lanes, sparse street tree canopy (~0.20 m in truck diameter), sunken lawns and a narrow walkway on one side and a wide riverside walkway on the other side	18		Two driveway lanes, street tree canopy (~0.25 m in truck diameter), sunken lawns and a narrow walkway on one side and a wide riverside walkway on the other side
19		Two driveway lanes, no street tree canopy, lawns and a narrow walkway on one side and an upper walkway on the other side	20		Two driveway lanes, street tree canopy (~0.20 m in truck diameter), narrow walkways on both sides
21		Four driveway lanes, two non-motorized lanes, wide walkways, street tree canopy (~0.15-0.20 m in truck diameter), dense midrise buildings on both sides	22		Fastway under construction, wide walkways, street tree canopy (~0.25 m in truck diameter), dense midrise buildings on one side
23		Two driveway lanes, wide walkways, street tree canopy (~0.20 m in truck diameter), dense midrise buildings on both sides	24		Eight driveway lanes, wide walkways, street tree canopy (~0.15–0.20 m in truck diameter), dense low buildings on both sides
25		Eight driveway lanes, wide walkways, street tree canopy (~0. 0.20 m in truck diameter), dense low buildings on both sides	26		A city waterway, wide walkways, street tree canopy (~0.25 m in truck diameter), building awnings.
27		Four driveway lanes, wide walkways, street tree canopy (~0.20 m in truck diameter), dense low- or midrise buildings on both sides	28		Two driveway/walkway lanes, no street tree canopy (~0. 0.20 m in truck diameter), dense midrise buildings on both sides
29		Four driveway lanes, wide walkways, no street tree canopy, dense midrise buildings on both sides	30		A driveway, a wide walkway, street tree canopy (~0.25 m in truck diameter), dense midrise buildings on one side and a city waterway on the other side

(Continued)

TABLE 2 (Continued)

NO	Imagery information	Details	NO	Imagery information	Details
31		Six driveway lanes, wide walkways, street tree canopy (∼0.25 m in truck diameter) on one side, dense midrise buildings on both sides	32		Six driveway/ non-motorized lanes, wide walkways, street tree canopy (∼0.20 m in truck diameter), dense midrise buildings on both sides
33		Six driveway/ non-motorized lanes, wide walkways, street tree canopy (∼0.15–0.20 m in truck diameter) on one side, dense low-rise buildings on both sides	34		Four driveway lanes, narrow walkways, no street tree canopy, dense midrise buildings on both sides
35		Two driveway lanes, wide walkways, street tree canopy (∼0.15 m in truck diameter), dense low-rise buildings on both sides	36		Six driveway lanes, wide walkways, street tree canopy (∼0.15–0.20 m in truck diameter), dense midrise buildings on both sides
37		Five driveway lanes, no street tree canopy, dense high-rise buildings on both sides	38		Eight driveway lanes, two non-motorized lanes, wide walkways, street tree canopy (∼0.15–0.20 m in truck diameter), dense high-rise buildings on both sides
39		Four driveway lanes, two non-motorized lanes, wide walkways, street tree canopy (∼0.15 m in truck diameter), dense midrise buildings on both sides	40		Four driveway/non-motorized lanes, wide walkways, street tree canopy (∼0.15 m in truck diameter), dense low-rise buildings on both sides

Thermal stress	Extreme cold stress	Very strong cold stress	Strong cold stress	Moderate cold stress	Slight cold stress	No thermal stress	Moderate heat stress	Strong heat stress	Very strong heat stress	Extreme heat stress
Heat stress level	-5	-4	-3	-2	-1	0	1	2	3	4
Universal Thermal Climate Index (UTCI, °C)	<-40	-40 – -27	-27 – -13	-13 – -0	0 – 9	9 – 26	26 – 32	32 – 38	38 – 46	>46

FIGURE 5
Association between heat stress levels and UTCI.

Heat stress level		Moderate heat stress	Strong heat stress	Very strong heat stress	Extreme heat stress
		Level 1	Level 2	Level 3	Level 4
Walkable duration under different levels of heat stress (min)	Slightly uncomfortable	0-15	0-8	0-5	0-4
	Uncomfortable		9-15	6-11	5-7
	Very uncomfortable			12-15	8-12
	Extremely uncomfortable				13-15

FIGURE 6
Heat stress level and its impact on walkable duration.

in 13–15 min. Therefore, a walkable duration of 13–15 min under Level 4 heat stress suggested a maximum tolerant heat discomfort *H* ranging between 52–60 min. In this study, an aspirational value of 60 min was considered. It should be noted that the walkable duration and associated maximum tolerant heat discomfort had already included physical, psychological, and physiological responses of respondents, rather than only considering physical environments.

Accordingly, the remaining tolerant heat discomfort (R_t) is:

$$R_t = 60 - S_t \tag{4}$$

Numerical simulations of 15-min city thermal environments

To estimate spatial-temporal variations of thermal environments and associated heat stress, the ENVI-met model (Science version) was adopted. The ENVI-met model is currently the most holistic, three-dimensional microclimate model to present the high-resolution interactions among surfaces, plants, and the atmosphere. It has been widely adopted to calculate block- and neighborhood-scale microclimate and heat stress for climate-sensitive urban planning. The urban morphology, street network, tree planting and species, surface structure, and surface texture were obtained through satellite images, local urban planning council, and field observation. Given the large study area, we set 200 × 240 × 40 grids in horizontal, perpendicular, and vertical directions, with a grid resolution of 8 meters.

Weather condition is also important to simulate the ENVI-met model. The two hottest months of Mianyang are July and August. According to the data from China Meteorological Administration, an average temperature of 28°C was the most prominent in 2020 and mainly occurred in August. Therefore, typical weather conditions (wind direction, wind speed, air temperature, and relative humidity) were adopted for the simulation (Table 3). In the daytime, the temperatures were generally high and the walkable duration generally occurred between 8:00 and 19:00 h. In particular, the peak walking periods were 8:00–9:00 h and 17:00–18:00 h, when people go to and return from work. Compared with 8:00–9:00 h, the temperature at 17:00–18:00 h was much higher and heat stress was much worse, so the period returning from work was particularly analyzed.

Note that the above-mentioned simulation settings have been adopted to demonstrate the applicability of the DAM in walkable route planning. Comprehensive planning for a walkable route should be presented hour-by-hour, and the resolution should be higher to capture spatial heterogeneity of street sections, building heights, and tree heights. Moreover, to ensure people are better protected, an hour-to-hour local weather boundary condition, rather than the data from national weather stations which always fail to accurately present local climates, is needed to precisely capture the real-time maximum temperature and heat stress.

Result analysis and discussion

Verification of spatial heterogeneity of thermal comfort

Figure 7 presents the simulated thermal comfort (UTCI) of the FMC between 17:00 and 18:00 h. The UTCI ranged between 31.26 and 40.86°C, primarily showing strong heat stress and very strong heat stress that could be categorized as Level-2 and Level-3 heat stress (Figure 5). The thermal comfort distribution was highly heterogeneous. Overall, the thermal environments within each neighborhood were much better than on the streets. This was mainly linked to building shades, tree canopies, and grassland within the community. Nevertheless,

TABLE 3 Weather data adopted to simulate the ENVI-met model.

Data category	Detail	Data category	Detail
Geographic location	30°42′-33°03′N, 103°45′-105°43′E	Minimum air temperature	24.6°C (07:00)
Simulation time	0:00–19:00	Maximum air temperature	32°C (15:00)
wind direction	245°	Minimum relative humidity	66% (17:00)
wind speed	1.4 m/s	Maximum relative humidity	94% (09:00)

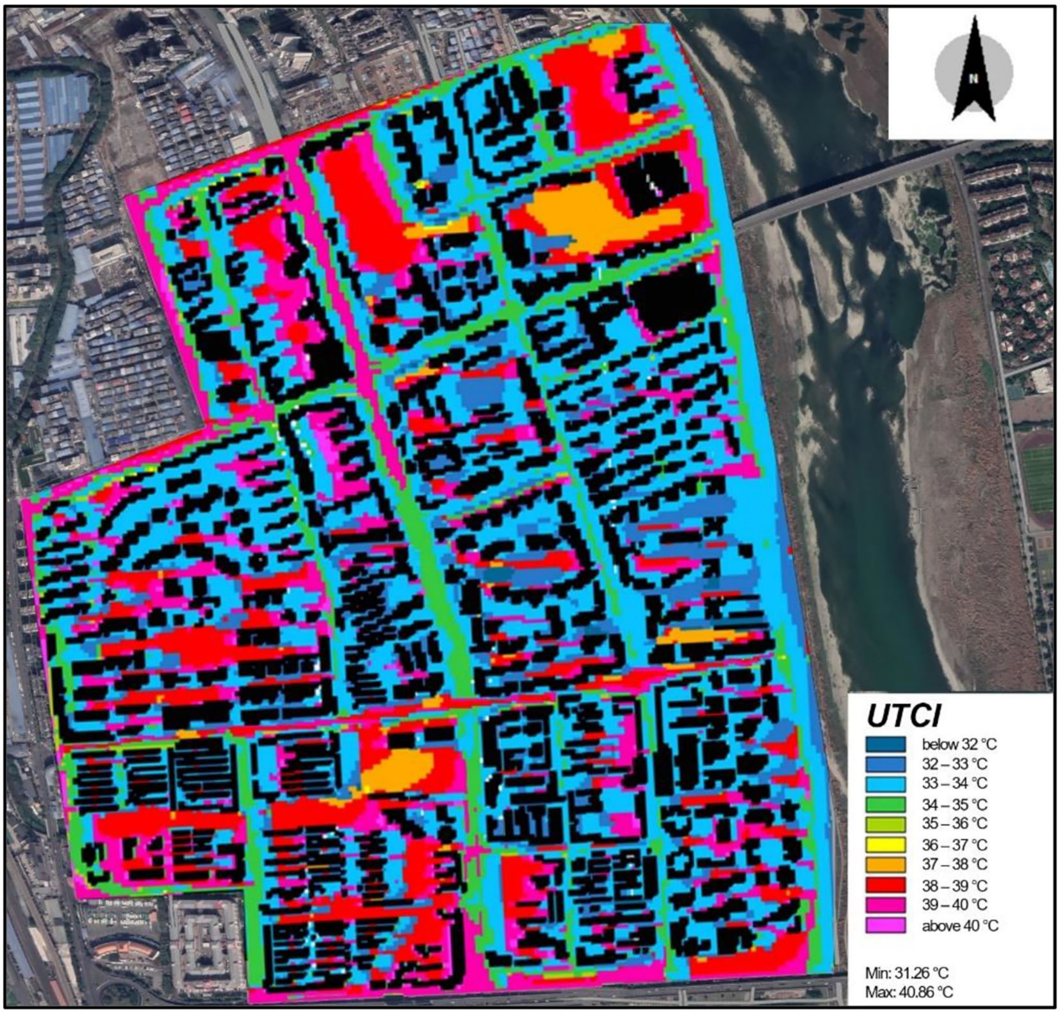


FIGURE 7
Distribution of simulated UTCI of the study area.

the neighborhoods were dense and enclosed, and in areas that were paved with cement and under direct solar exposure, the thermal environments were much worse. The riverside streets (Street 11–19) presented a good thermal environment with the UTCI ranging between 32 and 34°C. In comparison, north-south streets at 33–34°C exhibited a lower UTCI level than east-west streets at 36–40°C. The results are also dependent on the height of the buildings on the street. For instance, the middle section of streets 5 and 36 with low and mid-rise buildings had a higher UTCI level of 39–40°C than Street 38 with mid- and high-rise buildings at 33–35°C. Similarly, in streets 5 and 36, their central section was warmer than the

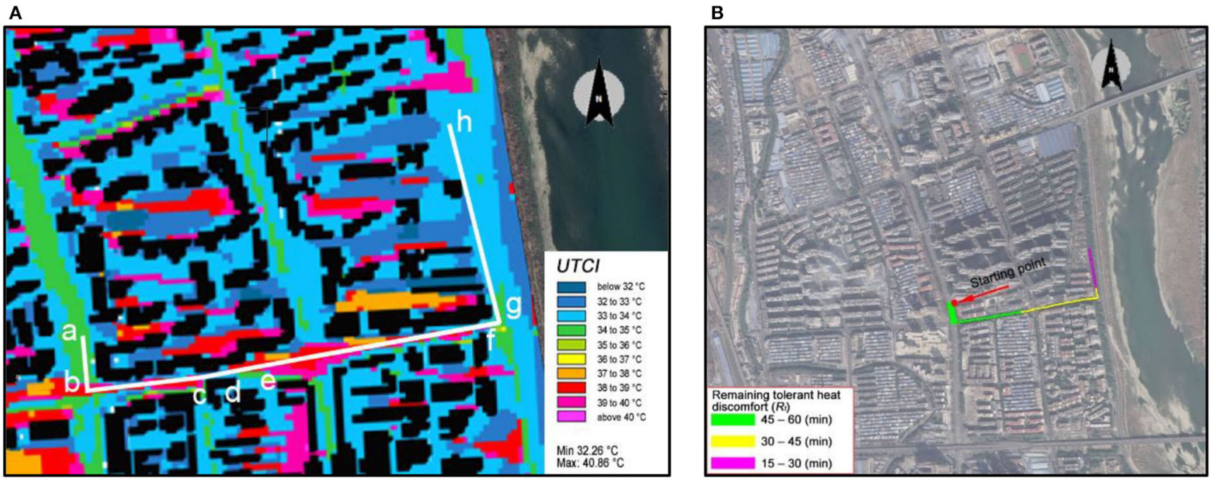


FIGURE 8
Street sections of a walking route in Neighborhood-F and the remaining tolerant heat discomfort. **(A)** Distribution of thermal comfort, **(B)** Walking route.

TABLE 4 Dynamic variation of the remaining tolerant heat discomfort of a walking route of Neighborhood-F.

Street	UTCI (°C)	L_{HS}	Street distance (m)	Walking duration (min)	R_t (min′)
ab	34–36	2	71.1	1.2	57.6
bc	38–40	3	171.7	2.9	48.9
cd	33–34	2	44.8	0.8	47.3
de	38–40	3	51.0	0.9	44.6
ef	37–40	3	292.0	4.9	29.9
fg	33–36	2	12.0	0.2	29.5
gh	32–36	2	257.3	4.3	20.9

sides due to the shade from trees and buildings. The results also indicate an open and wide street adjacent to the river could have a better thermal environment, for instance, Street 37 at 34–35°C.

Assessment of street walkability

According to the municipal roads and land boundaries within the study area, 12 neighborhoods were identified (Figure 4). Setting the entrance of these neighborhoods as the starting points for daily walking, the walking routes were analyzed taking into consideration heat stress. The maximum walkable distance was set as 900 m based on a walking speed of 1 m/s. Figure 8A exhibits a possible walking route (a-h) of Neighborhood-F, (Figure 5), and the DAM (Equations 2,4), the remaining tolerant heat discomfort was calculated, as shown in Table 4.

The results indicate that section ab had a UTCI range of 34–36°C, namely a heat stress level of 2. Its street distance of 71.1 m, corresponding to a walking duration of 1.2 min, led to cumulative thermal stress of 2.4 min, and thereby a remaining tolerant heat discomfort of 57.6 min, based on the maximum tolerant heat discomfort of 60 min. Following this, from point-a to point-h, the remaining tolerant heat discomfort for 900 m was 20.9 min. As shown in Figure 8B, in particular, the section ae had an R_t of 45–60 min, section e. g, 30–45 min, and section gh had 15–30 min.

Likewise, 15-min walkable routes were identified, as shown in Figure 9. It was observed that the 15-min walkable routes of neighborhoods A, B, C, D, and E were mainly in green and yellow color, representing a remaining tolerant heat discomfort above 30 min. In comparison, other neighborhoods presented green, yellow, and purple colors, indicating a remaining tolerant heat discomfort above 15 min. Such a comparison further indicates that neighborhoods F-L were more vulnerable in the 15-min walkability. While such results could directly help identify the travel paths for citizens to avoid strong heat stress, the results also suggest that there is a need to adopt urban heat mitigation and adaptation techniques and strategies to improve heat resilience. Different from existing studies on

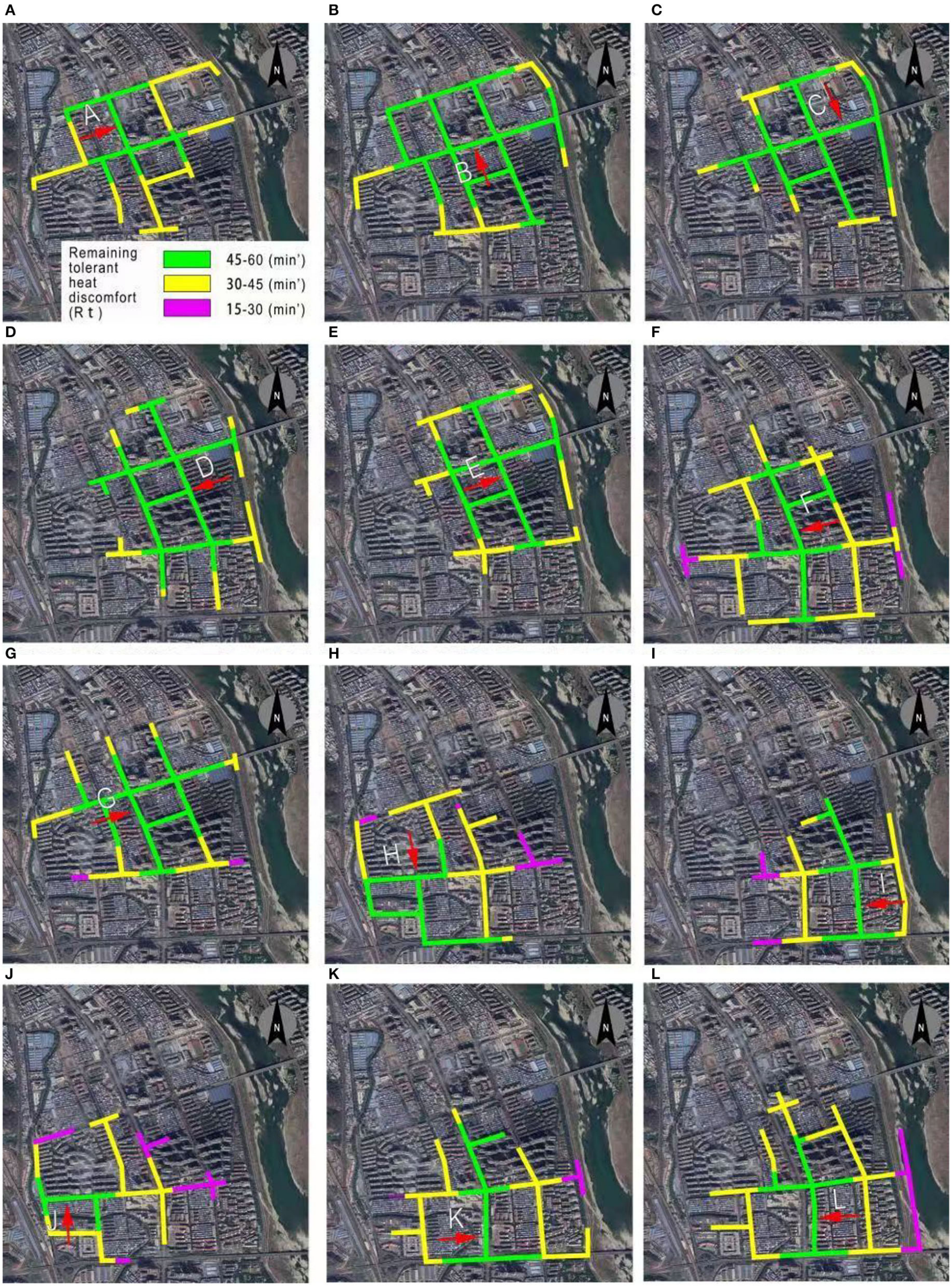


FIGURE 9
Identification of remaining tolerant heat discomfort of all possible walkable routes of 12 neighborhoods. **(A)** Neighborhood-A, **(B)** Neighborhood-B, **(C)** Neighborhood-C, **(D)** Neighborhood-D, **(E)** Neighborhood-E, **(F)** Neighborhood-F, **(G)** Neighborhood-G, **(H)** Neighborhood-H, **(I)** Neighborhood-I, **(J)** Neighborhood-J, **(K)** Neighborhood-K, **(L)** Neighborhood-L.

dealing with heat stress by adding location-based interventions, the current walkability-based study provides new insights into planning-based adaptation. For instance, for the walkable routes in Neighborhood-F (Table 4), interventions added to improve thermal environments in a-h sections can potentially improve the path walkability by reducing the heat stress of any section.

Assessment of the FMC walkability and implications

To support the FMC planning and design, this study further assessed the overall walkability of the study area. Based on street walkability (Figure 9), a population-based weighting algorithm (Equation 5) was adopted to adjust the heat stress of each street.

$$k_i = \frac{P_i}{\sum_1^n P_i} \tag{5}$$

Where, k_i is the weight of each neighborhood in the 15-min city; P_i is the population number of each neighborhood; and n is the total number of neighborhoods, set as 12 in this study.

The weight k_i of each neighborhood is presented in Table 5.

The overall street walkability of the FMC, after taking into consideration heat stress, is generated in Figure 10A. Overall, the central part exhibited the highest remaining tolerant heat discomfort, while the outmost areas had the lowest remaining tolerant heat discomfort. To improve walkability, there is a need to focus on the improvement of thermal environments. In general, it is better to improve the walkability of the central parts (with the highest weight) to extend the overall walkability. However, in this study, the central areas generally had a low UTCI (Figure 7) and weak heat stress so adding interventions in the central parts did not exhibit high potential. Instead, adding cooling interventions in the yellow section could help weaken heat stress and extend street walkability the most. The improvement of the thermal environments of the purple section is also recommended.

The overall walkability also generates implications on the configuration of public service which is a typical adaptation measure to reduce citizens' heat stress by foot. The public service was divided into three types, according to the visiting frequency: frequently-used, often-used, occasionally-used, and indirectly-used (Table 5). In general, the indirectly-used public service is the one people do not visit directly or seldom visit, so it was not considered in this study. Figure 10B presents possible locations of frequently-used, often-used, and occasionally-used public services. The frequently-used public service was configured at the street sections with the highest remaining tolerant heat discomfort, and the occasionally-used public service was set at the street sections with the lowest remaining tolerant heat discomfort. The often-used one was set in the green-yellow transition street section or a green section. Our empirical work also found that various existing public services which are frequently used and often used were configured in yellow- and purple-colored street sections, making many citizens rely on private cars rather than walking. Therefore, urban heat mitigation strategies should be added to improve the thermal environment and street walkability. Simultaneously, public services should be gradually relocated to improve the accessibility of public services within walkable areas.

Conclusion

The FMC concept has been implemented in various countries to build high-quality cities. Whilst the goals of inclusiveness, safety, and health have been widely accepted, the achievement of such goals is compromised since inclusiveness, safety, and health are interlinked with various factors. This study considered the issue of urban heat which is increasingly severe along with climate change and urbanization. This is a pioneering study on integrating heat-related impacts within the FMC framework by investigating walkability and developing a dynamic attenuation model (DAM) of heat stress. The model was applied to an FMC in Fucheng District, Mianyang, China. Some imperative results that were suitable for the case study have been obtained, and the results could generate implications for the (re)configuration of public services in urban planning and design. Overall, the findings could provide a practical reference for urban heat mitigation and adaptation. This paper has also meaningfully added new knowledge on heat-related FMC planning and design.

Whilst this study is the first one on the integration of heat-related walkability into the FMC concept, there are some limitations that should be considered. First, the remaining tolerant heat discomfort was developed based on the empirical study among 128 interviewees; the sample size might not be large enough to completely represent everyone's heat tolerance, and the empirical study had not integrated socioeconomic characteristics and public services that might intervene in people's heat responses for comprehensively assessing walkability. In particular, for vulnerable groups including children, older adults, and pregnant women, there should be an accurate heat stress threshold. Second, this study set four levels of heat stress for determining the remaining tolerant heat discomfort, while the constant heat stress could not present the variability of the thermal comfort and heat stress. As a result, the heat aggravation, continuance, and alleviation had not been well considered. Third, the model adopted the UTCI to assess the heat stress, while the capacity of other outdoor thermal comfort indicators such as PET, and WBGT had not been used in this study. Fourth, the study adopted an FMC in Fucheng as the case study. Whilst the results can provide strong implications for FMC planning and design, the applicability of the results for other cities might be uncertain since the clothing behaviors and heat-resistant capacity could vary with regions. Fifth, heat-induced impacts on thermal comfort happen throughout the

TABLE 5 Weight of each neighborhood for adjusting street walkability of the study area.

Block	A	B	C	D	E	F	G	H	I	J	K	L
Population (k)	3.0	2.7	2.2	12.7	2.7	6.1	3.4	8.2	2.8	6.2	9.8	13.0
Weight k_i	0.04	0.04	0.03	0.17	0.04	0.08	0.05	0.11	0.04	0.09	0.13	0.18

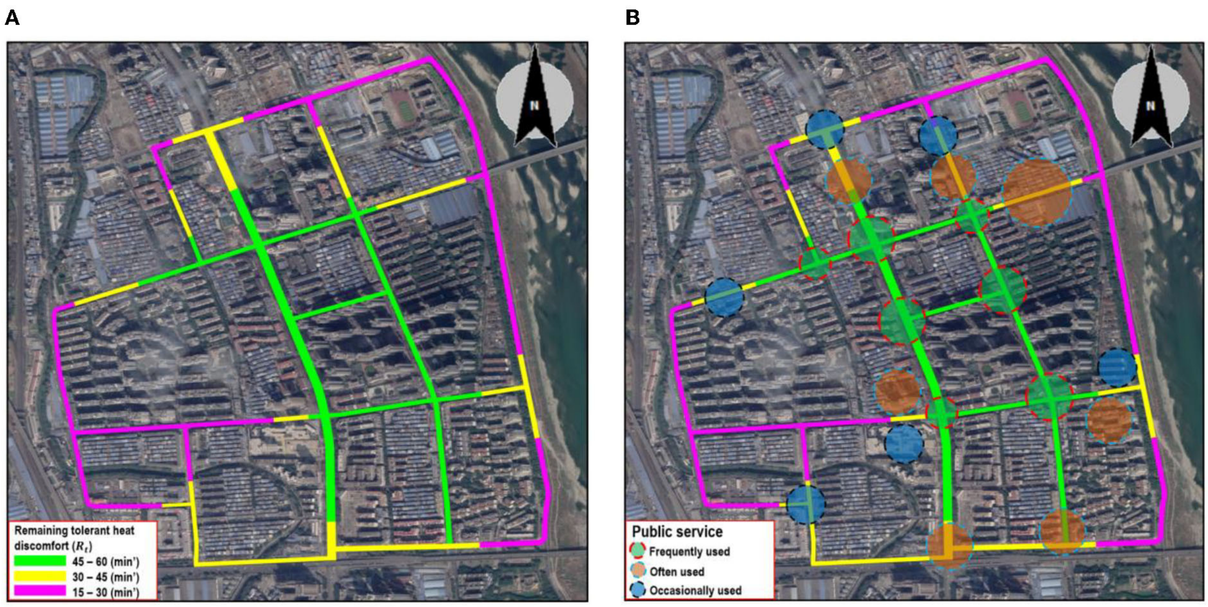


FIGURE 10
Overall street walkability of the FMC **(A)** and associated public service planning **(B)**.

day, especially in the daytime, while this study only considered the period between 17:00 and 18:00 h for walkability assessment and walkable route determination. Planning suggestions on public services were also given based on this time period, which could lead to biases if an urban design scheme was implemented based on the results presented in this paper. More efforts should be conducted to improve DAM accuracy, especially in social-economic, spatial, and temporal aspects, for broad applicability.

Data availability statement

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

Author contributions

YW: conceptualization, formal analysis, funding acquisition, investigation, methodology, software, validation, visualization, roles, and writing—original draft. B-JH: conceptualization, funding acquisition, project administration, methodology, resources, visualization, and writing—review and editing. CK and XC: investigation, methodology, and writing—review and editing. LY: investigation, methodology, and writing—review and editing. MY: investigation, and methodology. XL: conceptualization, formal analysis, and writing—review and editing. TZ: supervision, project administration, resources, and writing—review and editing. All authors contributed to the article and approved the submitted version.

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Conflict of interest

XL was employed by Architectural Design and Research Institute Co., Ltd.

The remaining authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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Flow experience and city identity in the restorative environment: A conceptual model and nature-based intervention

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Within environmental psychology, the restorative environment is receiving increasing attention due to its favorable impact on people's mental recovery, stress reduction, and psychophysiological well-being. Flow theory, as one of the foundations of positive psychology, is a popular theoretical framework for understanding human flourishing and well-being. The restorative environment is suggested to facilitate flow experience and city identity from the perspective of positive environmental psychology. Nonetheless, systematic research investigating them all together can hardly be traced. Thus, through a preliminary review of 169 relevant studies retrieved from the data source, this work proposes a novel theoretical model in which people's interactions within the restorative environment facilitate their experience of flow and perceived city identity. Additionally, this research provides conceptual guidance for city workers to engage in nature-based intervention and leisure therapy for improved well-being. Overall, this review endeavors to contribute to developing urban workers' restoration, happiness, and well-being from both practical and theoretical perspectives.

KEYWORDS

flow experience, optimal experience, city identity, place identity, urban identity, restorative environment, restorative experience

Introduction

Psychological stress has been identified as a significant health risk in modern societies and is, directly and indirectly, responsible for immense costs to health systems and socioeconomic well-being. Consequently, strategies for coping with psychological stress—e.g., facilitating a better working environment and promoting a healthier lifestyle—have increased interest in many research records worldwide. High levels of employee stress have been related to high levels of absenteeism and lower levels of productivity (1, 2). Workers who believe their workplaces are unsuited for their work duties are more likely to report worse well-being and poorer performance outcomes (3). Providing good work surroundings is a crucial aspect of modern office design (4). Increased utilization of urban green space during times of stress, such as the COVID-19 pandemic, has the ability to mitigate some of the stressor's detrimental consequences (5). People in the city of Shanghai in China are starting to realize and indicate their willingness to pay for green offices (6). Nonetheless, empirical studies are still needed in this field.

The "happy-productive worker" thesis states that a happy worker would perform better than an unhappy one (7). The hedonic perspective of well-being refers to a view of pleasure and the experience of positive emotions [e.g., (8)]. In contrast, the eudaimonic philosophy of well-being refers to a view of "worthwhileness" (reward) and commitment (engagement for meaning and life purpose) that is associated with the activities carried out at work (9, 10). Flow involves remaining "focused" and "engaged" in the task at hand (11). It is defined as when engaging in an activity (i.e., work), people will enter into an affective and cognitive state characterized as total absorption, full concentration, time distortion, and optimal enjoyment (12, 13). Defined as an environment that helps one recover from mental fatigue (the fatigue of directed attention), a restorative environment (14, 15) is commonly believed to be a predictor of the flow experience, a state of profound enjoyment and satisfaction elicited from daily activities (11, 14, 16, 17). Scholars have also suggested the mutually reinforcing relationships between the restorative environment and the place identity of people residing in the city (18).

Standing on the social identity approach, the self-awareness of one's membership in a place-related community, including the emotional and value-laden implications of this membership, is known as place identity (19). Place identity within environmental psychology is defined as "memories, conceptions, interpretations, ideas, and related feelings toward specific physical environments as well as types of settings" [(20), p. 60], and the "physical world socialization of the self" [(20) p. 57]. It is a facet of self-identity comparable to other identities but pertaining to people's identification with a specific geographic place (21), such as a city where people live in. Each city has its own identity, formed by images and recollections, both good and bad. As a result of much implicit evidence on flow-identity associations (21–26), it can be argued that there is an interaction between restorative environment, flow experience, and city identity. For instance, scholars have considered residential neighborhoods familiar, restorative, memorable, and beautiful environments that can significantly facilitate the flow experience (27). However, there are still no systematic studies simultaneously on these three constructs, to the best of our knowledge.

Nowadays, for those city workers and city dwellers whose a great deal of time is spent on long office hours during work, staring at the screen and immersing in diverse online virtual platforms after work (28), creating an environmentally friendly workplace and leisure space in the city that brings about restoration (29), is critical to promote more positive affective and cognitive psychological experience such as flow experience and city identity. The present work, guided by three specific goals, reviews the research on flow, city identity, and restorative environment and interprets this research within the framework of positive psychology (the flow theory—the foundations of positive psychology) and environmental psychology (attention restorative theory, ART). The first goal is to review empirical research to construct a new conceptual model relating to notions of restorative environment, psychological flow, and city identity. The second goal is to build a preliminary conceptual model based on the theoretical view of the restorative environment (14). The third goal is to identify nature-based interventions for city workers to promote their everyday flow experience and build and enhance city identity experience *via* a therapeutic process. The organization of this review maps these goals. It ends with a discussion of findings with corresponding implications for research and practice to make urban places more appealing to city workers in terms of restoration and physical activities.

Literature review

A brief literature review involved the following search terms by relevance filter within the web-based search engine Google Scholar in April 2022: flow ("flow" OR "flow state" OR "flow experience" OR "experience of flow" OR "psychological flow" OR "flow proneness" OR "optimal experience"), city identity ("city identity" OR "place identity" OR "identity of residents" OR "urban identity"), AND restorative environment ("restorative environment" OR "restorative experience" OR "restorativeness"). Since the number of recorded literature simultaneously on these three constructs was small and limited, we did not restrict the type of related publications (empirical studies, articles, editorials, commentaries, opinion papers, and textbooks) to mitigate the risk of missing something significant from a study that was not appropriately cataloged within a keyword catalog such as "city identity". However, we analyzed only the first 300 items sorted out by relevance with the following principles: (a) Articles were excluded if the abstract showed that the article did not even partially address the three variables as described above or if the construct under research was labeled as such yet addressed a different topic. If there was any doubt, the complete article was screened before deciding whether to include or exclude it; (b) They did not contribute in part to addressing the research question, or; (c) They were not available electronically or *via* other acceptable methods. The authors conducted this retrieval process twice to ensure its accuracy. We, therefore, found 165 articles (flow and city identity: 10; flow and restorative environment: 59; restorative environment and city identity: 96) among these 300 sourced items. Due to limited article space, we deleted articles with basically the replicated findings or comparably low citations after reading the abstract. There were no studies on the three

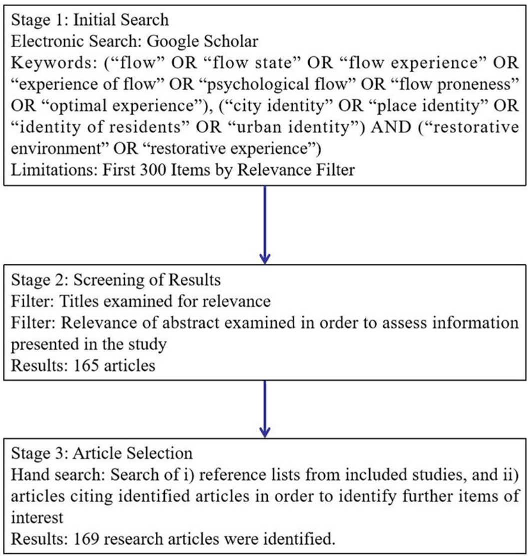

FIGURE 1
Steps for data sourcing.

pillars concurrently, yet there was still quite limited research exploring the relationship between flow and city identity. With other supporting evidence on the interventions included, a total of 169 works (e.g., 15 books, 2 conference proceedings, and 152 journal articles) were retained for review in the present work. The information sources, search terms used, and study selection procedure are outlined in Figure 1.

Nature experience and flow

Natural surroundings are more beneficial to the psychological restoration of city dwellers than an urban environment relatively devoid of nature (30). Potential pathways connecting greenspace to health are presented in three domains, which emphasize three general functions of greenspace: reducing harm (e.g., being less exposed to air pollution, noise, and heat), restoring capacities (e.g., attention restoration and physiological stress recovery), and building capacities (e.g., promoting physical activity and enhancing social cohesion). Interrelations among the three domains also deserve further investigation (31, 32). Scholars have indicated three significant findings in terms of flow experience and the natural environment: (1) Youth indicating a preference for nature might be more active and involved in daily tasks at hand; (2) Adults value nature's restorative qualities; youngsters prefer competitive and demanding experiences and; (3) Programs should encourage, educate, train, and provide the opportunity for youth to participate in healthy nature-based activities (33–35), laying a foundation for our research on nature-based intervention for the youngsters. Indeed, when interacting with the whole world and blurring the line between self and environment, a holistic feeling of flow matters since there is neither stress nor boredom in such an environment (26, 36).

Flow experience has three prerequisites (clear goals, detailed feedback, and challenge-skills balance), three characteristics (action-awareness merging, concentration on the task at hand, sense of control), and three consequences [loss of self-consciousness, the transformation of time, autotelic experience, (37)]. Take forest experience as an example of nature experience. First, such an immersion nature experience needs prerequisites. As for "clear goals," forest users' primary reasons seem to be a desire to escape from everyday hassle and alleviate stress (38, 39). According to the flow model, a forest experience can be classified as a challenge; to enjoy and be sensitive to a forest, one needs "skill" (i.e., training in hiking skills, knowledge about the destination landscape, and awareness of the potential dangers). Furthermore, according to Maslow's hierarchy of needs (40), the totality of a forest experience is stunning in that there is a complete concentration of attention on the forest. A person in a forest setting may be exposed to "forest stimuli" or impressed by the forest's magnificence and mystery. As for the consequences, when a person enters into a "flow" state, they may forget about the outside world (41) and, *via* communicating with nature in the forest, may achieve a condition of inner peace and tranquility similar to that experienced during a religious experience.

Additionally, some research has examined the flow concept regarding causal links with natural environments, experience levels, and related affective states (42). For instance, Tsaur et al. (43) have discovered that the transcendent aspect of high-altitude mountain climbing was a significant predictor of flow and that experiencing flow made climbers "happier". This association is confirmed in surfing activities (44). The visitors report varied emotional assessments (i.e., awe-inspiring, peaceful, upsetting, and uninteresting) and transcendence (diminutive and deep flow) experiences in two diverse natural habitats [wild cliffs and groomed gardens, (45)]. A critical requirement for experiencing flow for these various recreational experts was the ideality and restorativeness of the natural environment, irrespective of terrestrial or aquatic. Indeed, these qualities of the flow state are not only applied to a person experiencing hiking in a mountain or forest that is not often available in daily life (46); flow can also occur in parks and the urban greenspace, which plays a role in people's everyday lives in urban areas. Maurer et al. (47) find that trees are the most significant aspect of nature, contributing to the subjective well-being and connectedness to nature of the majority of participants. Also, it has been proved that increasing employees' interaction with vegetation can enhance employee well-being and performance (48). In a word, flow can be experienced through interaction with nature, which has implications for city workers' well-being.

Flow experience and restorative environment

The field of restorative environment research is thriving due to two major theories: Attention Restoration Theory (ART), (14) and Stress Reduction Theory (SRT) (49–51), as well as a substantial body of empirical studies. According to ART, continuous use of directed attention—actively and deliberately focusing on a task—contributes to mental fatigue, and that involuntary attention—attention that needs little to no effort—is required to alleviate directed attention fatigue. Individuals benefit from the opportunity to (1) "be away" from daily hassles and stresses, (2) encounter vast spaces and contexts ("extent"), (3) participate in activities that are "compatible" with our intrinsic motivations, and (4) critically experience stimuli that are "softly fascinating" (15). This combination of elements promotes "involuntary" or "indirect" attention while also allowing our "voluntary" or "directed" attention capabilities to repair and restore (15, 52). SRT indicates that psychological restoration may benefit affect, cognition, behaviors, and the physiological system. On the contrary, positive psychology says that people might achieve well-being and stress alleviation through what is known as flow experience, which entails people's deliberately participating in an engaging activity (11, 53), people's attention and concentration are distracted away from everyday duties and undesired ideas when they are engaged in an exciting activity (e.g., sports, yoga, writing, or socializing).

After affirming the interactive effects of attentional state with activity-setting and with social context (54), Staats (52) further describes ART and SRT theories' content, similarities, and differences. He then discusses research conducted in a variety of environmental domains, including nature (both wild and managed), the home, the workplace, museums, religious environments, hospitals, other healthcare settings, and favorite places.

As anticipated by ART, some research demonstrates people's preference for natural outdoor spaces over built-up outdoor and interior spaces such as urban settlement areas, loading docks, parking lots, and roadways (55–58). The restorative benefits of well-known cultural contexts (such as museums, industrial heritage sites, and historic city centers) that serve as tourist attractions (59) may differ from those of ordinary residential surroundings. Based on SRT and ART, evidence has shown that environmental preference has a phylogenetic basis and is intimately related to the claimed restorative benefits (60). Indeed, flow theory and SRT are expected to be connected by a significant decrease since stress and flow are embedded in an inverted U-shaped relationship (61).

Researchers have established a variety of conceptual frameworks for considering the human transformations that occur in nature, including "extraordinary experience" (62), "transcendent experience" (63), and "peak experience" (64). Extraordinary experiences include action and consciousness, attention or focus, personal integration, personal control, power awareness, joy and value, and a spontaneous letting go of process (65). Transcendent experiences are defined as those that exist beyond human observation and comprehension. They include "communion with nature that both escape from duties and the emotional relationship established by immersion in regions of unusual natural beauty" [(43) p.361]. According to Williams and Harvey (16), optimal experiences foster mental attention, immersion in the present moment, and personal growth.

Nature programs enable veterans to enjoy "optimal", "transcendent", or "extraordinary" experiences that incrementally demand and control skill and challenge levels (66). Grant et al. (67) also add an expanded flow theory to an ethnographic study of hobby fly fishing to demonstrate how customers' bodies, the environment, and fishing equipment contribute to restorative experiences. The experience of a VR-based restorative environment has a favorable healing impact on patients with mild-to-moderate anxiety and depression, as shown by its effects on positive and negative emotions, self-efficacy, and cognitive function (68). In a nutshell, restorative environment and flow experience are related to the individual well-being paradigm. The related intervention may be efficacious in improving attention and mood among city workers.

Flow and city identity

Flow experience (37) has been the subject of extensive empirical research spanning more than four decades. Nonetheless, progress in understanding—beyond what Csikszentmihalyi discovered in 1975—has been minimal. To rectify this, the idea of flow must be introduced to explore how factors external to the personal influence the present-moment experience. Relational places are composed of a complex of social, material, and ecological processes operating at several scales (69), with which a person interacts and is molded (70). Human beings are exposed to various everyday activities *via* their physical and environmental surroundings. The importance of activities in defining human-environment interaction has been extensively studied in the discipline of environmental psychology (21). While attention to place-related identity is growing in environmental psychology (71), less focus has been made on developing a deeper understanding of place identity at the local level and the social nature of urban identity (26).

The discovery model of identity development postulates that adolescents' subjective identity-related experiences, such as personal expressiveness, flow, and goal-directed behavior, partially reflect these development processes (72). Bonaiuto et al. (73) demonstrate that specific indicators measuring the quality and quantity of activities associated with a particular neighborhood community can be related to neighborhood attachment. Kyle and colleagues discover that hiking activity predicts one's place identity (74), implying a cognitive relationship between the self-concept and the location of the activities (46). Bonaiuto and colleagues (36, 75, 76) have consistently found that distinct sets of activities performed by residents in different geographic locations (i.e., their neighborhood community, city center, and suburb) are related to how residents assess the environmental quality of these locations and how they ascribe belongingness to these locations (such as their neighborhood attachment and community identity).

Leisure activities contribute significantly to individual identity creation in urban industrial societies. For example, substantial studies have reviewed research on the association between teenage (positive) identity construction and leisure situations [flow, (77)]. Locations such as homes influence people's flow experience (78). Cohen (79) revisits the dialectics of escapism (flow experience), authenticity, and identity in leisure and tourist activities. Lee and Shen (80) discovered that participation in leisure activities (such as walking their dogs in urban parks) is associated with place loyalty. "An analysis of the reported experiences of people involved in various play-forms (i.e., rock-climbing, chess, dance, basketball, music composition) suggests that the qualities which make these activities enjoyable are the following: (a) a person can concentrate on a limited stimulus field, (b) in which he or she can use his or her skills to meet clear environmental demands, (c) thereby forgetting his or her own problems, and (d) his or her own separate identity, (e) at the same time obtaining a feeling of control over the environment, (f) which may result in a transcendence of ego boundaries and consequent psychic integration with personal meta systems" [(81), p 113]. Sports activities also aid career advancement by facilitating severe leisure and forming social identification (82).

Similarly, Orta et al. (83) reveal a strong link between flow experience and athletic identity. Based on the eudaimonistic identity theory (EIT), which emphasizes self-defining activities as critical for an individual's identification of their goals, values, beliefs, and interests related to the development or enhancement of one's own identity, and based on flow theory, which holds that certain salient features of an activity experience are associated with happiness and well-being, it has been shown that promoting a person's flow experience inside psychologically meaningful settings may help sustain or enhance one's place identity. Therefore, the people–place interactions support the flow-place identity link (21).

Emplaced flow considers the socio-spatial dynamics that impact a person when they strive to get engrossed in a geographically located activity and the effect of location on instantaneous sensations (84), which is a direction for future related research. Therefore, flow and city identity can be closely related, and this demands more empirical research to testify and design related interventions for city workers' enjoyable flow experience, identity building and well-being.

City identity and restorative environment

For the most part, theory and practical findings on place identity and restorative environment have received accumulating attention in recent years, though they have developed separately. For instance, Korpela (85) proposes that place identity is a product of environmental self-regulation. Korpela and Hartig (18) examine how people value their favorite environmental locations using restorative environment theory-based criteria because a "sense of community" includes not just social relationships but also the bonds that individuals build with their natural surroundings (86). By correlating location preferences to place meaning, Kyle et al. (87) also investigate the link between place motivation and attachment. Devine-Wright and Howes (88) reveal that for people with solid place attachments, the conflict between project and place (restorative environment for inhabitants) is seen as a challenge to identity, resulting in negative attitudes and oppositional behavior. Scholars have also highlighted the importance of the relationship between landscape, place identity, and restorativeness (89). Those with an urban place-related identity (i.e., city dwellers) have viewed urban and natural settings as equivalent in terms of their ability to aid recovery from directed attention fatigue; and, on average, urban geographical locations are judged to be "rather" likely to result in restoration instead of the non-restorative outcome predicted by ART (90). Urban green space has the potential to match the effect of nature on some restoration outcomes, and environmental preferences are indicative of place identity (91). Built environments that are "attractive" are just as restorative and emotionally uplifting as natural spaces in the urban environment (92). A particular sense of place [(93), coined the term "seasides"] shows itself *via* positive and uplifting perceptions of the multisensory seaside environment; participants report a belief in the seaside as a "tonic". The expansive views, fresh air, sea scent, and sound of crashing waves are constantly alluded to and characterized in restorative terms. Morton et al. (94) hypothesize that the restorative capacity of surroundings is governed, at least in part, by social and psychological processes associated with identity.

Besides, Bornioli et al. (95) reveal that particular interactions with place linked to personal relationships, place identity, and positive feelings of the community that resulted in improved psychological well-being. Liu et al. (96) find that landscape elements enhance individuals' attachment to new environments. Restorative impressions are favorably associated with local landscape traits, place reliance, and place identity (97). In a word, though there are quite limited studies exploring the associations between restorative environment and city identity, place identity plays a crucial role in mediating the naturalness-wellbeing link

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(98). Based on this, a more nuanced understanding of the potential relationship between city identity and a restorative environment is necessary, since a diversity of (natural and urban) locations may be restorative and related to city workers' identity (29).

Flow, city identity, and restorative environment

Research records on the relationships among flow, city identity, and restorative environment cannot be traced for the time being, but much implicit sparking evidence can be traced in extant works, such as the following: Tsaur et al. (99) identify 6 factors to quantify the fit between recreationists and their environment based on Attention Restoration Theory and Affordance Theory: natural resources, interpersonal opportunities, environmental functions, facilities, activity knowledge/skills, and operation/management. It is *via* flow experiences that we strengthen our place attachment, choose our favorite places, and generate intrinsic motivation to enter certain places but not others (100). A growing body of research shows that adventurous nature sports can promote diverse hedonic and eudaimonic aspects of well-being, including: (a) facilitating feelings of connection to nature; (b) fostering physical and mental benefits associated with physical activity, (c) providing opportunities to overcome challenges and have optimal experiences; (d) increasing positive psychological outcomes such as positive affect, self-efficacy, and resilience; (e) restoring cognitive resources; (f) providing opportunities to experience self-determination (e.g., *via* psychological need fulfillment and intrinsic value orientations); and (g) promoting social connectedness (101).

Williams and Harvey (16) divide forest experiences into six distinct categories, one of which—deep flow—can be characterized as transcendent experience. The deep flow experience is distinct. It includes a high degree of compatibility and a moderate degree of novelty and is thus likely to be reported as relaxing or eliciting a sense of belonging.

Rosenbaum and Massiah (102) demonstrate how consumer reactions to social, symbolic, and natural stimuli often serve as the catalyst for solid person-place attachments and how a servicescape's inherently restorative feature may alleviate mental fatigue and enhance customer health and well-being.

Bell et al. (103) examine how symbolic, achievement-oriented, immersive, and social experiences contribute to participants' sense of well-being in their local coastal regions, using a unique adaption of the therapeutic landscape concept.

Morton et al. (94) establish that exposure to nature vs. urban images enhances cognitive ability and good motivational states, and salient identities influence how individuals react to natural environments. In a nutshell, they argue that the environment's restorative capacity is partly influenced by social and psychological processes associated with identity, and a more nuanced understanding of the potential psychological benefits of exposure to nature is necessary and that a diversity of environments (natural and urban) may be restorative.

Lee et al. (104) investigate the mechanisms behind the therapeutic benefits of the urban forest on middle-aged women through their participation in an urban forest therapy program. Following these women's acquisition of information about the forest and emotional connection with one another, their mental attitudes shift, allowing them to identify with nature and think about their own lives. They are then able to cultivate coping mechanisms that eventually result in self-healing. This work demonstrates how participants self-heal through interactions with nature, guides, and other group members.

Giusti and Samuelsson (105) propose that when environmental attitudes (including identification with nature) and natural environments interact statistically, almost all restorative experiences (including feeling immersed in the place—one core element of flow) are predicted more accurately than when these factors are independent predictors, that is, there is synergistic compatibility between environmental attitudes and healthy ecosystems that triggers restorative processes.

Most importantly, Peng et al. (36) find that community identity mediates the path from flow experience and green space to life satisfaction, indicating the importance of subjective enjoyable flow and objective green areas in reshaping community residents' well-being in life-challenging environments (i.e., COVID-19).

From the above discussion, we propose that the three variables are implicated in reciprocal feedback loops, as shown in Figure 2.

Practical intervention for city workers

In recent years, it has become more apparent that urban planning and environmental design influence mental health and well-being. According to the "happy-productive worker hypothesis", people who are more content with their jobs are also more productive and engaged. Promoting workplace well-being and reducing work-related stress may have far-reaching repercussions, not just for knowledge-sector employees but also for the productivity of organizations, and employers have increasingly recognized this. Building on a long tradition of urban greenspace provision as a public good supporting population health [e.g., by the urban parks and garden cities movements, (106)], much recent research examining the relationship between the physical environment and health has focused on the role of green space (26, 36). By examining the

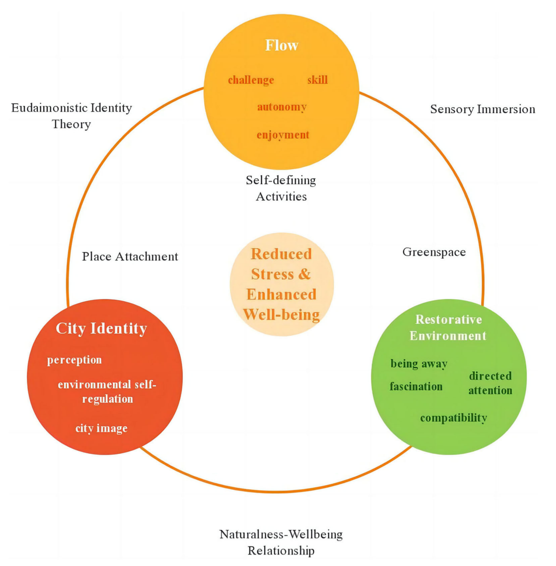

FIGURE 2
The proposed conceptual model among flow, city identity, and restorative environment.

links between restorative environment, flow experience, and city identity, this paper demonstrates how workplaces may be structured to accommodate these aspects. These results have implications for the planning and design of urban business sites and the development of interventions to increase employee well-being.

Creating restorative environment

Although numerous studies have indicated that the scenic view of nature is restorative, many city workers may not have ready access to natural settings in modern society. Fieldhouse (107) finds that some characteristics of the plant-human connection facilitate people's engagement with their environment, promoting their health, functional level, and subjective well-being. Due to the allotment's embeddedness within communities, it has enormous promise as a medium for occupational therapy and a method for social integration. The evidence for environmental restoration support is divided into four categories: residential contexts, work and school settings, care settings, and other settings. We concentrate only on workplace interventions for young city workers. With the importance of nature in the workplace (48), there is a wealth of studies demonstrating a clear correlation between workers' well-being and greenspace (108–110) as well as landscapes (111). For instance, Bringslimark et al. (112) discovered that employees in windowless offices were more likely to bring plants to work or decorate their office space with a photograph of nature than those with a window view, which can be viewed as a compensatory strategy for the lack of access to the outdoors provided by windows (e.g., restoration for those in need of it). Additionally, Boubekri et al. (113) establish that workplace windows (114, 115) and daylight exposure are predictors of job satisfaction and overall health for office employees. Wang et al. (116) find that all the seven different types of forest resting environments in a virtual reality video can produce stress relief effects to some extent.

Both open space utilization and views of specific vegetation types, such as trees, lawns, shrubs, and blooming plants, are positively and independently linked with employees' self-reported well-being levels (117). For example, Zurawik (118) indicates that indoor plants are connected with a decrease in office employees' sick absence frequency and increased productivity, owing to the assistance offered by plants for healing over time. Inadequate indoor air quality adds to employee health and well-being degradation, further reducing productivity; the design solution should, therefore, incorporate aspects that promote cooperation and teamwork among workers and adaptable and ergonomic furniture to boost productivity. Environmentally friendly materials and furnishings should also be chosen to safeguard staff health, well-being, and global ecosystems (119). White et al. (120) report that spending at least 120 min a week in nature is associated with good health and well-being, so stakeholders should pay attention to such a "threshold" and actively develop possible weekly nature exposure guidelines for their employees.

Gritzka et al. (121) conducted a systematic review of the scientific evidence on the usefulness of nature-based interventions in promoting mental health and well-being among workers in real work contexts.

There is considerable consensus about the beneficial impacts of exposure to nature. For instance, natural elements decorated with green in the office help with stress reduction, with red, yellow, and orange stimulating positive emotions (122). Adding one to three green plants to the office table facilitates employees' productivity, focused attention, and stress reduction, hence promoting well-being (123). Designing offices with outdoor natural window views promotes work productivity (124), and equipping green areas in the community promotes dwellers' sense of belonging and attachment (76). As a result, nature-based interventions in the workplace have been advocated as a cost-effective strategy for promoting employee health (121). Research on the effect of green space on employee mental health and well-being is worthy to assist in the design of workplaces. Thus, we suggest that all stakeholders engage in creating a restorative environment by, for instance, developing a workplace equipped with a small green space (indoors: e.g., indoor garden, or outdoors near the workplace, 108), designing an employee break room decorated with nature elements (125), and exploiting virtual reality nature simulations [such as playing a video with natural sceneries, (126)], and so on and so forth.

Flow interventions for city workers

Although several flow-based interventions have been developed and evaluated (127), most have targeted general workers, not those who may not have ready access to natural settings. According to Wöran and Arnberger (17), leisure specialization and restorative surroundings are linked to flow experience. It is widely proven that employees' leisure activities are related to recovery experiences, job performance, and subjective well-being (128–130). According to Caldwell (131), leisure activities (e.g., learning how to generate a flow-like experience) may contribute to physical, social, emotional, and cognitive health through prevention, coping (adjustment, remediation, diversion), and transcendence. Flow is essential for adherence to regular workplace physical activity, such as football and Zumba (132). Also, the importance of mindfulness training in the workplace cannot be overstated (133, 134).

Various factors can contribute to frontline employees' job flow experience, such as personal factors, job characteristics, and leadership (135, 136). Even in a dynamic workplace environment, the rhythms of attentional states remain context and time-dependent (137). Focus is most significant in the mid-afternoon, while boredom is at its peak in the early afternoon. People are happiest while performing routine tasks and most agitated when performing focused tasks. Mondays are the most boring day of the week, but they are also the most concentrated (138). While flow-like experience is not exclusive to leisure episodes, the more robust flow experience is more likely to occur during freely selected activities that produce intrinsic interest for the receiver (139). Plester and Hutchison (140) examined the relationship between fun and workplace engagement using three distinct types of workplace fun: managed, organic, and task fun. They discovered that particular workplace fun provides individual employees with a refreshing break, resulting in positive affect and increased workplace engagement and task engagement.

Martens (141) emphasized the value of setting aside time and space for relaxation or taking a stroll after intense work to relieve some of the stress associated with sitting and working (e.g., writing, designing, etc.,) in one location, and justified the inclusion of gaming rooms, relaxation lounges, and greenspace in or near workplaces. Concentrated work is much easier when surrounded by nature and without distractions. Suh et al. (142) highlight the central role of the aesthetic experience on gamification in the workplace.

Through meaningful occupations in a restorative environment, nature-based rehabilitation changes everyday occupations' perceived values [including self-rewarding value—flow, (143)]. Taken together, we remind all stakeholders to realize optimal work environments and nature-based rehabilitation by considering implementing some flow interventions through goal setting (127) and deep acting (144).

City identity interventions for city workers

To our best knowledge, there are so far no city-identity-based interventions focused on supporting city workers to cope with work stress. We try to propose some potential strategies inspired by place identity intervention. Research on community attachment reveals that integration into the local region significantly predicts connection to place. Local social interactions—particularly with friends, relatives, organizational affiliations, and local shopping—are the most persistent and substantial sources of emotional attachment to local locales (145). Place identity is highly correlated with neighborhood satisfaction (146). Second, long-term residency leads to the development of place identity; the length of stay strengthens local social bonds (147). It also offers a chronological background for imbuing a place with personal significance. The Hukou system continues to be a barrier to Chinese migrant workers; despite their economic, social/cultural, and identity absorption into urban life over time, human capital plays a critical role in migrants' economic and identity integration (148). Workers' intention to leave their current location is connected to their sense of place identity and fairness judgments (149).

The place identity is built *via* people's cognitive identification and satisfaction with the place, as well as their affective enjoyment and sense of security when interacting with the place. Place identity is a dynamic and dialectic process, and the memory of a residential place has a positive relationship with place identity and place attachment (150). Unsuitable interventions will erode both the physical environment and the sensation of attachment rooted in people's attachment (151). Thus, planners must incorporate visions of place identity not only from politicians and economic interests but also from residents and other members of civil society because the identities ascribed to a place by various stakeholders are contested and may play a role in social conflicts (152).

City identity may develop through individual, group, or cultural processes. More recently, our research team has found that a better-perceived quality of the residential place (i.e., neighborhood community) is associated with a higher level of community identity (26). Community involvement, including social bonds, community participation, and community empowerment, is the most critical factor in determining the degree of community attachment (153). Therefore, governments, companies, and other stakeholders should take measures to enhance the city identity of young frontline workers by giving value to the city through place memory, including increasing welfare entitlements (154), community involvement, as well as justice perceptions (149), thereby increasing their belongingness and reducing their work stress.

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Combined interventions

Similarly, there are to date almost no interventions simultaneously on flow, city identity, and restorative environment developed to address workplace stress. We try to propose some practical interventions in the time and effort they demand of all parties and the resources necessary to implement them, which is also the most significant contribution of the present study.

Valera and Vidal (155) discussed several theoretical advancements in environmental psychology and made a case for their inclusion in a Positive Environmental Psychology agenda. On the one hand—space as a source of well-being—they examine the aesthetic quality of landscapes, the restorative potential of surroundings, and the evolution of place identity and place attachment. On the other hand—space as a context for positive experiences—they propose some reflections on urban placemaking processes, such as the tradition of Placemaking, Community Participation, and Planning, or the Socially Restorative Urbanism movement, which aims to restore social well-being and a sense of belonging to urban environments.

Uzzell et al. (156) examined the effects of social cohesion, residential satisfaction, and place identification on place-related social identity and its consequential impact on attitudes to environmental sustainability, suggesting a significant relationship between identity and sustainable behavior that is suggestive for future research, i.e., companies should create nature-based suitable accommodation for workers. Free-time physical activity in natural surroundings after work is a potential strategy for enhancing employee vitality across time (157). Employees are expected to have quality restorative break time after work. Time-flexible work policies can reduce stress, improve health, and save money (158), which should be encouraged. Job control and work-life balance practices moderate frontline employees' stress (159). Employee recreation welfare is quite essential (160). Employee recreation/fitness programs in the rest space and worksite lifestyle change programs should be encouraged (161). Psychological commitment mediates the influence of leisure involvement on the flow experience during hiking activity, so some training programs in the wild to develop employees' organizational commitment are significant (162). High technology should also be introduced, such as a portable biofeedback device (163). Live plants and window views of green spaces affect employee perceptions of job satisfaction (164), so qualified leaders should be selected for young city workers to collaborate with the faculty of forestry, the institute of mental health, and the botanical garden in the local place to improve employees' health. Also, a competent support crew is expected to adopt a biophilic design and increase (indoor) green plants.

Increased conversation between flow and therapeutic environments elucidates aspects that assist therapeutic experiences, therefore, defining how person-place interactions might be created to promote well-being. Pitt (84) establishes flow in community gardens by examining how spatial factors affect the therapeutic activity and how social relationships affect the possibility of discharge. Other therapeutic activities might be explored similarly to ascertain other socio-spatial variables that facilitate or obstruct flow experience. Further study might be beneficial in determining if therapeutic hobbies such as gardening have a decreasing return when repeated or routine and whether brief getaways have long-term effects on wellbeing.

Hawkins et al. (66) argue that nature-based interventions typically incorporate foundational elements from Flow Theory (e.g., challenge matching skills) and ART, as well as other theoretical qualities such as buffering effects; a sense of remoteness, escape, and awe; and an attachment of a sense of meaning to the place itself. At the heart of their methodology are nature-based therapies motivated by the individual's internal and external strengths and current assets (e.g., character strengths and skillsets). These advantages distinguish nature-based treatments from conventional medical model interventions. A recreation therapist aware of these talents and abilities before the intervention *via* an assessment process will call on them during the intervention to facilitate a positive experience. Finally, the model's top layer depicts the results of nature-based therapy, which include enhancements in social, cognitive, and spiritual domains and outcomes related to identity, purpose, and overall healing from life issues.

Cole et al. (165) specifically examine putative connections between green building design principles and psychological processes of place attachment (i.e., affect, identity, and dependence) in non-residential buildings and reveal four critical green design strategies for promoting place attachment: (1) biophilic design and opportunities for connection to nature, (2) visible environmentalism, (3) opportunities for pro-environmental behaviors and (4) an indoor environmental quality that promotes physiological comfort.

Greenspace in urban areas is a vital health resource, facilitating physical activity, promoting social interaction, and restoring exhausted psychological resources, all of which can positively affect physical and mental health (26, 166–168), thus all relevant parties and stakeholders should increase the greenness and improve the environment surrounding workplaces.

In a nutshell, managing job stress requires all relevant parties and stakeholders' cooperation to jointly create sustainable workplaces, including employee self-regulation, human resource management partnership, and compassionate city planners (169, 170). And the overlapping relationship between the

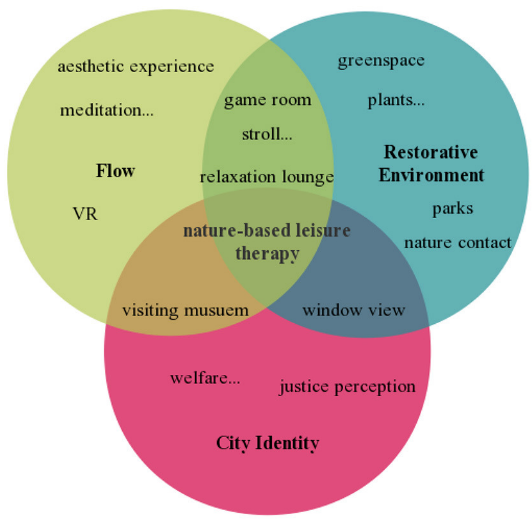

FIGURE 3
The proposed intervention model synthesizing flow, city identity, and restorative environment.

interventions within each of the three pillars is shown in Figure 3.

Discussion

Standing on the theoretical underpinnings (i.e., eudaiministic identity theory, attention restoration theory, and stress reduction theory) within positive environmental psychology, this review proposed a novel conceptual framework suggesting that a restorative environment could facilitate city workers' daily flow experience and city identity. We have explored the possibility of combining the three constructs of flow, city identity, and restorative environment to propose interventions in today's stressful workplace. The conceptual model guiding this review posits that exposure to natural environments predicts positive change in people's positive affective and cognitive experiences such as flow, which impacts their attitudes, belongingness, perceived values and norms, influencing their working city identities and behaviors. We believe that flow, city identity, and restorative environment are among the most significant topics in Positive Environmental Psychology literature, and we wish such a review helps all stakeholders recognize the full potential of flow for human flourishing and well-being at the workplace, the positive psychophysiological impact of restorative environment on city workers' health. To this end, we wish to bridge people and places (i.e., cities) *via* positive environmental psychology for a healthier life and a better working environment with which they are strongly identified.

Study limitations

We identify the following points as defining psychological research on "city identity": heterogeneity of terms and their spatial extension, divergent theoretical foundations and fragmented formulations, a lack of appropriate measuring instruments, and a scarcity of empirical work. This, combined with the small number of studies simultaneously on the three constructs, makes it challenging to identify a pattern and should be considered when interpreting the results. The fundamental affective and cognitive flow is likewise perceived differently by various instruments. Thus, the continued development and use of empirically validated measures is a critical next step for research on the dynamic relationship between flow, city identity, and restorative environment. Another issue is that although there were significant overlaps between adopting flow and healthy environments, many studies only look at the restorative environment (141). In a word, we try to put forward a conceptual model within which the three constructs studied separately are simultaneously discussed here.

This review represents the first creative synthesis of the specific mechanisms of the restorative environment through which people's flow experience is associated with their city identity, evidencing several theoretically coherent patterns. It should be noted, of course, that studies on a particular pathway or process were sometimes too few to draw definitive conclusions. This review should be considered preliminary, and more work is needed to understand further and verify these clear pathways. Nevertheless, this review can help orient researchers to the paths by which a restorative environment can contribute to city workers' reduced stress, increased flow, and stronger city identity.

One limitation of the present review is that the literature search is done from Google Scholar, only taking highly relevant articles (the first 300 items) into account. For this reason, more complex and potential relationships may be discovered, and comprehensive results may be obtained by examining as many databases as possible in future work. Another limitation of the present review is that there are various populations in the modern city, such as teachers vs. students, elderly residents vs. the young, and so on and so forth. However, in this study, we only included and explored some feasible interventions for city workers, therefore, further studies to qualitatively and quantitatively explore other population groups might advance our understanding of the influential factors for the development of sustainable cities, park cities, and happy cities.

Implications

The current review advances related theories by identifying pathways that explain how people's flow experience and city identity are associated with the restorative environment and examining the interventions that may contribute to city workers' subjective well-being. This review makes a timely, theoretical contribution to the study of the restorative environment. Most scholarly attention is given to direct relations between a restorative environment and people's better health, and so little is known regarding the explanatory processes that account for these associations. The present review addresses this need by sensitizing researchers to the social-cognitive mechanisms through which a restorative environment might influence people's optimal enjoyment and identity and make it more or less effective over these social-cognitive mechanisms. The practical implications are that urban planners and company managers who act in turbulent environments may include new relationships between relevant and current variables in their city/workplace design, such as those associated with the city identity and restorative environment. These new approaches may help business executives use interventions that approach more of the business reality, making their workplace more harmonious and enjoyable.

Conclusion

Through the lens of environmental psychology and positive psychology *via* restorative environment and positive affective and cognitive experience of flow, the present work attempts to develop a novel conceptual model by emphasizing that engaging in the natural restorative environment is inducive to the universal human experience of enjoyable flow and enhanced city identity, as well as their stress recovery and well-being. To date, no systematic research has contemporarily addressed the underlying mechanisms among these three constructs. Therefore, this review represents a starting point and hopes to encourage further empirical research on how to assist city workers' well-being and develop sustainable cities through brief and practical nature-based interventions for facilitating flow and city identity. We hope there could be further cues for a positive environmental psychology agenda to promote city workers' human flourishing and well-being, build their city identity, and facilitate the public health of the cities.

Author contributions

MX: conceptualization and writing—original draft. YM: conceptualization, writing—revision and editing, and funding acquisition. RY: conceptualization and writing—revision and editing. All authors have read and agreed to the published version of this manuscript.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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Vertical evaluation of air quality improvement by urban forest using unmanned aerial vehicles

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Urban forest is considered an effective strategy for mitigating urban air pollution *via* deposition, absorption and dispersion processes. However, previous studies had focused mainly on the deposition effect or removal capacity near the ground, while the net effect of the urban forest on air quality is rarely evaluated in the vertical dimension. In this study, $PM_{2.5}$ (particulate matter with diameter less than 2.5), PM_{10} (particulate matter with diameter less than 10 μm), carbon monoxide (CO), sulfur dioxide (SO_2), nitrogen dioxide (NO_2), and ozone (O_3) concentrations, air temperature, relative humidity, and atmospheric pressure at 0, 2.5, 5, 10, 15, 20, 30, 40, 60, 80, and 100 m in urban forest, street, and community areas were collected by unmanned aerial vehicles (UAVs) equipped with Sniffer4D V2 on overcast and sunny days. The PM, CO, NO_2, and O_3 concentrations increased with height below 20 m and then slightly decreased with height on an overcast day, whereas SO_2 concentrations decreased with height within 20 m. The urban forest increased PM concentrations in the morning of an overcast day, whereas it decreased PM concentrations in the afternoon of the overcast day. The forest obstructed PM dispersion from the canopy when PM concentrations grew lower in the morning, but it hindered PM from deposition when PM concentrations grew higher in the afternoon.

KEYWORDS
air pollutants, urban forest, vertical dispersion, UAVs platform, PM

Introduction

The United Nations (UN) Sustainable Development Goals (SDGs) state that good health and wellbeing of people, sustainable cities, and communities are indispensable to achieving the SDGs (United Nations, 2015; Diao et al., 2021) for which they were formulated. The continuous urban expansion and industrial development have made air pollution a serious problem in urban areas (Llaguno-Munitxa et al., 2017; Ren et al., 2022; Xiong et al., 2022), thereby affecting the environment. The World Health Organization (WHO) reported that the air quality of almost 97% of cities in low- and middle-income countries failed to meet the WHO standard (World Health Organization, 2018). Air pollution caused by particulate matter (PM), nitrogen dioxide (NO_2), ozone (O_3)

carbon monoxide (CO), and sulfur dioxide (SO_2) is a serious environmental issue that threatens human health and hinders the realization of the SDGs in the urbanized areas (Tomson et al., 2021; Miao et al., 2022).

Urban forest has been highlighted to offer a mitigation potential to improve air quality (Pataki et al., 2021; Ren et al., 2021) and is the focus of current attention with regard to scaling down pollution. It regulates air pollutant concentrations through various processes such as dispersion, absorption, and deposition (Chen et al., 2019; Santiago and Rivas, 2021). It also removes air pollutants from the atmosphere through stomatal absorption, and the interception at tree canopies and surfaces (Abhijith et al., 2017). Deposition and absorption effects on air quality are always positive, whereas aerodynamic effects can be positive or negative (Jennings et al., 2021; Santiago and Rivas, 2021). For example, some studies have reported that the presence of trees reduced ventilation but increased air pollutant concentrations in the built environments (Vranckx et al., 2015; Buccolieri et al., 2018).

The net effect of an urban forest on air quality is balanced with deposition, absorption and dispersion processes, and its scale depends on the background air pollution, microclimatic factors, and forest structures such as leaf area index, height, barrier thickness, stand density and canopy area (Abhijith and Kumar, 2020; Jennings et al., 2021; Li et al., 2021). Diameter at breast height and the distance from the forest to pollution sources showed a more significant influence on the reduction in PM concentrations than the leaf area index, canopy area, or distance to forest edge (Zhu et al., 2019). The removal rate of air pollutants was defined as the relative concentration difference in air pollutants both inside and outside the forest (Hofman et al., 2016; Miao et al., 2021). The comparison of the PM removal rate of different forest types reported a higher value by coniferous forests than by evergreen forests, and a higher value by coniferous forests than by deciduous forests (Han et al., 2020). Sparse planting of trees could reduce PM concentrations, while high-density planting increased PM concentration (Wang et al., 2020).

The vertical pattern of air pollutants was mainly attributable to the combined effect of the diurnal variations of traffic emissions, meteorological conditions, photochemical reactions, and the dynamics of the low atmospheric boundary layer (ABL; Li et al., 2017; Lu et al., 2020). Given that the dispersion of air pollutants varies with height, research on the vertical distribution of air pollutants by the urban forest needs to be carried out to investigate the dispersion of air pollutants (Cavanagh et al., 2009; Wu et al., 2020). Although numerous studies have been conducted to investigate the net benefit of urban forest on air quality, these researches mainly assessed the deposition effect of the urban forest on air pollutants or compared the air pollutant reduction capacities of different plant species near the ground (Han et al., 2020; Viippola et al., 2020; Bonilla-Bedoya et al., 2021). A few works were even carried out to estimate the vertical airflow and air pollutants in the presence of trees in urban street canyon based on the numerical simulation (Ng and Chau, 2012; Buccolieri et al., 2018). They reported an 18% decrease of air pollutant concentration in the presence of trees paralleled with wind. Albeit with larger path areas than street trees, it remains unknown as to what extent an urban forest could affect the vertical profile of air pollutants, particularly from the field observation perspective. This knowledge gap limits the applicability of urban forest planning and management regarding air quality and public health improvement.

Unmanned aerial vehicles (UAVs) equipped with backpack monitoring equipment provide a feasible way to observe the vertical concentrations of air pollutants in urban environments. They ensure the acquisition of air pollutant concentrations with a high temporal and spatial resolution (Peng et al., 2015; Liu et al., 2020, 2021; Wu et al., 2021). Several previous studies based on UAVs' observations were conducted to characterize the horizontal and vertical distribution of air pollutants in rural and urban areas (Li et al., 2017, 2018, 2019; Zheng et al., 2021). However, previous studies were mainly focused on the spatial or temporal distribution of air pollutants, whereas the response of vertical air pollutant distributions to urban structures such as buildings, and green infrastructure was rarely considered.

Overall, it is necessary to estimate the vertical impact of urban forest on air pollutant concentrations to understand better the air purification ability of an urban forest. In this study, a four-rotor UAV equipped with a portable instrument was used to observe $PM_{2.5}$ (particulate matter with diameter less than 2.5 μm), PM_{10} (particulate matter with diameter less than 10 μm), SO_2, CO, NO_2, O_3 concentrations and air temperature, relative humidity vertically in an urban forest, a street, and a community area. The pollutant concentrations and their correlation with air temperature and relative humidity were compared among the three areas. The vertical purification effect of an urban forest was also presented and discussed. The results offer a new understanding of air pollutant behavior in relation to the urban forest and provide proper guidelines for forest management to improve the quality of outdoor air.

Methodology

UAV platform and Sniffer4D V2

A four-vector UAV (Dajiang M100) was used to carry portable instruments such as Sniffer4D V2 to observe the $PM_{2.5}$, PM_{10}, SO_2, CO, NO_2, and O_3 concentrations, air temperature, relative humidity, and atmospheric pressure per second. The UAV weighs 2.355 kg and has a maximum carrying weight of 3.6 kg. The maximum climate and descent rates of the UAV are 5 m/s and 4 m/s, respectively. The vertical hovering accuracy is 0.5 m, and the horizontal accuracy is 2.5 m. Moreover, the size of Sniffer4D V2 is 158 × 103 × 87.5 mm. It is a portable mobile monitoring device with a weight of less than 500 g. It can be installed on the top of UAVs or cars traveling at a speed of less than 80 km/h to record air pollutant concentrations. The PM sensor in the Sniffer4D V2 is a miniaturized laser photometer, which estimates the PM concentrations based on the light scattering principle with a resolution of 1 $\mu g/m^3$. The gaseous pollutant sensors for SO_2, CO, NO_2, and O_3 are electrochemical sensors, which calculate the concentrations by reacting with the measured gas to generate an electrical signal proportional with a resolution of < 1 ppb (parts per billion; Li et al., 2020).

Field campaigns

The field campaigns were conducted in Shenyang (41°48′11.75″N, 123°25′31.18″E), the capital of Liaoning Province, China. This province has a temperate continental monsoon climate with four distinct seasons. It covers an area of 12,860 km^2 and has a permanent resident population, which had reached 9 million by December 2020. The annual air temperature is 6.2–9.7°C, and the annual precipitation stands at 600–800 mm. In this study, the vertical concentrations of $PM_{2.5}$, PM_{10}, SO_2, CO, NO_2, O_3, air temperature, relative humidity, and atmospheric pressure were collected by UAV equipped with Sniffer4D V2 at three sites including urban forest, street and community areas to estimate the air purification of the forest (Figure 1). The three areas were located in and beside the Shenyang Arboretum, the Institute of Applied Ecology. The Arboretum is located in the central area of Shenyang and covers an area of 5 hectares. Wanliutang street is oriented North–South (N–S) and consists of five traffic lanes in each direction. The community area is composed of six-floor buildings.

Different dispersion capacities of air pollutants under different weather conditions form different vertical distributions of air pollutants within the low troposphere (Li et al., 2018). In this study, UAV measurements were taken on overcast and sunny weekdays, with a similar traffic volume. The UAV flight was operated at 0–100 m to estimate the vertical influence of the urban forest on air quality in the urban surface. In total, 11 monitoring heights were selected: 0, 2.5, 5, 10, 15, 20, 30, 40, 60, 80, and 100. The UAV hovered at different monitoring heights for 50 s, because the air pollutant monitors need some buffer time to obtain reliable measurements (Zheng et al., 2021). The first 20 s at each height was considered as the buffer time and the data collected during this period were removed to ensure the accuracy of the data. The measurements were taken at 10:00, 14:00, and 18:00 local time on the overcast (3 September 2021) and sunny (17 September 2021) days, respectively. Sniffer 4D V2 observed air pollutant concentrations in the air pumped into the instrument, while the accuracy of the observation can be affected by the airflow around. To eliminate the effect of airflow generated by the UAV during the flight, Sniffer 4D V2 was placed on top of the UAV (Li et al., 2022).

Data analysis

Vertical line charts were plotted to compare the distribution of air pollutants in street canyons, forests, and community areas on overcast and sunny days. Then, pair plots were used to display a matrix of plots for viewing distributions of air pollutants and their correlation relationship with air temperature and relative humidity. The vertical line charts and pair plots were plotted *via* Hiplot at https://hiplot-academic.com/.

Results

Figure 2 shows the hourly vertical distribution of $PM_{2.5}$ and PM_{10} concentrations on overcast and sunny days, respectively. Similar concentration trends were found between $PM_{2.5}$ and PM_{10} at the three sites on overcast and sunny days. Both $PM_{2.5}$ and PM_{10} concentrations increased with height below 20 m and then maintained a similar value or slightly decreased with height on overcast days, whereas no obvious changes in PM concentrations with height were observed on sunny days. The PM concentrations at 10:00 were significantly higher than those at 18:00 and higher than those at 14:00 on overcast and sunny days. The PM concentrations in the forest were significantly higher than those on the street at 10:00, whereas the situation was reversed at 14:00 and 18:00 on overcast days. The PM concentrations in the forest were significantly lower than those on the street, while no significant difference was found at 14:00 and 18:00 on sunny days. The PM concentrations in the community at 18:00 were significantly higher than those in the forest on overcast and sunny days.

The CO concentrations at 10:00 were significantly higher than those at 18:00 and higher than those at 14:00 on overcast and sunny days (Figure 3). They increased with height below 15 m and then decreased with the increase of height at the street on overcast days. The CO concentrations first decreased, then increased, and then decreased with the increase of height in the forest on overcast days. The CO concentrations on the street were significantly higher than those in the forest below 20 m, whereas no significant difference in CO concentrations was found above 20 m at 14:00 and 18:00 on the overcast days. They were significantly higher on the street than those in the forest within 100 m at 10:00 on overcast and sunny days. No significant difference was found between CO concentrations on the street and in the forest at 14:00 and 18:00 on sunny days. The CO concentrations in the community were significantly higher than those in the forest and on the street at 18:00 on sunny days.

The SO_2 concentrations decreased with the increase of height within 20 m, whereas no significant difference in SO_2

FIGURE 1
Location of the Arboretum in Shenyang and unmanned aerial vehicles' (UAVs') observation sites in the street canyon, forest, and community areas.

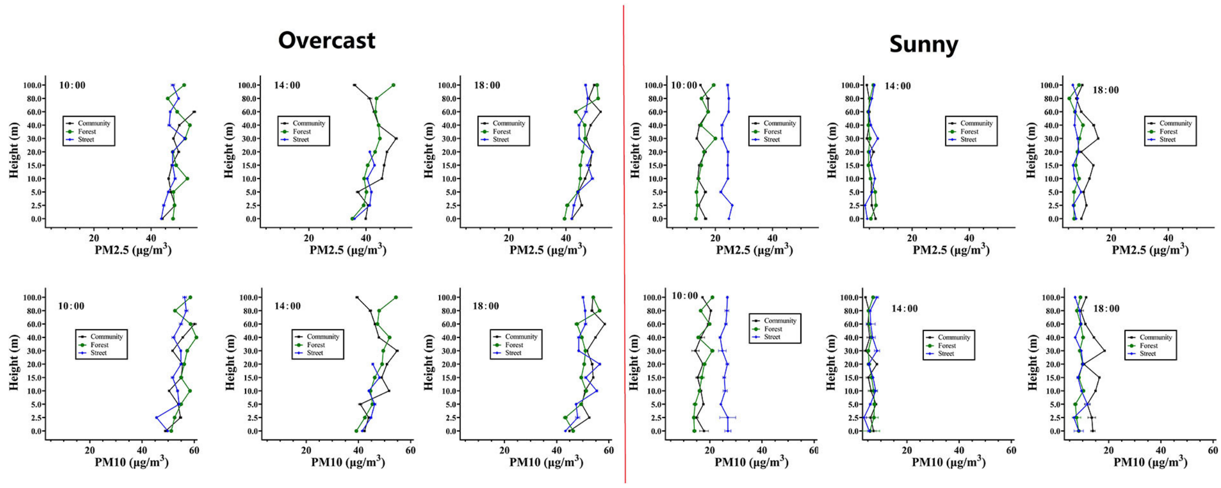

FIGURE 2
Hourly vertical distributions of $PM_{2.5}$ (particulate matter with diameter less than 2.5 μm) and PM_{10} (particulate matter with diameter less than 10 μm) concentrations (mean ± SE) in the overcast and sunny days, respectively.

concentrations was found when the height increased from 20 m to 100 m on overcast and sunny days (Figure 3). The SO_2 concentrations in the forest were lower than those at the street at 10:00 and 14:00, while the situation was reversed at 18:00 on overcast days. They were significantly lower in the forest than those on the street at 10:00 and 18:00 on sunny days. The SO_2 concentrations in the forest decreased slower than those at the street when the concentration decreased.

The NO_2 concentrations near the ground were higher than those at 2.5 m at 10:00, 14:00, and 18:00 on overcast and sunny days (Figure 3). They increased with the increase of height to 20 m from 2.5 m and then decreased with the height on the overcast day and sunny days. The NO_2 concentrations were significantly lower in the forest than those on the street at 10:00, 14:00, and 18:00 on overcast days. Similar results were found at 10:00 and 18:00 on sunny days, whereas the situation was reversed at 14:00 on sunny days. The NO_2 concentrations at 14:00 were significantly lower than those at 10:00 and 18:00 on sunny days. The O_3 concentrations increased with the height increasing within 20 m at 10:00, 14:00, and 18:00 on overcast

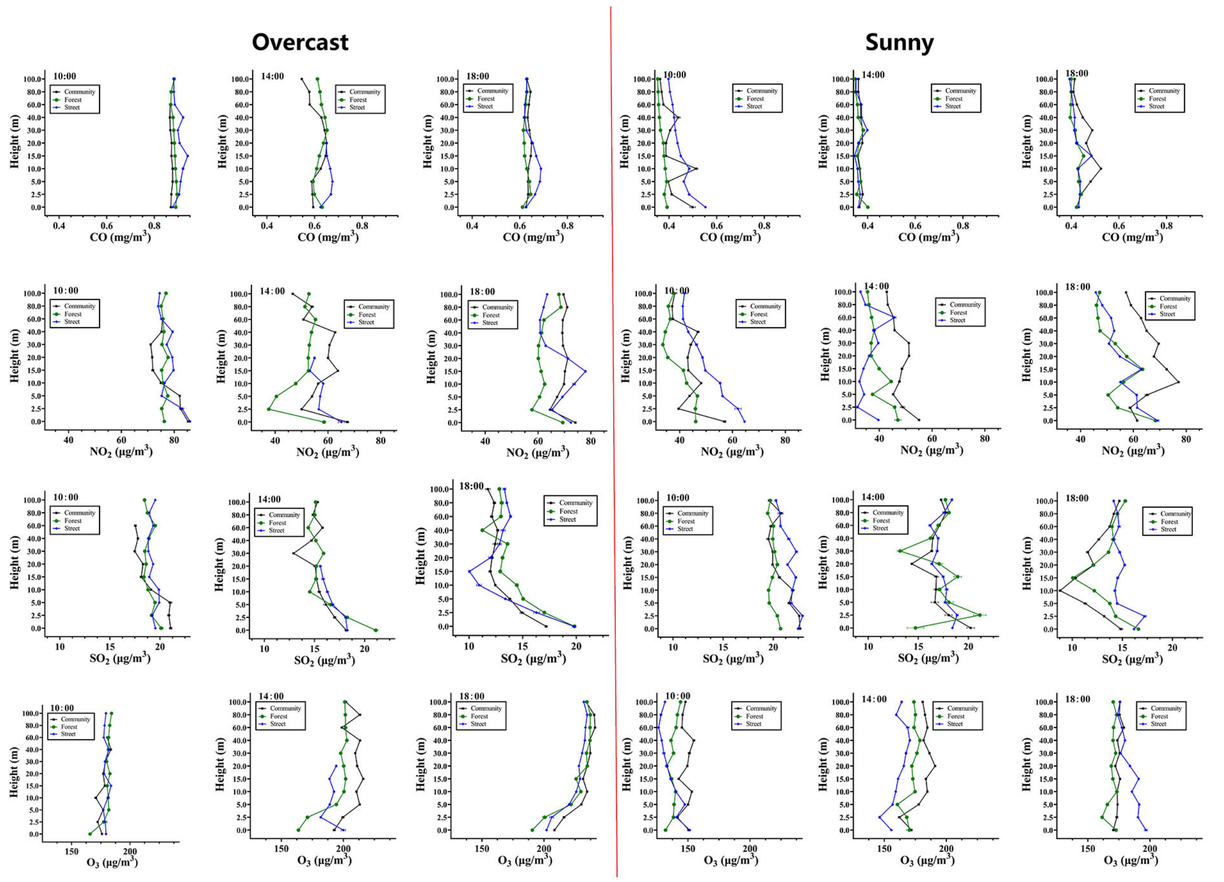

FIGURE 3
Hourly vertical distributions of carbon monoxide (CO), sulfur oxide (SO_2), nitrogen dioxide (NO_2), and ozone (O_3) concentrations (mean ± SE) on overcast and sunny days, respectively.

days, and at 14:00 on sunny days. The differences among O_3 concentrations at the three sites on sunny days were larger on overcast days. The O_3 concentrations in the forest were higher than those on the street at 14:00, while they were lower than those on the street at 18:00 on sunny days. The O_3 concentrations in the community were significantly higher than those in the forest than those on the street at 14:00 on overcast and sunny days.

Easy pair plots were drawn to view the distribution of air pollutants, air temperature, relative humidity, and the correlation between the two of them (Figure 4). Double peaks were found in the distribution of $PM_{2.5}$ and PM_{10} concentrations, whereas one peak was found in the distribution of chemical pollutant concentrations such as CO, SO_2, NO_2, and O_3. For PM concentrations, a significantly positive correlation was found with relative humidity at the three sites, whereas only a significantly negative correlation with air temperature was found in the forest. The correlation coefficient between $PM_{2.5}$ concentration and relative humidity ($r = 0.86$) in the forest was higher than that on the street ($r = 0.85$), than that in the community ($r = 0.82$). For CO concentrations, a significantly positive correlation ($r = 0.82$) was found with relative humidity, whereas no significant correlation was found with air temperature at the three sites. For SO_2 concentrations, a significantly positive correlation ($r = 0.29$) was found with relative humidity at the three sites, whereas a significantly negative correlation was found with air temperature in the forest ($r = -0.35$) and at the street ($r = -0.42$). For NO_2 concentrations, a significantly negative correlation was found with air temperature ($r = -0.34$), whereas a significantly positive correlation was found with relative humidity ($r = 0.76$) at the three sites. The correlations between NO_2 concentration with air temperature and relative humidity in the forest were stronger than those in the street. For O_3 concentrations, a significantly positive correlation was found with air temperature ($r = 0.35$) at the three sites, and a significantly positive correlation was found with relative humidity ($r = 0.21$) in the forest and the community.

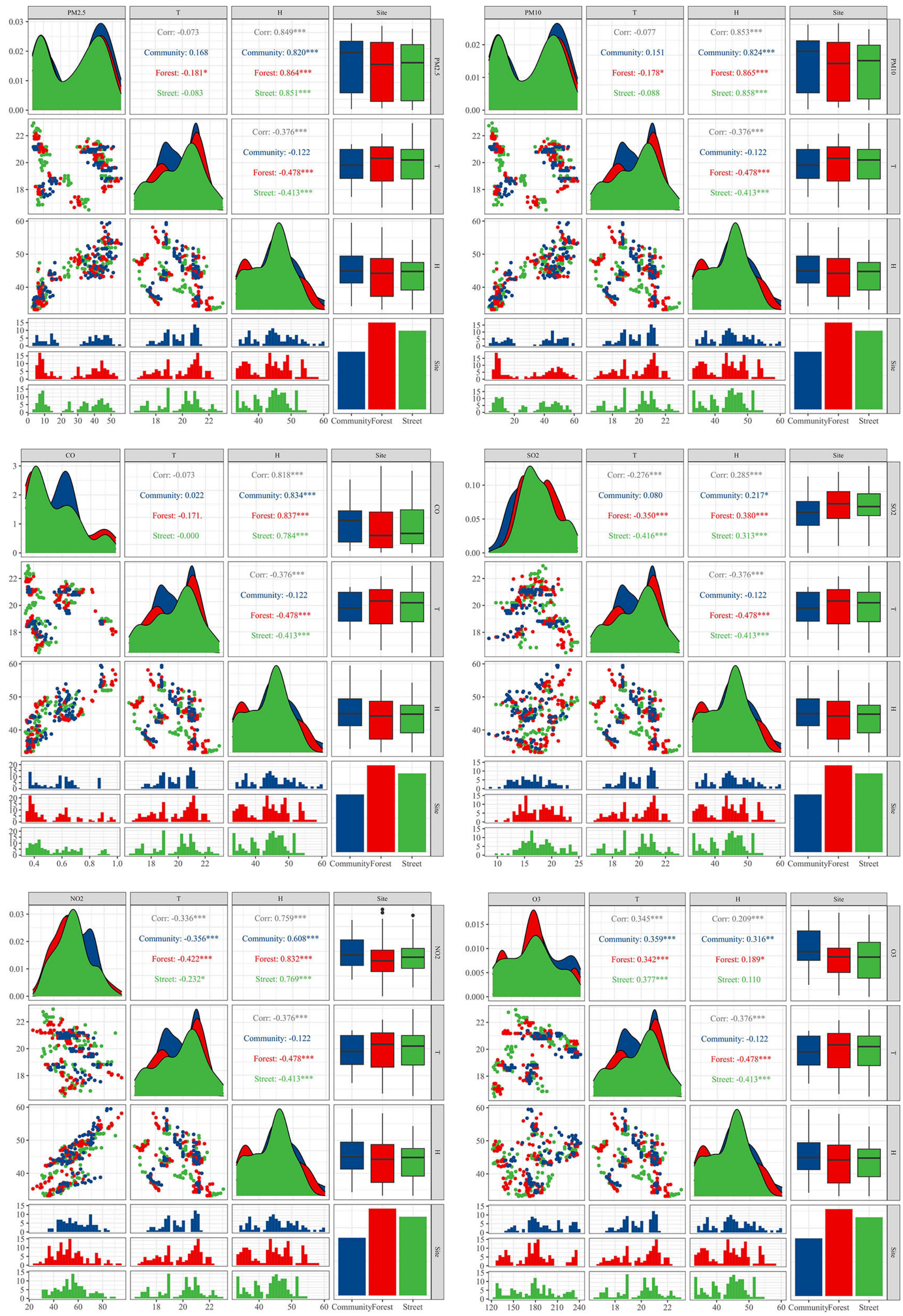

FIGURE 4
Pair plots for viewing correlation and distributions of air pollutant concentrations, air temperature, and relative humidity. The numbers in the figure show Pearson's correlation coefficient between air pollutants and relative humidity and air temperature totally in the community, forest, and street, respectively.

Discussion

The vertical pattern of air pollutants

In this study, PM concentrations increased with height below 20 m and then slightly decreased with height on overcast days, whereas no obvious changes in PM concentrations with height were observed on sunny days (Figure 2). The different trends between overcast days and on sunny days are probably due to the different background concentrations and meteorological conditions. Two peaks appeared in the distribution maps of PM concentrations, and the vertical distribution of PM concentrations was different on the overcast and sunny days (Figure 4). The higher PM background concentrations and relative humidity, and weaker solar radiations on overcast days were probably the main reasons for the different vertical distributions of PM on sunny days (Li et al., 2017).

The concentrations of gaseous air pollutants, such as CO, NO_2, and O_3, increased with height within 20 m and then decreased with height on overcast days. Miao et al. (2023) also found a similar trend in NO_2 and O_3 concentrations in an urban street canyon. However, the SO_2 concentrations decreased with the increase of height within 20 m, whereas no significant difference in SO_2 concentrations was found when the height increased from 20 m to 100 m on overcast and sunny days (Figure 3). The different vertical trends of SO_2 from the other gaseous air pollutants were observed probably due to the lower SO_2 background concentration, which made it more sensitive to the impact of traffic emissions and human activities (Lu et al., 2020). The vehicle emissions led to a high SO_2 concentration near the ground.

During the day, the PM, CO, and NO_2 concentrations decreased from 10:00 to 14:00, and then increased to 18:00, whereas the O_3 concentrations increased from 10:00 to 14:00. The increase of O_3 is probably due to the high intensity of photochemical reactions that are enhanced by solar radiation during the day (Li et al., 2017; Liu et al., 2020). The higher concentration at 10:00 than at 14:00 was possibly associated with higher traffic emissions hour and lower vertical convection of air masses that hinder the air pollutant dispersion at 10:00 (Li et al., 2017; Lu et al., 2020; Zheng et al., 2021). The increased solar radiation led to rising turbulent effects and a deeper ABL from 10:00 to 14:00 within a day, which improved the vertical diffusion of traffic-emitted pollutants (Lu et al., 2020). The increase from 14:00 to 18:00 took place probably due to the deposition of air pollutants, cooking and traffic emissions, and a rapid shrinkage of ABL (Li et al., 2018). At 18:00, along with sunset, the land cooled rapidly and the thermal-inversion layer was gradually formed. This could trap traffic-emitted particles in the shallow ABL, leading to a rapid increase in PM concentrations (Lu et al., 2020).

On overcast days, $PM_{2.5}$, PM_{10}, CO, and NO_2 concentrations in the community were lower than those on the street at 10:00. The difference between them decreased at 14:00, and the concentrations at the community became higher than at the street at 18:00. The decrease in $PM_{2.5}$, PM_{10}, CO, and NO_2 concentrations from 10:00 to 14:00 was found probably due to the vertical and horizontal transport of air pollutants and decreased traffic volume (Lu et al., 2020). High $PM_{2.5}$, PM_{10}, CO, and NO_2 concentrations in the community at 18:00 were attributable to human activities such as cooking and parking (Ezhilkumar and Karthikeyan, 2020). Whereas O_3 concentrations in the community were higher than those on the street and in the forest at both 10:00 and 14:00. The heat stored in the building surface materials increased the ambient temperature, promoted photochemical reactions, and thus increased ozone concentrations (Wang et al., 2021).

Vertical air purification capacity of urban forest

According to the concentration differences between the forest and the street, the forest increased PM concentrations in the morning of the overcast day, whereas decreased PM concentrations were detected in the afternoon on the overcast day. The forest obstructed the horizontal and upward transport of PM when the PM concentrations grew lower in the morning of the overcast day, but it can intercept air pollutants and prevent them from entering the canopy when the PM concentrations grew higher in the afternoon. This is consistent with what Gromke and Ruck (2009) reported that urban forest beside the street hinders the transmission of air pollutants and increases pollutant concentrations. Therefore, the reduced wind velocity and ventilation performance in the urban forest slow down the reduction rate of pollutant concentration when the background concentration decreases (Ng and Chau, 2012). On the other hand, the urban forest can act as a sink for turbulence and provide surfaces for PM deposition (Lin et al., 2020). The forest intercepts air pollutants and prevents them from depositing into the canopy when the background concentration increased. Moreover, the forest decreased PM concentrations on the morning of the sunny day. The purification capacity of the forest on PM was significant when the background concentration was low.

Generally, the forest decreased CO concentrations within 100 m at 10:00 on overcast days. It decreased CO concentrations below 20 m, whereas no significant difference was found above 20 m at 14:00 and 18:00 on the overcast days. That means, the forest hindered the horizontal transport of CO within its canopy height. Moreover, the forest was characterized by low solar heating, which greatly restricted the upward transport of ground-level air pollutants (Lu et al., 2020). Low air temperature in the forest reduced the mixing height of air masses and then formed stable atmospheric conditions that hinder air pollutant dispersion (Ganguly et al., 2019; Miao et al., 2023).

The forest decreased SO_2 concentrations at 10:00 and 14:00, while the situation was reversed at 18:00 on overcast days. It decreased SO_2 concentrations at 10:00 and 18:00 on sunny days. The SO_2 concentrations in the forest decreased slower than those in the street when the concentration decreased. The forest decreased NO_2 concentrations at 10:00, 14:00, and 18:00 on overcast days. It decreased NO_2 concentrations at 10:00 and 18:00 on sunny days, whereas the situation was reversed at 14:00 on sunny days. The forest increased O_3 concentrations at 14:00, while it decreased O_3 concentrations at 18:00 on sunny days. The probabilities in the formation of secondary aerosols were high under low solar heating in the forest (Lu et al., 2020). The vertical convection was more important in shaping the ozone vertical distribution than horizontal transport processes (Li et al., 2017).

All the PM, CO, SO_2, and NO_2 concentrations were significantly positively correlated with relative humidity. The overcast days were always characterized by higher relative humidity and severe air pollution compared with clean days (Miao et al., 2023). Photochemical pollutants such as NO_2 and O_3 showed a significant correlation with air temperature. The NO_2 concentrations were significantly negatively correlated with air temperature, whereas O_3 concentrations were significantly positively correlated with air temperature. High air temperature can promote photochemical reactions and ozone formation (Li et al., 2017; Wang et al., 2021). Wang et al. (2021) reported a negative correction between O_3 and NO_2 concentrations in residential streets. Low NO_2 concentrations could reduce the titration of O_3 and thus increase O_3. The correlations between NO_2 concentration with air temperature, and relative humidity in the forest were stronger than those in the street. Moreover, a positive correlation was found between PM concentrations and air temperature in the community areas, rather than in the forest or on the street, probably due to the kitchen exhaust of residential buildings (Ezhilkumar and Karthikeyan, 2020).

Strengths and limitations

Urban forest has attracted worldwide attention for their potential to mitigate local air pollution (Jia et al., 2021). The impact of urban forests on the vertical pattern of air pollutants is conducive to the understanding of pollutant dispersion and net purification of the urban forest. This study obtained $PM_{2.5}$, PM_{10}, CO, SO_2, NO_2, and O_3 concentrations at 0, 2.5, 5, 10, 15, 20, 30, 40, 60, 80, and 100 m in the urban forest and at a street by UAVs equipped with Sniffer4D. The results indicate that the purification of an urban forest depends on the change in background concentrations. The forest filtered PM significantly when the background concentration was low. The forest might obstruct the dispersion of air pollutants when the background concentrations decreased, but it hinders the PM deposition into the forest when the background concentrations increased.

This study estimates the vertical purification of urban forests on overcast and sunny days in autumn, and the results provide some implies on air pollutant dispersion in urban forests. Although the overcast and sunny days with different background concentrations were involved in estimating the vertical purification, the sampling days and seasons were limited. The air purification of a forest in different seasons remains unknown. Additionally, wind velocity is likely to provide sophisticated means for a thorough understanding of the dispersion of air pollutants and transport over the urban surface (Zheng et al., 2021). In case the wind speed and direction cannot be quantified during the rotation of the UAV wing, the analysis of pollutant dispersion could be deeper if the local wind information was considered.

Conclusion

In this study, a residential area in Shenyang was taken up as a case study to explore the vertical purification of urban forests on overcast and sunny days. The study indicates that UAVs platform can provide a high-quality vertical profile of an air pollutant that can be used to understand better the transport and distribution of air pollutants. Results showed that air purification by the urban forest varied during the day. The PM and SO_2 concentrations in the forest decreased slower than those in the street when the PM concentrations rose lower in the morning of the overcast day. While the PM concentrations in the forest increased slower than those in the street when the PM concentrations grew higher in the afternoon. The forest could not only obstruct the horizontal and upward transport of PM, but it can also intercept air pollutants and prevent them from getting deposited into the canopy. The purification capacity of the forest on PM was significant when the background concentration was low.

Data availability statement

The data supporting the conclusions of this article will be made available by the authors, without undue reservation, upon request.

Author contributions

CM conceived the article and wrote the first draft. CM, AC, YH, and ZX conducted the field investigation. WC and XH edited subsequent drafts. All authors contributed to the article and approved the submitted version.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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Coupling coordination analysis of low-carbon development, technology innovation, and new urbanization: Data from 30 provinces and cities in China

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Technology innovation capability as an endogenous driving force plays an increasingly important role in the low-carbon transformation of new urbanization. This paper's purpose is to delve into the coupling coordination relationship among the three variables, and promote system's and region's synergy development. Based on the coupling coordination degree model, spatial autocorrelation model and obstacle degree model, this paper investigated the coupling coordination of low-carbon development (LCD) quality, technology innovation (TI) capability and new urbanization (NU) level in China from 2009 to 2019. The results indicate: (1) The coupling coordination degree (CCD) of LCD quality, TI capability and NU level in all regions of the country were fluctuating for a long time, and the regions that reach the coordinated development level showed a slow rising trend with obvious regional differences. (2) Three subsystems' CCD showed significant spatial correlation characteristics, and the degree of spatial agglomeration was constantly increasing. (3) The obstacles affecting the systems' synergy mainly reflected in economic and social indexes. In the end, this paper proposed that policy coordination and linkage should be strengthened, emphasizing the integrated development of the three subsystems. It is necessary to formulate development plans in combination with geographic location and resource endowment to enhance the regional driving effect.

KEYWORDS

low-carbon development, technology innovation, new urbanization, coupling coordination degree, spatial autocorrelation

Introduction

With the acceleration of industrialization in recent years, the greenhouse effect has increased, which has caused a series of serious problems such as global warming and frequent extreme weather. In the context of global climate change, the low-carbon development model is considered the best choice for all countries in the world (1).

According to statistics, since the mid-twentieth century, about 90% of greenhouse gas emissions have been attributed to human activities and behaviors in urban areas (2). Cities play an important role in LCD (3). As a result, countries around the world have taken measures to address climate change and ecological breakdowns, advocating the reduction of greenhouse gas emissions and shifting to low-carbon cities for sustainable urban development (4, 5). Low-carbon development (LCD) and urbanization have been becoming important issues in the field of climate change (6).

China is the world's largest developing country, energy consumer and carbon dioxide emitter (7). The construction of new urbanization (NU) through low-carbon means has gradually become the main way of urbanization development in China. Unlike European and American countries, China's urbanization starts late. It faces more stringent environmental protection requirements and low-carbon emission requirements. China's NU requires both urbanism and carbon emission control. Also, it requires modernization while preserving heritage culture. All these have posed great challenges to China's LCD and NU construction. China has experienced a rapid urbanization over the past three decades (6). In addition to the dramatic increase in carbon emissions brought about by increasing urban population density, accelerating production practices and surging infrastructure needs, the over-reliance on energy resource inputs and production scale expansion for industrial development have also led to serious damage to the ecological environment (8). However, with the rapid development of modern information technology, the integration of scientific technology with low carbon has gradually entered people's research horizon. LCD technologies is not only necessary for mitigating and adapting to climate change, but also for ensuring the security of energy supply and building a resource-saving and environment-friendly society. Meanwhile, the central government is paying more and more attention to technology innovation (TI) with the socio-economic development. Regional TI is an important technological guarantee for regional sustainable development. Improving the regional TI capability is an important way to enhance the ability of regional health and sustainable development (9). Therefore, the TI capability is also playing an increasingly important role in NU construction and LCD.

In the context of carbon neutral and peak carbon dioxide emissions, the only way to achieve this goal is scientific and technological support, which relies on major technology innovation breakthroughs. However, due to the differences in regional development, there is a big gap between regional NU level, LCD quality and TI capability. On the basis of NU, the combination of LCD and TI will effectively increase the supply of low-carbon products and green services. At the same time, it will also guide the green consumption and industrial transformation to realize the regional and even national socio-economic green transformation and modernization development. Obviously, what needs to be clarified at this time is whether there is a link between TI capability, NU level and LCD quality in China's development process over the years? To what extent do they interact and influence each other? Is there a spatial correlation? The existing studies have not been clearly elaborated. Therefore, this paper's purpose is to explore the coupling coordination relationship and development characteristics among TI capability, LCD quality and NU level in various provincial administrative regions in China, and to explore regional differences and optimization strategies of low-carbon city construction and low-carbon technology development.

As the second largest economy in the world, China's green transformation plays a very important role in the global green transformation. Moreover, the great achievements of NU with Chinese characteristics and the concept of people-oriented urbanization construction have become a benchmark of global significance. China's LCD and NU both focus on low-carbon economy and social transformation, advocate clean energy and low-carbon lifestyles, which aims to realize the coordinated development of industrialization and ecological environment (10). China's advanced experience in coordinating the relationship between ecological civilization, technological progress and socio-economic development, and leading the green transformation and urbanization development with scientific and technological innovation will bring great reference significance to the world, especially developing countries. The data from 2009 to 2019 are mainly obtained from *China Statistical Yearbook*, *China Education Statistical Yearbook*, *China Science and Technology Statistical Yearbook*, *China Energy Statistical Yearbook*, *China Environmental Statistical Yearbook*, *China Population and Employment Statistical Yearbook*, *China Health Statistical Yearbook* and *China High Technology Industry Statistical Yearbook*. Due to the absence of some data in Tibet, Taiwan, Hong Kong and Macao, they are not included in the statistical scope.

This article proceeds as follows: In the second section, we introduce the literature review of the three subsystems of LCD quality, NU level and TI capability, and then clarify the research contents of the existing studies. The third part introduces the construction of the index system and models. The fourth part is an empirical study. It firstly compares and analyzes the comprehensive development level of each subsystem. Secondly, the evolution of CCD in each region is analyzed from the view of space-time. Its spatial correlation is verified by combining global autocorrelation and local autocorrelation. Thirdly, this paper clarifies the indexes affecting the synergistic development of each system based on the obstacle degree model. Section 5 discusses the results and proposes policy recommendations. Meanwhile, the theoretical and practical implications, limitations and future research directions of this study are elaborated.

Literature review

Low-carbon development

The UK government put forward the concept of "*low carbon*" in its *Energy White Paper: Our Energy Future—Creating a Low Carbon Economy* in 2003 (11). In the book, the new concept of "*Low-Carbon Economy*" explained the challenge of global warming to human survival. How to promote the "*Green Economy*" has become an urgent task. Subsequently, low-carbon concept gradually received widespread attention from governments and academia. In 2007, Japanese government advocated the concept of "*No Low-carbon Society, No Low-carbon Economy*" and introduced the concept of "*Low-Carbon Society*" (5). On June 5, 2008, the United Nations Environment Program (UNEP) proposed a "*Low-Carbon Lifestyle*" for individuals. In 2010, Chinese scholars were the first to propose the concept of "*Low-Carbon Cities*" in mainland China based on the above-mentioned concepts of western developed countries. In 2021, China launched the research report "*Carbon Neutral: China in Action*" to proactively explore China's low-carbon transformation and upgrading path. Currently, research on low-carbon is mainly focused on "*Low-Carbon City,*" "*Low-Carbon Life,*" "*Low-Carbon Technology,*" and "*Energy Consumption and Regeneration*", etc. (12–14). In recent years, research has extended to the dimensions of "*Green Building*" (15), "*Green Logistics*" (16), "*Low-Carbon Competitiveness*" (17), and "*Carbon Emission Reduction*". For countries around the world, LCD is a sustainable development model characterized by low energy consumption, low pollution and low emissions, which plays an important positive role in economic and social progress (3). However, for a country, cities are the basic unit of economic development. As the engine of future economic growth, cities play an increasingly important role in LCD (18). Therefore, low-carbon city construction is an important way to achieve sustainable development strategies and promote social wellbeing (5).

How should the regional LCD quality be measured? Generally speaking, if a region achieves economic growth with lower carbon emissions per unit of GDP, the region will have the higher LCD quality. In today's world, LCD takes various forms. London focuses on energy efficiency projects. Copenhagen and the United States focus on promoting the production and application of renewable energy. Germany strongly supports environmental protection industries. Japan advocates the development of low-carbon innovative technologies. While, China encourages investment in clean energy. It implies that the LCD concept involves not only greenhouse gas emissions, energy consumption and regeneration, but also economic, environmental and social production (18). On this basis, the evaluation index system of LCD quality should also be a unified subject involving the coordinated and orderly development of many aspects (18, 19). As a result, a large number of scholars have extensively explored its evaluation system in terms of economy, society, environment, resources, urban design and people's quality of life. Jia et al. (11) established the evaluation system of LCD quality from carbon emission status, carbon source's control level, carbon capture capacity, human development index and urbanization level. Tan et al. (18) established an evaluation index framework for low-carbon cities from the perspectives of economy, energy pattern, society and life, carbon and environment, urban transportation, solid waste and water.

Technology innovation capability

The coordinated promotion of innovation and economic development is an inevitable issue for Chinese cities (20). Innovations arise from complex interactions between actors with complementary capabilities (technical competence, leadership, or investment level). These actors include businesses, research organizations, government departments, non-governmental organizations, and other intermediary organizations. They contribute to the development and diffusion of innovation (21). Generally speaking, technological talents mainly refer to enterprises, schools, research institutes, and some natural persons with invention patents and innovative technologies. They have the comprehensive strength of invention and innovation in a certain scientific and technological field. Universities, research institutions and industries are important subjects of TI (22). Knowledge structure, R&D experience, technological equipment and innovation spirit of scientific researchers will have an impact on the organization's TI capability. Technological change is the main source of productivity growth. R&D investment and R&D activities play a key role in TI progress (23). Improving the TI capability will directly enhance local industrialization, attract foreign investment and promote employment. There is a positive effect of TI capability on enterprises competitiveness, especially green technology innovation capability (24). Xie et al. (25) used dynamic panel generalized moment estimation to find that technology introduction had a negative effect on the green transformation of industries in resource-based cities, while TI could have a positive effect. In the short term, TI promotes sustainable regional development, while in the long term, the two remain in dynamic equilibrium.

It is evident that TI capability is a powerful driving force leading the cities' development (26). The evaluation system of TI capability has been expanded with the depth of research, and many research institutions have assessed it in terms of technological innovation input, output, and benefit, etc. Chen et al. (27) constructed a system of urban TI in terms of regional economic growth, research expenditure, manpower, R&D personnel's quality, number of patents granted and transportation facilities levels. Yang et al. (28) integrated economic, environmental and social benefits on this basis, and then studied the coupling coordination relationship between TI system and ecological environment system.

New urbanization level

Urbanization is a process of urban spatial expansion in which non-agricultural industries and non-agricultural populations cluster in towns and cities (29). The proportion of the population living in urban areas is a key index of modernization. It is used to represent the urbanization level in this area. Urbanization is more closely related to the level of productivity, industrialization and technology of a region. Urbanization at the conceptual level includes demographic urbanization, economic urbanization, geospatial urbanization and social civilization urbanization, involving industrial economy, human geography, urban construction and other aspects. Compared with the traditional urbanization concept of "*Object-Oriented*", the NU insists on the "*People-Oriented*" concept and emphasizes that all people should enjoy the fruits of urbanization together. China's NU not only requires the harmonization of population, land and economy, but also advocates the protection of ecological environment and LCD of the region (30, 31).

Scholars' studies on the coupling coordination of NU mainly focus on the coupling relationship between carbon emissions, land use efficiency and ecological environment system (32). Tian et al. (33) analyzed the spatial and temporal coupling interactions between urbanization and ecosystem services in the Beijing-Tianjin-Hebei region using a CCD model and a spatial autocorrelation statistical model. The region was encouraged to strengthen sustainable ecological network management and mutually beneficial cooperation across administrative boundaries, and subsequently promote sustainable regional development. On this basis, Gan et al. (34) studied the coupling coordination of cities, population and industries as a way to explore the level of urbanization-industry integration, and found that the low-level and slow-development of industrial subsystems would lead to a poorly coordinated level of urbanization-industry integration. However, a city's radiation capacity has a great impact on the industrial structure and product distribution of the surrounding areas (29), so the study emphasizes the radiation role of central cities to promote the region's synergetic development (34). Therefore, the NU construction should pay more attention to the coordinated development of economy, society and environment. It is important to reduce energy consumption and improve energy productivity.

Scholars have found that environmental pressure is higher in cities (35, 36). In the coupling relationship between urbanization and environmental systems, social urbanization and environmental regulation are key factors in decision making to adjust coordinated development (37). Zhao et al. (35) affirmed the important role of ecological levels when studying the relationship between cities and the environment based on data collected from 209 countries and regions worldwide. It also pointed out that economic urbanization had a positive impact on the coupling of the two systems, with higher income levels tending to exhibit a more harmonious and coordinated relations. It is thus clear that the changes in productive activities of urban populations brought about by urbanization have an important impact on the structure and function of urban ecosystems (29). However, in the future, the majority of the world's future population will live in urban areas, and cities will gradually become the focus of sustainable development in all countries (38). In this context, NU has become a necessary path to modernization for all countries and a strong driving force for regional economic development. As a result, more and more scholars have started to inject the evaluation elements of "*people-oriented*" and "*green-coordinated development*" on the basis of traditional urbanization research (34, 39–41). For example, Wu and Zhao (41) selected 26 indexes from four aspects: economic, social, environmental, and urban-rural coordination to comprehensively measure the NU level of each city. Gan et al. (34) assessed it in terms of transportation level, public services, environmental management, population employment, living standard, income expenditure level and industrial scale.

Variable linkage and research methods backtracking

With the deepening of the connection between NU and LCD, some scholars hold that urbanization promotes carbon emissions (42). The reason is that population growth during rapid urbanization will bring increased demand for transportation and infrastructure. China's energy consumption will also expand at an unprecedented rate, accompanied by high coal-based energy consumption and high carbon dioxide emissions (43, 44). For instance, Zhu and Peng (14) found that consumption level was highly correlated with carbon emissions, and population urbanization was the key factor for the increase of carbon emissions in China. Increasing population, wealth and urbanization level would increase carbon dioxide emissions (10). With the continuous acceleration of urbanization, cities have a growing number of people and productive assets. In addition, the increase in household consumption and the expansion of urban infrastructure would lead to rapid urbanization, which will most likely result in more carbon emissions (6). Some other scholars consider that the increase in urbanization rate inhibits carbon emissions and has a negative effect on the carbon emissions efficiency. Meanwhile, energy intensity and carbon intensity decrease with the development of urbanization and the advancement of industrial structure (43). Urbanization is accompanied by rapid economic development. China's economy will grow faster than energy consumption and carbon dioxide emissions for a certain period of time (43). Subsequently, the coordination level and spatial correlation between urbanization and the ecological environment will be constantly strengthened, and the balance between the two will reach beyond expectation (45, 46). Many provinces are committed to raising the LCD level and accelerating the construction of low-carbon cities. Low-carbon cities are characterized by economies of scale and regional differences. The larger scale of urbanization, the more perfect infrastructure and the higher level of technology will lead to the greater positive effect of green growth in the region (47).

For regional development, however, technological empowerment will be even more influential. It will effectively spawn a new batch of smart cities and smart governments. Smart cities imply the use of science and technology and the collective intelligence of cities to achieve smarter urban mobility, more robust infrastructure, and more interactive urban management systems (48). For example, cities can use new industrial and communication technologies to develop energy-efficient buildings and smart energy grids (49, 50). Smart cities involve technological, social, and political processes aimed at solving public problems using more advanced technologies, providing innovative urban services, improving the quality of life of citizens, and achieving healthy and sustainable urban development. Moreover, urban innovation is not only dependent on local innovation activities, but is also enhanced when cities are deeply integrated into intercity innovation networks (51). Moreover, the TI capability would offset the negative impact of urbanization on the environment and reduce carbon emissions (61). The TI capability not only provides practical methods for realizing low-carbon and zero-carbon cities from the technical level, but also plays an important role in promoting the development of green and low-carbon industrialization. It can be seen that the three variables are mutually promoting and interacting in theory and practice. In the construction of NU, LCD and TI provide a new focus and impetus for urban construction and national development from the perspective of concept strengthening and technological empowerment.

Among the existing research methods, the coupling studies is mainly based on coupling coordination model and gray multivariable coupling model, supplemented by relative development degree model and spatial autocorrelation model. Exploring the relationship between variables depends on empirical studies and case studies. The advantages and limitations of different research methods are shown in Table 1. Combined with the research purposes, we choose to combine the coupling coordination degree model and spatial autocorrelation model to analyze the coupling coordination of variables at the spatio-temporal level, and use the obstacle degree model to assist in identifying the specific indicators affecting the coupling coordination degree.

Literature summary and research design

From the existing studies, the research on LCD has been increasingly linked to carbon emissions, energy restructuring and rural development in recent years. Admittedly, a comprehensive understanding of low-carbon emissions is the first step of LCD. Low-carbon concept has gradually penetrated into all areas of urban development, including production methods, consumption patterns, social culture and development policies (3). This requires a balance between industrialization, urbanization and low-carbonization. Therefore, an independent and complete industrial system should be established on the basis of economic development to realize the sustainable development of population, resources and environment. This coincides with the concept of NU. The current coupling research related to NU and carbon emission is gradually gaining attention, which provides guidance for the government to formulate carbon emission reduction strategies. It also provides valuable references for decision making in other regions to accelerate the construction of LCD and NU.

However, there are existing the following shortcomings: (1) Carbon emission intensity is only one dimension of LCD quality, and cannot reflect the comprehensive LCD quality of a certain region. (2) Most of the research focus on the micro-level, selecting certain provinces or large city clusters to start the research. Few studies are conducted at the national level as a whole. (3) The impact factors of TI are not included in the scope of the coupling study. (4) The research methods are relatively homogeneous. The influence factors of the coupling coordination situation have not been clarified. In view of this, what is the relationship between the level of LCD and NU? Is there a synergistic relationship between TI capability in the NU level and LCD quality of the region? What are the evolutionary paths of the coupling coordinated development levels among the three systems in time and space? Does the level of coupling coordination among the three systems have spatial correlation? What are the indexes that mainly affect the level of coordination among the systems? The above are exactly the questions that this study tries to address.

Methodology and data

Index system construction and measurement

In order to comprehensively reflect the overall situation of LCD quality, TI capability and NU level of China's provincial

TABLE 1 Review of research methods.

Category	Research methods	Advantage	Limitation	Related literature
Coupling relationship between variables	Coupling coordination degree model	Analyze coordinated development level and dynamic correlations in different regions.	Unable to specify the micro indexes affecting the coordinated level.	(37, 52, 53)
	Relative development degree model	Identify subsystems that are lagging behind in the synergistic development of multiple subsystems.	Unable to clarify the magnitude of the system's CCD.	(54)
	Multivariable coupling model	Eliminate overlapping information; Calculate coordination coefficients; Reflect the positive/negative interaction between the indicators.	Mainly revolves around independent systems; Less used in regional comparisons.	(55)
	Cointegration model	Clarify the long-run equilibrium relationships between different systems/factors; Clarify the magnitude of the impact.	Difficult to reflect regional differences; Unable to estimate the coupling coordination size.	(56)
	Spatial autocorrelation model	Spatial dependency judgment; Measures the degree of aggregation and dispersion of spatial element attributes.	Mainly used as a complementary analysis to explore the spatial correlation characteristics of coupling coordination.	(31, 46)
Influence mechanism between variables	Literature review; Empirical studies	Explore the mechanism of influence between independent variables; Identify mediating and moderating variables.	Unable to verify the association effects of variables in times and space.	(57, 58)

administrative region, this paper constructs the evaluation index system of these three variables (Table 2).

The LCD quality needs to consider many indexes such as economic development, social progress, living consumption, energy structure and environmental situation of the region. Low-carbon city concepts encourage the region to change to a new development model with less energy consumption, less carbon emission and high social and economic benefits (59, 60). In this paper, the LCD quality is evaluated as a subsystem from four dimensions: economic, social, energy and green environment, in which the *Secondary Industry/GDP*, *Per Capita Daily Consumption of Tap Water for Residential Use*, *Electricity Consumption by Region*, *Volume of Sulfur Dioxide Emission* and *COD Discharged of Industry Waste Water* are negative indexes, and all other indexes are positive indexes.

TI capability refers to the extent to which a region's government provides services to innovation subjects. It includes the specific activities and output of local industries, enterprises, higher education institutions and research institutes for TI and technology development. In this paper, we divide regional TI capability into three dimensions: TI agglomeration, TI transformation results and TI support, which are measured in terms of TI inputs, outputs and performance. All indexes are positive indexes.

This paper emphasizes that NU should focus more on ecological environment and social progress. Therefore, this paper will measure the NU level of the region in four dimensions: demographic, economy, society and ecology. The *Registered Unemployment Rate in Urban Area*, *Particulate Matter Emission in Waste Gas* and *Amount of Pollutants Discharged in Waste Water* are negative indexes, while all other indexes are positive indexes.

Data processing and index assignment

In order to minimize the influence of subjective factors on the evaluation results, this paper uses the entropy weight method to determine the index weights.

Firstly, standardize the data. The i denotes the sample ($i = 1, 2, \ldots, n$), and j denotes the index ($j = 1, 2, \ldots, m$). X_{ij} is the original value of the j-th index in the i-th sample of a year, X_{ij}' is the standardized value, $maxX_{ij}$ and $minX_{ij}$ are the maximum and minimum values of the index in all spatial units.

$$\text{Positive indexes}: X_{ij}' = \frac{\mathrm{X_{ij}} - \mathrm{minX_{ij}}}{\mathrm{maxx_{ij}} - \mathrm{minx_{ij}}} \quad (1)$$

$$\text{Negative indexes}: X_{ij}' = \frac{\mathrm{maxX_{ij}} - \mathrm{X_{ij}}}{\mathrm{maxX_{ij}} - \mathrm{minX_{ij}}} \quad (2)$$

TABLE 2 The index system of LCD quality/TI capability/NU level.

Target layer	Factor layer	Index layer	Unit	Effect	Code
Low-carbon development quality	Economy	Gross regional product	100 million yuan	+	L1
		Secondary industry/GDP	%	–	L2
		Tertiary industry/GDP	%	+	L3
	Society	Environmental protection expenditure/GDP	%	+	L4
		Per capita daily consumption of tap water for residential use	Liter/day	–	L5
		Public buses and trolley buses per 10,000 population	Unit	+	L6
	Energy	Electricity consumption by region	100 million kW·h	–	L7
	Environment	Per capita public green areas	sq.m	+	L8
		Forest coverage rate	%	+	L9
		Daily disposal capacity of city sewage	10,000 cu.m	+	L10
		Volume of sulfur dioxide emission	10,000 tons	–	L11
		COD discharged of industry waste water	Ton	–	L12
Technology innovation capability	TI agglomeration	The R&D expenditure input intensity	%	+	T1
		Full-time equivalent of R&D personnel by region	Man-year	+	T2
		The number of R&D institutions	Unit	+	T3
	TI transformation	Scientific papers issued of higher education institutions	Piece	+	T4
		Patent in force of higher education institutions	Piece	+	T5
		Domestic patent granted by region	Piece	+	T6
	TI support	Expenditure on new products development	10,000 yuan	+	T7
		Intramural expenditure on R&D by region	10,000 yuan	+	T8
New urbanization level	Demographic urbanization	Proportion of urban population	%	+	U1
		Population density of urban area	Persons/sq.km	+	U2
		Registered unemployment rate in urban area	%	–	U3
	Economic urbanization	Per capita GDP	Yuan	+	U4
		Per capita disposable income in urban area	Yuan	+	U5
	Social urbanization	The proportion of expenditure on social security and employment in total government expenditure	%	+	U6
		Health technical personnel in health care institutions per 1,000 persons	Person	+	U7
		Public buses and trolley buses per 10,000 population	Unit	+	U8
		Per capita area of paved roads	sq.m	+	U9
	Green urbanization	Particulate matter emission in waste gas	10,000 tons	–	U10
		Amount of pollutants discharged in waste water	10,000 tons	–	U11
		Green covered area rate of completed area	%	+	U12

Secondly, calculate the proportion of the *i-th* sample in the *j-th* index.

$$\rho_{ij} = \frac{X'_{ij}}{\sum_{i=1}^{n} X'_{ij}} \tag{3}$$

Thirdly, calculate the information entropy of the index e_j. N denotes the number of samples. In this paper, N = 30. To avoid $\ln \rho_{ij}$ is meaningless, it is stipulated that if $\rho_{ij} = 0$, then $\lim_{\rho_{ij}\to 0} \rho_{ij} \ln \rho_{ij} = 0$.

$$e_j = -\frac{1}{\ln N} \sum_{i=1}^{n} \left(\rho_{ij} \times \ln \rho_{ij}\right), \left(0 \le e_j \le 1\right) \tag{4}$$

Fourthly, calculate the difference coefficient d_j and index weight w_j.

$$d_j = 1 - e_j \tag{5}$$

$$w_j = \frac{d_j}{\sum_{j=1}^{m} d_j} \tag{6}$$

Coupling coordination model

The coupling coordination model involves the calculation of three index values: the coupling degree (C-value), the comprehensive coordination index (T-value) and the coupling coordination degree (D-value). Finally, the system's coupling coordination status is obtained by combining the D-value and the coordination level division standard. The C-value mainly reflects the strength of correlation between systems/elements. It does not distinguish the pros and cons, nor the level of system coordination. The T-value is used to measure the contribution value of the overall development level of the system/factor to the coupling degree. While, the D-value can indicate the size of benign coupling degree in the interaction, reflecting the degree of good or bad coordination status. This study uses the D-value to reflect the coupling coordination degree (CCD) of interaction between the LCD quality, TI capability and NU level.

Comprehensive evaluation functions

Calculate the comprehensive development levels of each subsystem in different years according to the linear weighting method (Formula 7).

$$Q = \sum_{i=1,j=1}^{n,m} w_{ij} \times X_{ij}^{+} \left(or\ X_{ij}^{-}\right) \tag{7}$$

Coupling coordination degree model

The established studies involve binary system coupling and ternary system coupling, and this study refers to the studies of Wang et al. (61), Cheng et al. (47), and Zhang and Li (62) to derive specific measurement models as follows:

$$C = \sqrt[3]{\frac{Q1 \times Q2 \times Q3}{\left(\frac{Q1+Q2+Q3}{3}\right)^3}} \tag{8}$$

$$\begin{cases} T = \delta Q_1 + \varepsilon Q_2 + \vartheta Q_3 \\ D = \sqrt{C \times T} \end{cases} \tag{9}$$

In Formulas (8) and (9), Q1, Q2, and Q3 denote the comprehensive evaluation index of LCD, TI, and NU subsystems. C is the coupling degree of the three subsystems, with the value domain space of [0, 1]. D is the coupling coordination degree. T is the comprehensive evaluation index. Their value domain space are both [0, 1]. $\delta,\varepsilon,\vartheta$ are the coefficients to be determined, indicating the importance of the three subsystems. They satisfy $\delta + \varepsilon + \vartheta = 1$. In this paper, we consider LCD, TI and NU as equally important, so we make $\delta = \varepsilon = \vartheta = 1/3$.

In order to intuitively represent the coupling coordination status of the three subsystems, the above CCD is divided into the following levels (Table 3).

TABLE 3 Coupling coordination degree level type of LCD quality/TI capability/NU level.

Category	Coupling coordination value (D)	Coordination level
Maladjusted	0.0 ≤ D ≤ 0.2	Severely maladjusted
	0.2 < D ≤ 0.3	Moderately maladjusted
	0.3 < D ≤ 0.4	Slightly maladjusted
General coordination	0.4 < D ≤ 0.5	On the verge of maladjustment
	0.5 < D ≤ 0.6	Barely coordinated
	0.6 < D ≤ 0.7	Primary coordination
Higher coordination	0.7 < D ≤ 0.8	Moderately coordinated
	0.8 < D ≤ 0.9	Good coordinated
	0.9 < D ≤ 1	Pre-eminently coordinated

Exploratory spatial data analysis

In order to explore the spatial correlation characteristics of the coupling level of the "LCD-TI -NU" system in China, this paper conducts spatial autocorrelation test and analyze the spatial correlation between systems based on *Global Moran's I* index. The formula is as follows:

$$Global\ Moran's\ I = \frac{n \sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij}(y_i - \bar{y})(y_j - \bar{y})}{\left(\sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij}\right) \sum_{i=1}^{n} (y_i - \bar{y})^2} \tag{10}$$

In Formula (10), *I-value* indicates the global autocorrelation Moran index, which is used to determine whether there is a correlation between spatial entities in a certain range. The range of *I-value* is $-1 \leq I \leq 1$, $I > 0$ means positive spatial correlation, $I < 0$ means negative spatial correlation, and $I = 0$ means no correlation. n indicates the number of spatial units. y_i and y_j indicate the observed values of coupling coordination of province i and province j. y indicates the average value of coupling coordination of each province. w_{ij} is the distance spatial weight of provinces i and j, $w_{ij} = 1$ when i and j are adjacent, $w_{ij} = 0$ when i and j are not adjacent.

To further explore whether there is spatial heterogeneity, this paper performs a local spatial autocorrelation test based on the *Local Moran's I* index.

$$Local\ Moran's\ I_i = \frac{n(y_i - \bar{y})\sum_{j=1, j\neq i}^{n} w_{ij}(y_j - \bar{y})}{\sum_{i=1}^{n}(y_i - \bar{y})^2} \quad (11)$$

In Formula (11): I_i represents the local Moran's coefficient for the *i-th* region. $I_i > 0$ indicates that the high (low) value of *province-i* is surrounded by the high (low) values. $I_i < 0$ indicates that the high (low) value of *province-i* is surrounded by the low (high) values. y_i and y_j are observed values. $\bar{y}$ is the mean value. w_{ij} is the spatial weight value.

Obstacle degree model

This paper hopes to identify the subsystems and indexes that have a significant impact on the CCD of "LCD-TI-NU", with the aim of proposing reasonable optimization solutions for improving the synergistic development of the three subsystems in each region. The obstacle degree model is often used to identify the obstacles affecting things development (63) and specify key factors and effect degree. In this paper, this model is more operationally feasible and practically valuable given the relationship between the formulas. The formula is as follows.

$$O_{ij} = \frac{(1-X'_{ij})\times w_j}{\sum_j^m w_j\times(1-X'_{ij})} \quad (12)$$

In Formula (12), O_{ij} represents the obstacle degree of the *j-th* index in the *i-th* sample. X_{ij}' is the standardized value of the *j-th* index in the *i-th* sample. The difference between 1 and $X_{ij}'s$ indicates the difference between the actual value of the index and the optimal value. w_j is the weight of the index (64, 65).

Empirical research and analysis of results

Based on the data of 30 China's provincial regions from 2009 to 2019, this paper calculated the comprehensive evaluation index of each subsystem using MATLAB software, and obtained the coupling degree and CCD of the three subsystems based on the coupling coordination model (Table 3). In order to explore the spatial differences and evolutionary characteristics of the coupling coordination, this paper analyzed and examined the spatial autocorrelation of the data with the help of ArcGIS and GeoDa software.

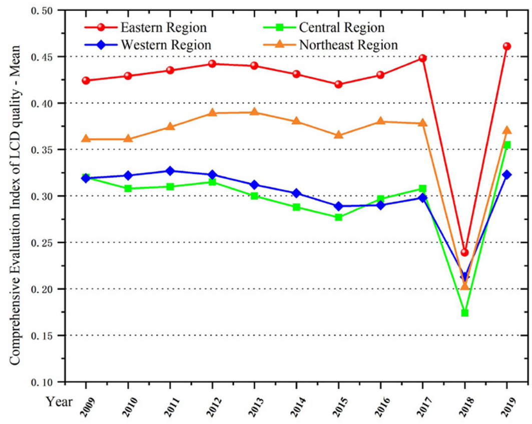

FIGURE 1
Comprehensive evaluation index of LCD quality in four regions of China, 2009–2019.

Comprehensive evaluation index analysis of the LCD/TI/NU subsystem

As shown in Figure 1, the region's LCD quality shows a slow improvement and up-and-down fluctuation from 2009 to 2019. During this period, the LCD quality of the eastern region is significantly superior to other regions, followed by the northeast region. LCD quality of the central and western regions is the lowest. Compared with the eastern region, the northeast region's industrialization shows a continuous trend of expansion. Economic growth is heavily dependent on the secondary industry, resulting in high energy consumption in the region. However, there are more traditional industries and resource-consuming industries in the central and western regions, which lead to large consumption of electricity and water resources. Meanwhile, due to their relatively backward awareness of green development, the LCD quality of these two regions is not good enough. In 2018, the comprehensive evaluation index of LCD reached an inflection point, and it declined sharply in various regions. In terms of the international situation, global carbon emissions from energy consumption grew in 2018 at the fastest rate since 2010. At the same time, many of the world's major energy consumers, particularly the United States, China and Russia, have experienced large amounts of unusual weather, which has boosted demand for heating or cooling. Meanwhile, China's energy-intensive

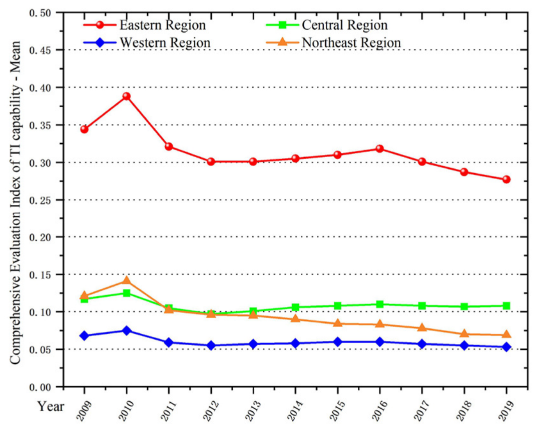

FIGURE 2
Comprehensive evaluation index of TI capability in four regions of China, 2009–2019.

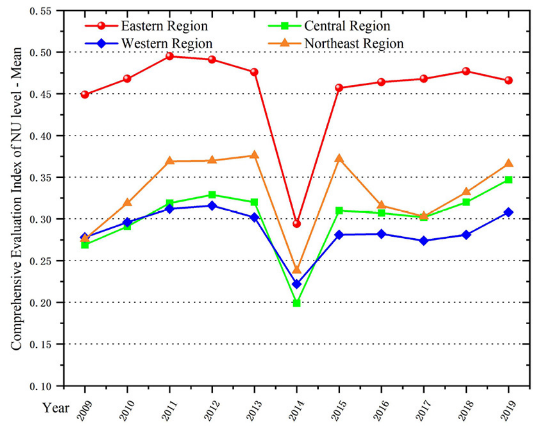

FIGURE 3
Comprehensive evaluation index of NU level in four regions of China, 2009–2019.

industries were undergoing transformation in 2018. The cyclical nature of industrial transformation has led to a rebound in energy demand and consumption. Moreover, while population density has increased, infrastructure development has lagged slightly. These factors directly contributed to a further decline in the quality of LCD across the country in 2018, marking an inflection point. On the whole, the regions with high qualities of LCD include Beijing, Guangdong, Shanghai and Jiangsu. These regions have a relatively high level of economic superiority and rapid industrial upgrading. The tertiary industry in these regions accounts for a high proportion, and the supporting service industry is relatively well developed. Therefore, they are outstanding in the efficient use of resources, energy and environmental pollution control. Also, these regions have stricter enforcement standards on emission targets so that they emit less pollutants and have obvious advantages in LCD.

In terms of the comprehensive development level of TI (Figure 2) from 2009 to 2019, the national level of TI has been continuously improved, and the TI capability in the eastern region is far ahead of other regions, showing a fault-type leading situation. The reason for this is the high level of economic development in eastern regions. Furthermore, the concentration of qualified technical talents and the increased number of high-tech enterprises lead to the abundance of innovation energy in the region. The western region, on the other hand, has a low overall innovation capacity due to the limited innovation environment, innovation resources and insufficient transformation of results in most provinces. Several provinces and cities with more prominent TI capabilities mainly include: Beijing, Guangdong, Jiangsu, Sichuan and Shaanxi.

In terms of the comprehensive development level of NU (Figure 3), the eastern region is still ahead of other regions, followed by the northeast region. The reason is that the northeast region of China covers most of the heavy industrial industries. These places have a higher level of industrialization, more developed railroad transportation and higher urbanization rates. In 2014, the NU level in all regions declined sharply and reached an inflection point. According to the observation data analysis, we found that in December 2013, the government made the first attempt to implement the *National New Type Urbanization Plan (2014–2020)*, and carried out a series of comprehensive pilot projects nationwide. However, due to the initial stage, each region was facing multiple pressures. Population urbanization took precedence over land urbanization, and regions expanded industries to absorb more people, which also led to extremely prominent environmental pollution problems as a result. Moreover, the registered unemployment rate in urban areas has increased significantly. It was particularly prominent in developed regions and neighboring provinces. Since 2015, the level of NU in various regions has begun to rise. The growth rate of NU was very fast in central and western regions, such as Guizhou, Yunnan, Gansu, Guangxi and Ningxia provinces. These regions had relatively low urbanization rates due to their mountainous terrain with little flat land, lagging education development and late start of industrialization. However, it has shown a trend of steady increase in recent years.

Spatial-temporal characteristics of the "LCD-TI-NU" system

As shown in Table 4 and Figure 4, the mean values of coupling degree and CCD of "LCD-TI-NU" system from 2009 to 2019 is 0.804 and 0.472, respectively. This indicates that the LCD quality, TI capability and NU level in China are at a high level of synchronization, showing an obvious interaction relationship.

TABLE 4 Coupling coordination degree of the "LCD-TI-NU" system, 2009–2019.

Region	Province	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019
Eastern region	Beijing	0.813	0.765	0.805	0.802	0.812	0.762	0.820	0.816	0.805	0.707	0.785
	Tianjin	0.522	0.551	0.539	0.549	0.559	0.515	0.550	0.551	0.547	0.475	0.507
	Hebei	0.445	0.468	0.446	0.436	0.438	0.404	0.442	0.443	0.446	0.403	0.457
	Shanghai	0.674	0.680	0.664	0.662	0.649	0.608	0.650	0.650	0.654	0.569	0.621
	Jiangsu	0.711	0.742	0.717	0.724	0.718	0.660	0.705	0.712	0.701	0.626	0.687
	Zhejiang	0.677	0.700	0.672	0.651	0.652	0.599	0.642	0.649	0.646	0.591	0.656
	Fujian	0.512	0.537	0.512	0.506	0.504	0.458	0.494	0.496	0.502	0.465	0.514
	Shandong	0.572	0.613	0.584	0.580	0.576	0.517	0.553	0.566	0.568	0.505	0.562
	Guangdong	0.725	0.765	0.740	0.723	0.710	0.653	0.702	0.732	0.745	0.677	0.751
	Hainan	0.290	0.318	0.321	0.317	0.308	0.277	0.301	0.299	0.297	0.276	0.308
	Mean	0.594	0.614	0.600	0.595	0.592	0.545	0.586	0.591	0.591	0.529	0.585
Central region	Shanxi	0.385	0.387	0.390	0.389	0.397	0.365	0.390	0.395	0.374	0.343	0.395
	Anhui	0.457	0.460	0.474	0.472	0.474	0.434	0.466	0.466	0.474	0.435	0.500
	Jiangxi	0.432	0.457	0.428	0.422	0.417	0.378	0.408	0.420	0.436	0.396	0.449
	Henan	0.466	0.469	0.463	0.464	0.454	0.427	0.462	0.472	0.474	0.437	0.492
	Hubei	0.514	0.525	0.521	0.513	0.510	0.471	0.502	0.511	0.506	0.464	0.519
	Hunan	0.485	0.498	0.480	0.474	0.476	0.446	0.477	0.478	0.482	0.447	0.524
	Mean	0.457	0.466	0.460	0.456	0.454	0.420	0.451	0.457	0.458	0.420	0.480
Western region	Inner Mongolia	0.348	0.374	0.360	0.365	0.371	0.340	0.363	0.370	0.356	0.308	0.338
	Guangxi	0.404	0.440	0.392	0.385	0.375	0.340	0.360	0.359	0.373	0.341	0.377
	Chongqing	0.431	0.461	0.467	0.471	0.464	0.508	0.458	0.457	0.459	0.419	0.473
	Sichuan	0.505	0.496	0.512	0.514	0.510	0.467	0.493	0.494	0.501	0.465	0.524
	Guizhou	0.338	0.379	0.352	0.348	0.340	0.313	0.341	0.338	0.337	0.303	0.347
	Yunnan	0.404	0.444	0.405	0.392	0.377	0.353	0.390	0.392	0.388	0.349	0.398
	Shaanxi	0.553	0.535	0.549	0.541	0.542	0.497	0.518	0.519	0.505	0.461	0.526
	Gansu	0.373	0.390	0.377	0.385	0.374	0.346	0.372	0.372	0.357	0.318	0.356
	Qinghai	0.291	0.315	0.289	0.280	0.272	0.248	0.237	0.218	0.248	0.208	0.248
	Ningxia	0.312	0.333	0.309	0.304	0.308	0.287	0.306	0.297	0.315	0.289	0.331
	Xinjiang	0.341	0.385	0.325	0.313	0.319	0.304	0.330	0.324	0.304	0.358	0.299
	Mean	0.391	0.414	0.394	0.391	0.387	0.364	0.379	0.376	0.377	0.347	0.383
Northeast region	Liaoning	0.516	0.523	0.533	0.526	0.524	0.472	0.503	0.497	0.496	0.440	0.487
	Jilin	0.431	0.458	0.437	0.440	0.437	0.399	0.416	0.406	0.395	0.362	0.412
	Heilongjiang	0.477	0.521	0.488	0.492	0.499	0.463	0.495	0.477	0.464	0.415	0.467
	Mean	0.474	0.501	0.486	0.486	0.487	0.445	0.471	0.460	0.451	0.406	0.455

However, due to the low level of comprehensive development of each subsystem and the differences between regions, the overall CCD is not high. This further shows that there is still a huge potential for system optimization.

From the perspective of time evolution, the year of 2014 is the cut-off point for the system's CCD of China's regions. Before 2014, it showed a state of fluctuation, and after 2014, the overall CCD showed a slow downward trend. Combined with the comprehensive evaluation index, this paper finds that the comprehensive development level of TI subsystem fluctuates, and the overall trend is declining. The indexes are reflected in the *Number of R&D Institutions*, the *Full-Time Equivalent of R&D Personnel by Region*, and the *Decrease of Expenditure on New Products Development*. Also, the differences between regions are distinct. At the same time, the overall coupling coordination pattern of provinces and cities has obvious gap and is extremely unbalanced. During the study period, the overall CCD of LCD quality, TI capability and NU level in each region are still in the breaking-in period. Turning points occurred in 2014 and 2018. Generally speaking, subsystem's development level is related to the coupling coordination level of the whole system. In 2014, the overall CCD dropped sharply from 0.479 to 0.444 due to the short lag of the NU subsystem. Similarly, in 2018, the LCD subsystem faced the increasing energy consumption and pollution deterioration, which led to the low comprehensive evaluation index, and finally affected the coupling coordination development of the three subsystems. The CCD decreased from 0.472 to 0.428 during the year, reaching the lowest value in the study period. In order to improve the coordinated development level of "LCD-TI-NU" system among regions, it is necessary to emphasize the integrity and synergy of relevant policies and measures, and promote the overall optimization on the basis of improving the comprehensive level of each subsystem.

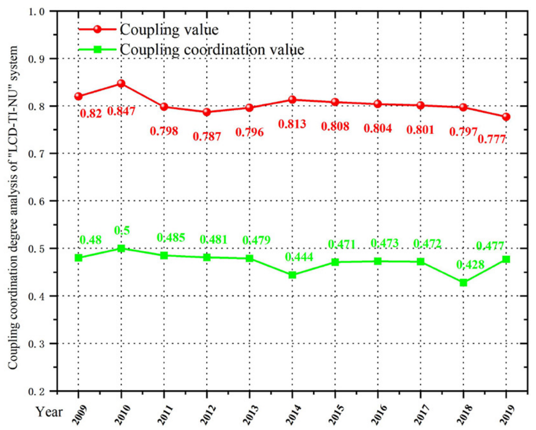

FIGURE 4
Coupling coordination degree analysis of "LCD-TI-NU" system in China, 2009–2019.

From the perspective of spatial distribution (Figures 5, 6), the coupling coordination level of the three subsystems in China is gradually decreasing in the eastern, northeast, central and western regions. Specifically, the CCD in the eastern region fluctuates from 0.529 to 0.614, and is always higher than the national average level, reaching the level of barely coordination. Among them, Beijing, Shanghai, Jiangsu and Guangdong perform better. These four regions show a good coordination trend, followed by Zhejiang and Shandong provinces, which maintain the primary coordination level. The average level of coupling coordination between northeast and central regions is about the same, and the CCD is concentrated around 0.45, which belongs to the verge of maladjustment. In central regions, with the exception of Hubei Province in some years (2014 and 2018), the CCD is above 0.5, which is at the level of barely coordinated. The CCD of Hunan Province and Anhui Province shows a slow upward trend, reaching 0.5 in 2019, from the level of near maladjustment to the barely coordinated level. In western regions, the CCD of almost all provinces and cities is lower than 0.5 except Shaanxi Province and Sichuan Province, which reach the barely coordinated level. The CCD of almost all regions is about 0.3 and 0.4. This means that the LCD quality, TI capability and NU level in these regions are in a slightly maladjusted level, which needs to be paid attention to. As the TI capability of the

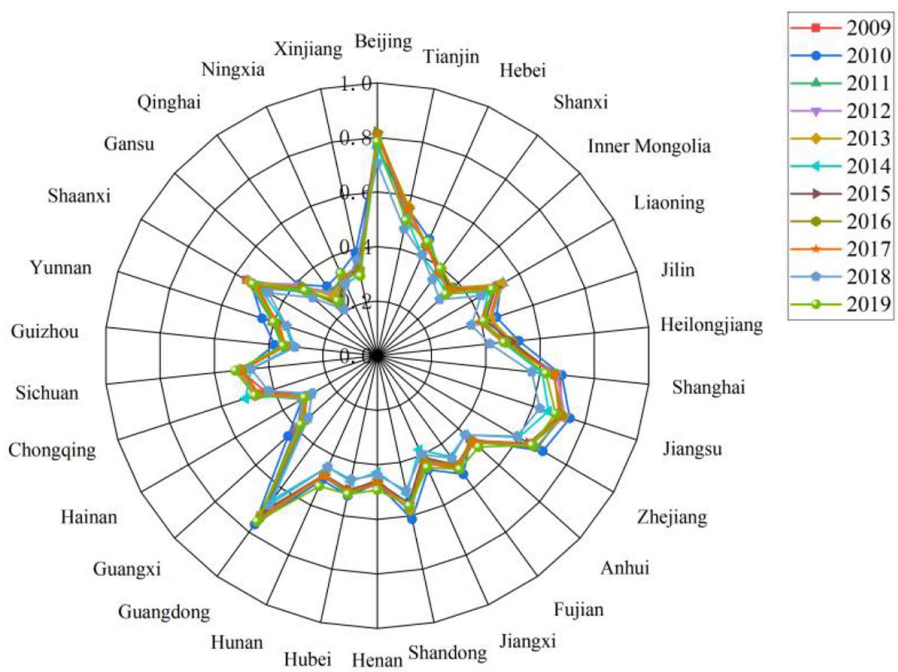

FIGURE 5
Coupling coordination degree of "LCD-TI-NU" system in China's provinces and cities, 2009–2019.

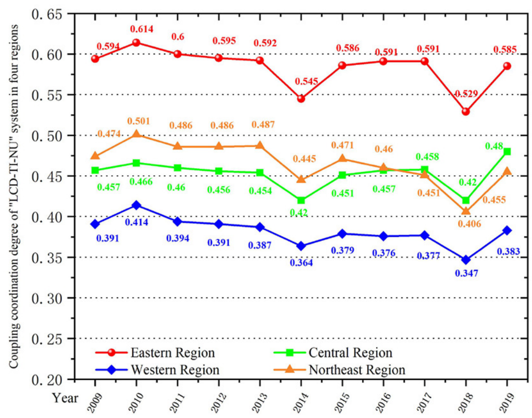

FIGURE 6
Coupling coordination degree analysis of “LCD-TI-NU” system in four regions, 2009–2019.

western region is significantly lower than that of other regions, the TI capability lags behind the LCD quality and NU process, resulting in a large gap between subsystems. This also leads to the lowest CCD in western regions. Although in recent years, the country has a certain policy tilt and encouragement measures to the western regions so that TI capability has been improved to a certain extent. However, it is still in a backward position in the whole country. This requires these western regions to balance the relationship between LCD, TI and NU. Moreover, attention should be paid to the role of TI capability in realizing low-carbon environmental protection development and smart city construction.

From the perspective of spatial pattern (Table 5; Figure 7), there is spatial and temporal variability in the coupling coordination levels of “LCD-TI-NU” system. In 2010, the CCD is divided into five grades: “*slightly maladjusted*” to “*moderately coordinated*”. In the year of 2014, 2018, and 2019, it is divided into 6 grades from “*moderately maladjusted*” to “*moderately coordinated*”. The CCD’s span of the other years is from “*moderately maladjusted*” to “*good coordinated*”, a total of 7 grades. This also indicates that there are huge regional differences in the coupling coordinated development level of this system. In Table 5, from 2009 to 2013, the regions with CCD > 0.5 (that is, reaching the coordinated level) accounted for 40%. It fell to 26% in 2014 and 20% in 2018, and then increased to 43% in 2019. It can be seen that the increase of the overall CCD is not high, but the regions that reach the level of coordinated level show a slow upward trend. In Figure 7, the spatial characteristics in 2009, 2013, 2018, and 2019 are more representative. It can be seen from this that from 2009 to 2018, the regions on the verge of maladjustment do not show a trend of leapfrog to the direction of barely coordinated, but show a trend of malignant development. For example, Yunnan, Guangxi and Jiangxi all enter the grade of slightly maladjusted in 2018 (Figure 7C). In 2019 (Figure 7D), the situation begins to improve, with the Sichuan, Shaanxi, Hubei, Hunan, Fujian and Anhui provinces all reaching the barely coordinated level. Guangdong Province also enters the moderately coordinated level. In terms of spatial pattern, the provinces with coupling maladjustment are mainly concentrated in the western region, while the central and northeast regions are mainly on the verge of maladjustment and barely coordinated, and there is still a lot of room for improvement. The eastern region has the highest overall level of coordinated development, with the exception of Hainan, Hebei and Fujian in some years, all provinces have reached the primary coordination level. Furthermore, the standard deviation of the CCD of 30 provincial administrative regions in China is 0.1337 in 2009 and decrease to 0.1312 in 2019, while the standard deviation reflects the degree of dispersion of the sample data. The decrease in standard deviation indicates a tendency for the differences between provinces to narrow.

Spatial correlation analysis of the “LCD-TI-NU” system

Global spatial autocorrelation

The results show that the Moran’s I of the coupling coordination levels are all significantly positive with $P < 0.01$ and $Z > 2.5$ during the period 2009–2019 (Table 6). It indicates that there is a significant positive correlation between the three subsystems and shows a significant agglomeration effect. The CCD is higher in the surrounding areas of areas with high CCD. Moran’s *I*- and *Z*-values show a fluctuating increase with the passage of time. This further indicates that the system’s spatial agglomeration degree is increasing.

Local spatial autocorrelation

This paper used local Moran’s I index scatter plots with LISA agglomerative plots in typical years (2009/2010/2019) to reflect the local situation of spatial linkage. The scatter plot represented the observed values’ linear combination in any region and the observed values in other regions.

In Figure 8, the horizontal axis represents the standardized data (observed values) of CCD in province-*i*, and the vertical axis represents the linear combination’s observed values of CCD in other regions. The quadrants one and three in the coordinate axes indicate the clustering of high-high values and low-low values, respectively, which represent positive spatial autocorrelation and indicate the clustering of similar values. On the contrary, quadrants two and four represent the clustering of low-high value (Province-*i* is low value, but all surrounding areas are high value) and high-low (Province-*i* is high value, but all surrounding areas are low value), respectively, indicating that there is negative spatial autocorrelation in this region, which is a

TABLE 5 Number of provinces and cities with different coupling coordination levels in China, 2009–2019 (unit).

Classification	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019
Good coordinated	1	0	1	1	1	0	1	1	1	0	0
Moderately coordinated	2	3	2	2	2	1	2	2	2	1	2
Primary coordination	2	3	2	2	2	3	2	2	2	2	3
Barely coordinated	7	6	7	7	7	4	5	4	6	3	8
On the verge of maladjustment	10	10	9	8	8	10	10	11	8	12	7
Slightly maladjusted	6	8	8	9	9	9	9	7	9	9	8
Moderately maladjusted	2	0	1	1	1	3	1	3	2	3	2

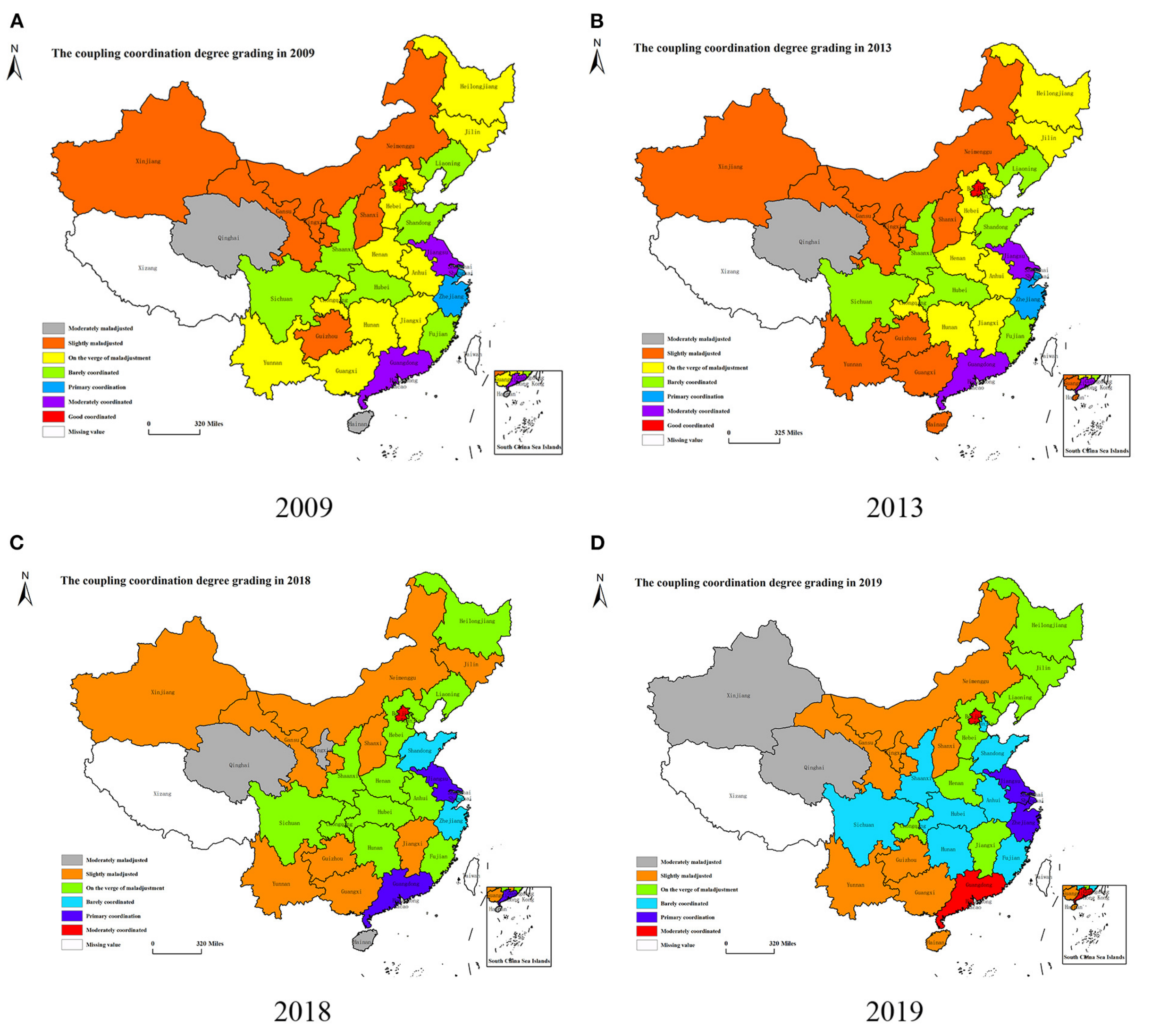

FIGURE 7
(A–D) Spatial distribution of coupling coordination degree of "LCD-TI-NU" system in some years.

spatial anomaly. In Figures 8A–C, the local Moran's I in 2009, 2010, and 2019 are 0.182, 0.203, and 0.210, and the P-values are <0.05, which are statistically significant. Also, the numbers of scattered points falling into quadrants one and three are 18, 21, and 20, with proportions of 60, 70, and 66.7%, respectively. Overall, the spatial correlation of the CCD of the "LCD-TI-NU"

TABLE 6 Results of the Global Moran's *I*-test.

Variable	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019
Moran's *I*	0.321	0.359	0.328	0.327	0.330	0.317	0.338	0.341	0.376	0.330	0.365
Z-value	2.763	3.050	2.812	2.804	2.828	2.733	2.910	2.930	3.192	2.834	3.101
P-value	0.006	0.002	0.004	0.005	0.005	0.006	0.004	0.003	0.001	0.005	0.002

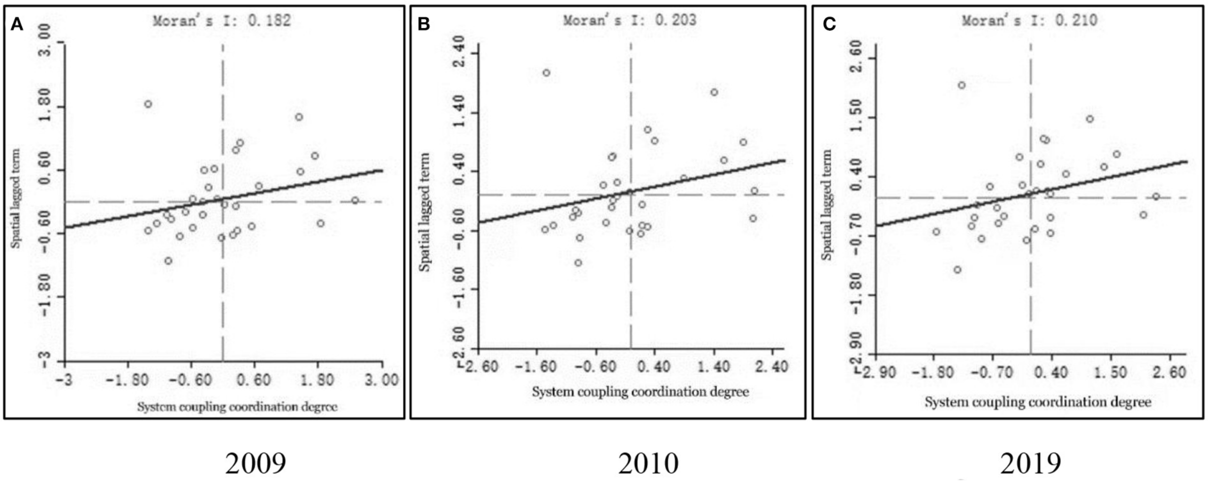

FIGURE 8
(A–C) Moran scatter plot of coupling coordination degree in 2009, 2010, and 2019.

system in Chinese provinces shows an increasing trend during the study period, with up and down fluctuations in a few years.

As shown in Figures 9A,B, the provinces with high CCD are mostly concentrated in the eastern regions, such as Jiangsu, Fujian and Shanghai. The regions with low values are mainly in the western regions of Gansu, Sichuan and Xinjiang. The main representative provinces of high-low agglomeration are Shaanxi Province in 2010 and Sichuan Province in 2019. These two regions are among the provinces with high CCD, but their surrounding areas are low-value provinces. Low-high agglomeration is exemplified by Hainan and Jiangxi provinces, which have a low CCD of their own, but their neighboring provinces such as Guangdong, Hubei and Fujian are high-value provinces. The state of positive spatial correlation (H-H and L-L) has increased. The increase of coupling coordination level in the eastern region will lead to the improvement of the overall situation in the central and western regions in turn.

Identification of obstacle factors in the "LCD-TI-NU" system

The obstacle factors affecting the synergetic development of the three subsystems are shown in Table 7. In this paper, the first three indexes of obstacle degree are selected. Figures 10, 11 list first three indexes in terms of obstacle degree for each province and city each year of LCD quality and NU level, respectively. There are differences in the color of the indexes at different layers, which facilitates the visual clarification of the main factor layer of the obstacle factors in different regions. The regional variability of index obstacle degree in TI subsystem is not significant, so the obstacle indexes for each region are not shown separately.

In the LCD subsystem (Table 7), the highest barrier rate in 2009–2012 and 2019 is the *Daily Disposal Capacity of City Sewage* (L10), and this index is found in the first three for each year. This is followed by *Secondary Industry/GDP* (L2), *Tertiary Industry/GDP* (L3) and *Gross Regional Product* (L1). *Environmental Protection Expenditure/GDP* (L4) is the most influential index in 2018 with a value of 59.9%. This result is consistent with the sharp decline and inflection point of the comprehensive evaluation index of the LCD in 2018. The situation starts to improve in 2019, with the obstacle degree of L4 dropping to 8.3%. From Figure 10, it can be seen that the indexes affecting the LCD quality are mainly at the economic level (L1-L3), followed by the environmental indexes (L8-L12). Spatially, the eastern and central regions are more affected by the social dimension (L6). The main obstacle factors in the central and western regions are roughly the same as the average. The

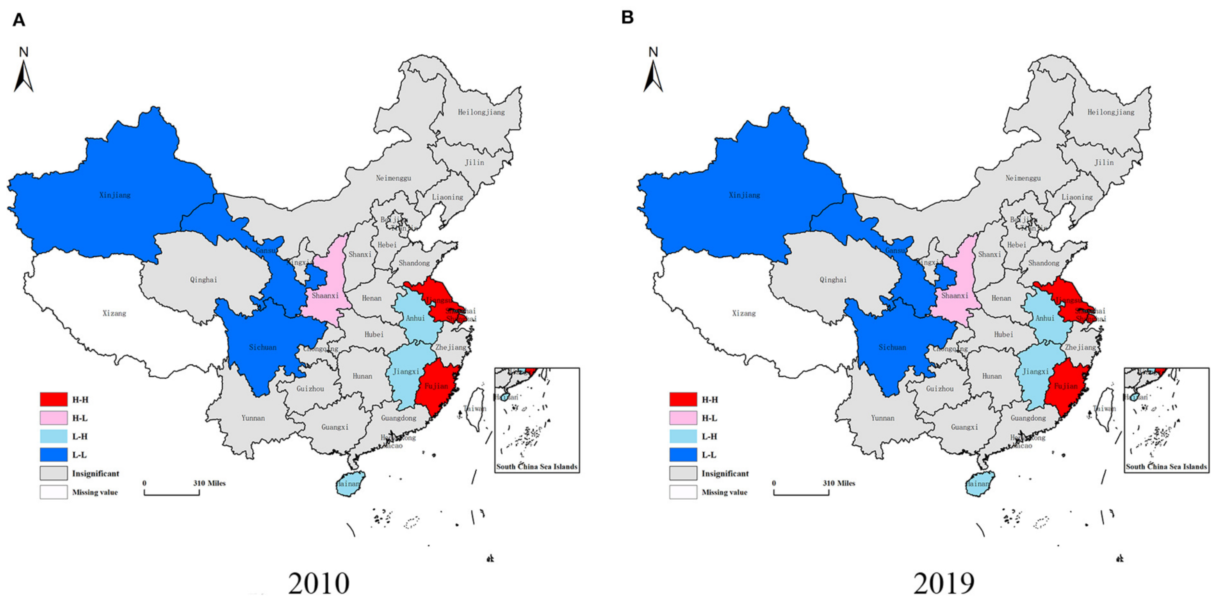

FIGURE 9
(A,B) LISA agglomerative plot of system coupling coordination degree in 2010 and 2019.

TABLE 7 Obstacle indexes of each subsystem, 2009–2019.

	LCD subsystem			TI subsystem			NU subsystem		
	1st	2nd	3rd	1st	2nd	3rd	1st	2nd	3rd
2009	L10 (16.1%)	L6 (15.7%)	L1 (14.6%)	T7 (20.9%)	T8 (20.1%)	T6 (15.7%)	U5 (15.5%)	U8 (13.7%)	U4 (12.8%)
2010	L10 (17.6%)	L2 (15.3%)	L1 (13.8%)	T7 (23.6%)	T6 (17.3%)	T3 (16.6%)	U5 (16.8%)	U8 (12.5%)	U3 (12.3%)
2011	L10 (16.5%)	L3 (13.8%)	L2 (13.1%)	T7 (20.4%)	T8 (19.3%)	T6 (16.0%)	U5 (18.5%)	U4 (12.6%)	U1 (11.7%)
2012	L10 (16.4%)	L3 (15.0%)	L2 (14.2%)	T7 (19.4%)	T8 (17.8%)	T3 (17.2%)	U5 (18.8%)	U4 (13.4%)	U3 (13.4%)
2013	L3 (16.0%)	L10 (14.9%)	L2 (12.7%)	T8 (19.1%)	T3 (19.0%)	T7 (18.9%)	U5 (18.9%)	U4 (13.8%)	U8 (13.7%)
2014	L3 (17.1%)	L2 (15.5%)	L10 (14.4%)	T7 (20.2%)	T8 (19.7%)	T3 (19.6%)	U12 (47.4%)	U5 (10.1%)	U4 (8.4%)
2015	L2 (19.1%)	L3 (18.7%)	L10 (13.3%)	T7 (20.7%)	T3 (20.0%)	T8 (19.6%)	U5 (18.1%)	U4 (12.6%)	U2 (12.4%)
2016	L2 (20.0%)	L3 (15.1%)	L10 (14.9%)	T3 (21.9%)	T7 (21.2%)	T8 (19.3%)	U5 (17.9%)	U4 (12.6%)	U3 (11.6%)
2017	L3 (19.1%)	L10 (16.3%)	L1 (14.4%)	T3 (23.1%)	T7 (21.1%)	T8 (17.9%)	U5 (18.5%)	U4 (12.1%)	U1 (11.9%)
2018	L4 (59.9%)	L10 (7.7%)	L3 (7.0%)	T3 (23.8%)	T7 (20.5%)	T8 (17.4%)	U5 (18.9%)	U6 (13.5%)	U4 (12.6%)
2019	L10 (18.2%)	L3 (16.6%)	L1 (16.5%)	T3 (23.5%)	T7 (21.0%)	T8 (17.9%)	U5 (21.3%)	U6 (14.4%)	U1 (13.2%)

1st, 2nd, and 3rd indicate the first, second and third obstacle factors of each subsystem, respectively.

eastern regions are less affected by the economic dimension and more by the environment with their superior economic and trade advantages.

In the TI subsystem (Table 7), before the year of 2012, it was strongly influenced by the *Domestic Patent Granted by Region* (T6). Since 2012, the indexes that negatively affect the comprehensive development level of TI subsystem are mainly the *Expenditure on New Products Development* (T7), *Intramural Expenditure On R&D by Region* (T8) and *Number Of R&D Institutions* (T3). The first three obstacle factors in most areas are consistent with the average level. In eastern regions, such as Jiangsu Province and Guangdong Province, T1 and T5 have a negative impact on the improvement of local TI capacity in different years. Beijing and Shanghai are more influenced by T6.

Among the indexes that hinder the improvement of the comprehensive level of the NU subsystem (Table 7), the highest obstacle is the *Per Capita Disposable Income in Urban Area* (U5), followed by *Per Capita GDP* (U4). In 2009–2013, the obstacle degree of U8 and U3 are higher. In recent years, the obstruction degree of U6 andU1 also increased year by year. The obstacle degree of *Green Covered Area Rate of Completed Area* (U12) was 47.4% in 2014, indicating that U12 is lower in all regions

Province	2009			2010			2011			2012			2013			2014			2015			2016			2017			2018			2019			Region
Beijing	L10	L1	L9	L10	L1	L9	L10	L1	L9	L10	L1	L9	L10	L1	L9	L10	L1	L9	L10	L1	L9	L10	L1	L9	L10	L1	L9	L4	L10	L1	L10	L1	L4	Eastern Region
Tianjin	L10	L1	L9	L10	L2	L1	L10	L1	L2	L10	L2	L1	L10	L1	L2	L2	L10	L3	L2	L3	L10	L2	L10	L1	L10	L1	L3	L4	L10	L1	L10	L1	L9	
Hebei	L6	L2	L10	L2	L10	L6	L3	L10	L2	L3	L2	L10	L3	L2	L10	L3	L2	L10	L2	L3	L10	L2	L3	L10	L3	L2	L10	L4	L3	L10	L3	L10	L1	
Shanghai	L9	L6	L1	L10	L6	L9	L9	L10	L1	L9	L10	L1	L9	L6	L1	L4	L6	L1	L4	L1	L10	L10	L1	L9	L1	L10	L9	L4	L10	L1	L10	L1	L6	
Jiangsu	L2	L9	L6	L2	L9	L6	L2	L9	L3	L2	L3	L9	L3	L2	L9	L2	L3	L9	L2	L3	L9	L2	L3	L9	L3	L2	L9	L4	L3	L2	L3	L9	L2	
Zhejiang	L2	L10	L6	L2	L10	L6	L2	L10	L3	L2	L3	L10	L3	L2	L10	L2	L3	L10	L2	L3	L4	L2	L3	L10	L3	L2	L10	L4	L3	L10	L3	L10	L2	
Fujian	L10	L6	L1	L10	L2	L1	L10	L3	L2	L10	L2	L3	L3	L10	L2	L3	L2	L10	L2	L3	L10	L2	L3	L10	L3	L2	L10	L4	L3	L10	L3	L10	L1	
Shandong	L2	L6	L9	L2	L10	L6	L2	L3	L9	L2	L3	L9	L3	L2	L9	L3	L2	L6	L2	L3	L4	L2	L3	L9	L3	L2	L9	L4	L3	L2	L3	L9	L10	
Guangdong	L6	L2	L5	L2	L6	L3	L2	L3	L12	L2	L3	L5	L3	L2	L6	L2	L3	L6	L2	L3	L4	L2	L3	L4	L3	L2	L6	L4	L3	L2	L3	L2	L6	
Hainan	L10	L1	L6	L10	L1	L6	L10	L1	L3	L10	L1	L3	L10	L1	L6	L10	L1	L3	L10	L1	L3	L10	L1	L3	L10	L1	L3	L4	L10	L1	L10	L1	L3	
Liaoning	L6	L2	L10	L2	L10	L6	L2	L3	L10	L2	L3	L10	L3	L2	L6	L3	L2	L6	L2	L3	L6	L2	L3	L1	L3	L1	L10	L4	L1	L3	L1	L3	L10	Northeast Region
Jilin	L10	L6	L1	L10	L2	L1	L10	L3	L1	L10	L3	L2	L3	L10	L2	L3	L2	L10	L2	L3	L10	L2	L3	L10	L3	L10	L1	L4	L10	L1	L1	L10	L3	
Heilongjiang	L10	L6	L1	L10	L2	L1	L10	L3	L1	L10	L3	L1	L3	L1	L10	L3	L1	L10	L3	L1	L10	L1	L3	L10	L10	L1	L3	L4	L10	L1	L1	L10	L3	
Shanxi	L6	L10	L1	L10	L2	L6	L10	L2	L3	L10	L2	L3	L10	L3	L2	L2	L3	L10	L2	L10	L3	L2	L10	L1	L10	L3	L1	L4	L10	L1	L10	L1	L3	Central Region
Anhui	L6	L1	L10	L2	L10	L6	L3	L10	L2	L3	L2	L10	L3	L2	L6	L3	L2	L10	L2	L3	L10	L2	L3	L10	L3	L2	L10	L4	L3	L10	L3	L10	L1	
Jiangxi	L10	L6	L1	L10	L2	L1	L10	L3	L2	L10	L3	L2	L3	L10	L6	L3	L2	L10	L2	L3	L10	L2	L3	L10	L3	L10	L2	L4	L10	L3	L10	L3	L1	
Henan	L6	L2	L10	L2	L10	L6	L3	L2	L10	L3	L2	L10	L3	L2	L6	L3	L2	L10	L2	L3	L6	L2	L3	L10	L3	L2	L10	L4	L3	L10	L3	L10	L1	
Hubei	L6	L10	L1	L10	L2	L1	L3	L10	L2	L3	L2	L10	L3	L10	L6	L3	L2	L10	L2	L3	L10	L2	L3	L10	L3	L2	L10	L4	L3	L10	L3	L10	L1	
Hunan	L6	L10	L1	L10	L2	L1	L10	L3	L1	L3	L10	L2	L3	L10	L6	L3	L2	L10	L3	L2	L10	L2	L3	L10	L3	L10	L2	L4	L10	L3	L10	L3	L1	
Inner Mongolia	L10	L6	L2	L10	L2	L6	L10	L2	L3	L10	L2	L3	L3	L10	L6	L3	L2	L10	L2	L3	L10	L2	L3	L10	L3	L10	L1	L4	L10	L1	L10	L1	L3	Western Region
Guangxi	L6	L1	L2	L1	L6	L2	L3	L2	L10	L3	L1	L2	L3	L6	L1	L3	L2	L6	L3	L2	L6	L2	L3	L1	L3	L1	L10	L4	L3	L1	L1	L3	L10	
Chongqing	L10	L6	L1	L10	L2	L1	L10	L2	L1	L10	L2	L3	L10	L3	L1	L10	L3	L2	L2	L3	L10	L2	L10	L3	L3	L10	L1	L4	L10	L1	L10	L1	L3	
Sichuan	L10	L6	L1	L10	L2	L1	L10	L3	L2	L3	L10	L2	L3	L10	L2	L3	L2	L10	L3	L2	L10	L2	L3	L10	L3	L10	L1	L4	L10	L3	L3	L10	L1	
Guizhou	L10	L1	L6	L10	L1	L6	L10	L1	L6	L10	L1	L3	L10	L1	L6	L10	L3	L1	L3	L2	L10	L2	L10	L3	L3	L10	L1	L4	L10	L1	L10	L1	L3	
Yunnan	L10	L1	L6	L10	L1	L2	L10	L1	L3	L10	L1	L3	L10	L3	L1	L3	L10	L1	L3	L2	L10	L10	L2	L3	L3	L10	L1	L4	L10	L3	L10	L1	L3	
Shaanxi	L10	L1	L2	L10	L2	L1	L10	L2	L3	L10	L2	L3	L3	L10	L2	L3	L2	L10	L2	L3	L10	L2	L3	L10	L3	L2	L10	L4	L3	L10	L3	L10	L1	
Gansu	L10	L1	L6	L10	L1	L6	L10	L1	L3	L10	L1	L3	L10	L1	L3	L10	L3	L1	L3	L10	L1	L10	L1	L2	L10	L1	L3	L4	L10	L1	L10	L1	L3	
Qinghai	L10	L1	L9	L10	L1	L2	L10	L1	L2	L10	L2	L1	L3	L10	L1	L3	L2	L10	L2	L3	L10	L2	L10	L3	L3	L10	L1	L4	L10	L1	L10	L1	L3	
Ningxia	L10	L1	L9	L10	L1	L2	L10	L1	L3	L10	L1	L2	L10	L1	L3	L10	L3	L2	L2	L3	L10	L2	L10	L1	L3	L10	L1	L4	L10	L1	L10	L1	L3	
Xinjiang	L10	L1	L9	L10	L1	L9	L10	L1	L3	L10	L3	L1	L3	L10	L1	L3	L10	L1	L3	L2	L10	L10	L3	L2	L3	L10	L1	L10	L1	L3	L10	L1	L3	
Average	L10	L6	L1	L10	L2	L1	L10	L3	L2	L10	L3	L2	L3	L10	L1	L3	L2	L10	L2	L3	L10	L2	L3	L10	L3	L10	L1	L4	L10	L3	L10	L3	L1	

Factor layer	L1	L2	L3	L4	L5	L6	L7	L8	L9	L10	L11	L12
	Economy			Society			Eergy	Environment				

FIGURE 10
Top three obstacle indexes of LCD subsystem in different regions, 2009–2019.

compared to the rest of the years and had a more negative impact compared to the other indexes. This also directly leads to the lowest comprehensive evaluation index of NU in 2014. In Figure 11, the main obstacle indexes are concentrated in the economic (U4–U5) and population urbanization dimensions (U1–U3), followed by the social dimension (U6–U9). NU is less influenced by environmental indexes. Furthermore, the obstacle indexes of NU have obvious spatial variability. In eastern regions, the indexes of the social dimension are significantly more than those of the economic dimension. It indicates that compared with other regions, NU in the eastern region focuses more on people's livelihood and basic public service level due to its higher economic level. The central and western regions, on the other hand, are more influenced by economic indexes. In terms of temporal evolution, the obstacle degree of social indexes has gradually increased in recent years, which indicates the growing demand of urban residents for quality public services and social security, etc. However, the current growth rate of investment in livelihood expenditure is low compared to other aspects. In order to create a more harmonious social ecology, the central and western regions should steadily promote infrastructure development on the basis of vigorous economic development. The eastern and northeast regions can expand the investment in public services to improve the quality of life of their people.

Discussion and conclusion

Conclusions

Since the synergistic development relationship between the three subsystems has not yet been clarified, this paper firstly constructed the evaluation index system of LCD quality, TI capability and NU level in combination with current development requirements. Secondly, this paper calculated and analyzed the data based on the entropy method and the coupling coordination model. Subsequently, the comprehensive evaluation index, coupling degree and coupling coordination degree of the three systems in different years of each region were clarified. Finally, this paper conducted descriptive statistics and spatial correlation analysis. On this basis, the obstacle indexes that affected the comprehensive evaluation index of each subsystem were found out by using the obstacle degree model, which also provided ideas for improving the coupling coordination between systems. The result is as follows:

Province	2009			2010			2011			2012			2013			2014			2015			2016			2017			2018			2019			Region
Beijing	U2	U9	U6	U2	U6	U9	U2	U6	U9	U2	U6	U9	U2	U6	U9	U12	U6	U2	U2	U6	U9	U2	U6	U9	U2	U6	U9	U6	U2	U9	U6	U2	U9	Eastern Region
Tianjin	U3	U7	U5	U3	U2	U5	U6	U3	U5	U3	U6	U5	U5	U6	U2	U12	U5	U6	U6	U5	U7	U3	U5	U6	U5	U7	U3	U5	U3	U6	U5	U7	U6	
Hebei	U5	U8	U4	U5	U3	U4	U5	U4	U1	U5	U4	U3	U5	U4	U8	U12	U5	U4	U5	U4	U1	U5	U4	U3	U5	U4	U1	U5	U4	U1	U5	U5	U1	
Shanghai	U3	U8	U2	U3	U8	U6	U3	U8	U6	U3	U6	U8	U8	U3	U6	U12	U8	U6	U6	U8	U3	U3	U8	U6	U3	U8	U7	U6	U8	U3	U6	U8	U12	
Jiangsu	U7	U8	U5	U2	U5	U6	U6	U5	U2	U6	U2	U5	U5	U6	U2	U12	U2	U5	U6	U2	U5	U5	U6	U2	U5	U7	U6	U6	U5	U7	U6	U5	U7	
Zhejiang	U7	U2	U8	U2	U6	U3	U6	U2	U8	U6	U2	U3	U6	U2	U8	U12	U2	U6	U6	U2	U5	U6	U2	U5	U6	U5	U2	U6	U5	U2	U6	U5	U2	
Fujian	U7	U3	U8	U3	U5	U8	U5	U6	U3	U6	U3	U5	U5	U6	U8	U12	U5	U6	U5	U6	U2	U5	U3	U6	U5	U3	U7	U5	U6	U3	U5	U6	U7	
Shandong	U7	U8	U5	U5	U2	U8	U5	U1	U2	U5	U2	U3	U5	U2	U8	U12	U5	U2	U5	U2	U6	U5	U3	U2	U5	U1	U2	U5	U6	U1	U5	U6	U1	
Guangdong	U8	U7	U4	U8	U2	U6	U6	U5	U4	U6	U5	U4	U5	U8	U6	U12	U5	U6	U6	U5	U8	U5	U6	U8	U5	U6	U7	U6	U5	U4	U6	U5	U7	
Hainan	U5	U8	U4	U5	U4	U8	U5	U4	U1	U5	U4	U2	U5	U4	U8	U12	U5	U4	U5	U4	U2	U5	U4	U1	U5	U4	U1	U5	U4	U6	U5	U6	U1	
Liaoning	U5	U8	U7	U5	U8	U2	U5	U3	U8	U5	U3	U2	U5	U8	U2	U12	U2	U5	U5	U2	U8	U5	U4	U3	U5	U4	U8	U5	U4	U3	U5	U7	U1	Northeast Region
Jilin	U5	U8	U7	U5	U2	U3	U5	U4	U8	U5	U3	U4	U5	U8	U4	U12	U5	U4	U5	U4	U8	U5	U4	U8	U5	U4	U1	U5	U4	U1	U5	U1	U8	
Heilongjiang	U5	U3	U4	U5	U3	U4	U5	U4	U3	U5	U3	U4	U5	U4	U8	U12	U5	U4	U5	U4	U8	U5	U4	U3	U5	U4	U3	U5	U4	U3	U5	U1	U7	
Shanxi	U5	U8	U4	U5	U8	U4	U5	U4	U8	U5	U4	U3	U5	U4	U8	U12	U5	U4	U5	U4	U8	U5	U4	U8	U5	U4	U8	U5	U4	U1	U5	U1	U6	Central Region
Anhui	U5	U8	U4	U3	U8	U6	U5	U4	U1	U5	U4	U3	U5	U4	U8	U12	U5	U4	U5	U4	U1	U5	U4	U1	U5	U4	U1	U5	U4	U1	U5	U7	U1	
Jiangxi	U5	U4	U7	U5	U4	U8	U5	U4	U1	U5	U4	U1	U5	U4	U8	U12	U5	U4	U5	U4	U8	U5	U4	U8	U5	U4	U1	U5	U4	U1	U5	U7	U1	
Henan	U5	U8	U4	U5	U8	U1	U5	U4	U1	U5	U4	U1	U5	U4	U8	U12	U5	U4	U5	U4	U1	U5	U4	U1	U5	U4	U1	U5	U1	U4	U5	U1	U6	
Hubei	U5	U7	U3	U5	U3	U4	U5	U4	U3	U5	U4	U3	U5	U4	U8	U12	U5	U4	U5	U4	U2	U5	U4	U1	U5	U4	U1	U5	U4	U1	U5	U1	U7	
Hunan	U5	U4	U3	U5	U3	U4	U5	U4	U1	U5	U3	U4	U5	U4	U8	U12	U5	U4	U5	U4	U1	U5	U3	U4	U5	U4	U1	U5	U4	U1	U5	U1	U6	
Inner Mongolia	U8	U5	U3	U5	U8	U2	U5	U8	U2	U5	U2	U3	U5	U8	U2	U12	U5	U2	U5	U2	U8	U5	U4	U8	U5	U8	U4	U5	U4	U6	U5	U6	U1	Western Region
Guangxi	U5	U4	U7	U5	U4	U8	U5	U4	U1	U5	U4	U1	U5	U4	U8	U12	U5	U4	U5	U4	U2	U5	U4	U1	U5	U1	U4	U5	U4	U1	U5	U1	U7	
Chongqing	U7	U8	U5	U5	U8	U4	U5	U4	U8	U5	U4	U2	U5	U4	U8	U5	U4	U2	U5	U2	U8	U5	U3	U8	U5	U7	U8	U5	U4	U7	U5	U7	U8	
Sichuan	U5	U4	U3	U5	U4	U3	U5	U4	U1	U5	U4	U3	U5	U4	U1	U12	U5	U4	U5	U4	U2	U5	U4	U3	U5	U1	U4	U5	U1	U4	U5	U1	U7	
Guizhou	U5	U4	U8	U5	U4	U1	U5	U4	U1	U5	U4	U1	U5	U4	U8	U12	U5	U4	U5	U4	U1	U5	U4	U1	U5	U1	U4	U5	U1	U4	U5	U1	U6	
Yunnan	U5	U4	U3	U5	U4	U1	U5	U4	U1	U5	U4	U3	U5	U4	U1	U12	U5	U4	U5	U4	U1	U5	U4	U1	U5	U1	U4	U5	U1	U4	U5	U1	U6	
Shaanxi	U5	U4	U3	U5	U4	U3	U5	U4	U1	U5	U4	U1	U5	U4	U1	U12	U5	U4	U5	U4	U1	U5	U4	U1	U5	U1	U4	U5	U1	U4	U5	U1	U6	
Gansu	U5	U4	U8	U5	U4	U1	U5	U4	U1	U5	U4	U1	U5	U4	U8	U12	U5	U4	U5	U4	U1	U5	U4	U1	U5	U4	U1	U5	U4	U1	U5	U1	U6	
Qinghai	U5	U4	U3	U5	U4	U1	U5	U4	U1	U5	U4	U1	U5	U4	U1	U12	U5	U4	U5	U4	U1	U5	U4	U1	U5	U4	U1	U5	U4	U1	U5	U1	U6	
Ningxia	U5	U3	U4	U5	U3	U2	U5	U3	U4	U5	U3	U4	U5	U4	U2	U12	U5	U2	U5	U2	U4	U5	U4	U3	U5	U4	U1	U5	U4	U6	U5	U6	U1	
Xinjiang	U5	U4	U3	U5	U4	U1	U5	U4	U1	U5	U4	U6	U5	U4	U1	U12	U5	U4	U5	U4	U1	U5	U4	U1	U5	U1	U4	U5	U1	U4	U5	U1	U6	
Average	U5	U8	U4	U5	U8	U3	U5	U4	U1	U5	U4	U3	U5	U4	U8	U12	U5	U4	U5	U4	U2	U5	U4	U3	U5	U4	U1	U5	U4	U6	U5	U6	U1	

Factor layer	U1	U2	U3	U4	U5	U6	U7	U8	U9	U10	U11	U12
	Demographic			Economy		Society				Environment		

FIGURE 11
Top three obstacle factors of NU subsystem in different regions, 2009–2019.

(1) There are regional imbalances in the level of LCD, TI, and NU in China's provinces. The eastern region has attracted a large number of people to gather with its geographical advantages and strong development strength. This has promoted NU level and TI capability locally, and the LCD quality has continued to lead. The comprehensive evaluation index of TI in the eastern region is far ahead of other places. Among them, Jiangsu, Guangdong and Beijing perform more prominently, followed by Zhejiang, Shanghai and Shandong. All of the above are in the eastern region. Sichuan and Shanxi provinces in the western region, and Hubei and Anhui provinces in the central region are behind. The TI capability of central regions has been increasing year by year, while other regions have fluctuated and declined slightly. The overall level of NU gradually increased from 2009 to 2012, decreased in 2013, and then began to slowly increase in 2014. Regionally, the growth rate of NU in northeast regions is significantly higher than that in other regions. The central and western region's growth rate ranks second, while the growth rate of eastern regions is relative to the minimum. The LCD quality in various regions shows a steady improvement in general, and the trend of changes between regions is in the same direction.

(2) The CCD of LCD quality, TI capability and NU level in various regions have been in a state of fluctuation for a long time, and the trend of increase and decrease is not obvious. This means that the regions are in a breaking-in period. This is due to the unsynchronized development of the three subsystems in various regions. The discrepancy between regions and systems is apparent, resulting in fluctuations in the trend of coupling coordination. Nevertheless, the overall development trend of the CCD of these three subsystems is ideal. In 2019, the proportion of provincial regions whose average CCD meets the coordination requirements (*D*-value > 0.5) reaches 43.3% (Beijing, Guangdong, Jiangsu, Zhejiang, Shanghai, Shandong, Shaanxi, Sichuan, Hunan, Hubei, Fujian, Tianjin, and Anhui). 23.3% of the regions face a crisis of near-maladjustment (Henan, Liaoning, Chongqing, Heilongjiang, Hebei, Jiangxi, and Jilin). 26.7% of the regions are slightly maladjusted (Yunnan, Shanxi, Guangxi, Gansu, Guizhou, Inner Mongolia, Ningxia, and Hainan), while 6.7% of the regions are moderately maladjusted (Xinjiang and Qinghai). Moreover, the regional CCD with different maladjusted levels is very close to the critical value of the previous level. It indicates that there is a lot of possibility for adjustment and improvement in the coordinated development of systems in various

regions. Most regions are likely to reach the standard of primary coordination.

(3) In terms of spatial characteristics, there are obvious regional differences in the level of coupling coordination between the "LCD-TI-NU" system, showing "high in the central, low in the north and south," "high in the east and low in the west" status. From the perspective of spatial correlation, the CCD has obvious clustering characteristics and positive spatial autocorrelation. The spatial correlation shows an increasing trend. Combined with the average CCD of each region from 2009 to 2019, most of the regions with higher values are concentrated in the eastern region. The lower values regions are concentrated in the western region. The central and eastern regions of the top 10 regions account for 80%. The second echelon is dominated by the central region. Most of the third echelon is the western regions.

(4) Among the obstacles affecting the LCD and the NU subsystems, the most prominent are economic indexes, mainly in the central and western regions. The eastern region is more subject to social security indexes. The spatial differences of obstacle indexes in the TI subsystem are not significant, and the obstacle indexes mainly reflect in the TI investment. In order to achieve system and regional coordination, it is necessary to strengthen cooperation among various departments, emphasize the integrity and synergy of policies and measures, focus on economic development, and then steadily promote social progress.

Policy implications

NU advocates "people-oriented" and sustainable development. It has become a new driving force for China's economic and social development. Promoting LCD will inject green power into accelerating the construction of NU and urban-rural integration, thereby enhancing the vitality of sustainable development in the region. As a technical means and power guarantee, regional TI will also help to create a high-quality living space for living and working on the basis of improving the ability of LCD. Ultimately, the NU construction will be significantly improved. Therefore, promoting the coordinated development of LCD, TI and NU is an important way to promote the coordinated development of China's regions. It is also an important support for relevant policies and long-time outline plan. In view of the above conclusions, this paper puts forward the following suggestions:

(1) Use policy incentives to bridge the gap between NU and LCD. LCD and NU are both the result of a balance between economic development and policy guidance. This is also evident in the obstacle factors of the two subsystems. Firstly, with the growing demand of urban residents for high-quality public services, ecological environment and health and safety, the government needs to increase investment in public services, such as social security and employment expenditures, environmental protection expenditures, etc. The government should focus on regional infrastructure construction. It is necessary to increase the investment in regional greening and optimize the investment in public transportation. It is also important to provide facilities in infrastructure construction and to achieve equalization of basic public services in urban and rural areas. Furthermore, publicity and guidance should be done to promote low-carbon behaviors. Secondly, relevant departments can restrict the total carbon emissions of enterprises through environmental supervision policies. Whether to impose carbon tax to force high-carbon enterprises to reduce emissions from their own initiative needs to be seriously discussed in the future. The imposition of carbon tax will increase enterprises' cost, reduce enterprises' profit space, and indirectly reduce the number of enterprises employed. In the short term, it may lead to a reduction in labor market demand, slowing the flow of rural people to cities, and thus slowing down the speed of urbanization. It may also cause costs to be passed on to consumers, indirectly affect per capita income, and hinder the improvement of the NU level. Furthermore, the current mechanism is not perfect. Therefore, China currently mainly adopts the carbon emission trading mechanism as its own emission reduction tool. Thirdly, in order to optimize the relationship between the government and enterprises as soon as possible, government departments should speed up the construction of a green industry system and promote the transformation and upgrading of traditional industries to green industries. The market can spawn and expand a number of green, low-carbon enterprises and create a new job market. It is necessary to promote the integration of secondary and tertiary industries, add service links in the industrial chain, and further expand the demand for labor. While promoting green and low-carbon production, it will stimulate more employment opportunities and promote the development of new regional urbanization.

(2) Combined with geographical location and resource endowment, each region should address the imbalance of TI capabilities according to local conditions. Firstly, all regions should strengthen policies and capital investment in TI, and encourage universities and research institutes to carry out technological research. Institutions should increase financial support for excellent research projects, promote the transformation and implementation of

project results, and then commend and reward front-line personnel who have made outstanding contributions. Secondly, each region needs to make effective use of local resources and location advantages. For example, the central and western regions can focus on creating competitive advantage such as low cost of living, livability and encouragement for entrepreneurship to attract innovative talents. The northeast region can highlight the dominant position of enterprises in innovation, and encourage enterprises to carry out technology introduction and innovation. Finally, expand radiation and spillover effects to narrow the development gap between regions. Due to the relatively slow development in the western region, the degree of talent agglomeration is low. The comprehensive development level and CCD in this area are lower than average. Therefore, some provinces can play the role of "leader". For example, advantageous enterprises in Sichuan and Shaanxi can carry out cooperative investment in neighboring provinces, strengthen the regional cooperation, industrial connection and technological exchanges, and promote technological innovation and achievement transformation.

(3) LCD, TI, and NU should be integrated and developed to improve the coupling coordination level. The integration of TI and LCD will spawn a wave of green entrepreneurial teams, green enterprises and green industry activities. The integration of TI and NU will promote the construction of smart cities and the improvement of modernization levels. The integration of LCD and NU will help to build low-carbon cities. Therefore, some policies can exert force from these three aspects. Firstly, each region insists on taking green technology research as a breakthrough to incubate entrepreneurial teams with patented technologies. Furthermore, the government and the market cooperate to build a service platform for green innovation ecology, and then gather green technology-based enterprises. It is also necessary to encourage enterprises to innovate and promote breakthroughs in key green and low-carbon technologies. Secondly, in the process of NU construction, the government should increase TI investment and financial support to encourage renewable energy's utilization. Based on intelligence, relevant institutions can combine digital technology with traditional power electronic technology to promote the intelligence and informatization in urban infrastructure construction. Thirdly, strengthen policy support in fiscal, financial, planning and construction. Accelerate the construction of low-carbon cities, such as building a conservation-minded government, creating green communities, and promoting green buildings. It is also important to advocate the concept of low-carbon life, encourage citizens to use environment-friendly products, continue to promote garbage classification, and develop a circular economy.

Contributions and limitations

The contributions of this paper mainly include the following aspects:

(1) The index system of LCD, TI, and NU are systematically constructed and supplemented. It can better evaluate and reflect the coordinated development characteristics, and make up for the lack of research on the relationship between the three systems in the existing literature. (2) The advantages of different research methods are combined to present a complete study. The analysis in terms of external representations of temporal evolution and spatial agglomeration strengthens the existing research on coupling coordination relationships, while complementary studies are conducted in internal mechanisms affecting the level of coupled coordination, expanding the scope of application of research methods across different fields and systems. (3) By means of the obstacle degree model, the obstacle indexes affecting the comprehensive and coordinated development level of each subsystem are analyzed. It would provide an effective decision-making basis for the formulation of the regional promotion. (4) In theory, it provides case data for regional governance theory. In practice, it is helpful for provinces and cities to implement targeted policy measures to solve such problems.

However, due to the availability of data and the limitation of research methods, this paper also has many limitations: (1) This paper only selected data at the provincial level, and yet the data at the city and county levels can better reflect regional differences. Future research can be supplemented and refined from the study area. (2) The "LCD-TI-NU" system involves multi-dimensional indexes, such as economy, society, environment, resources, and population. Future research can also supplement more indexes based on realistic background. For example, the proportion of green buildings and intelligent transportation can be supplemented in the index system of NU subsystem. (3) Subsequent research can use the spatial econometric model to investigate the influencing factors of the coupling coordination level, and decompose the influence effect. In this way, the direct and indirect effects of each factor can be explored more accurately from the temporal and spatial dimensions.

Data availability statement

The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding author.

Author contributions

YH contributions include writing original draft, investigation, and data curation. GL contributions include methodology, review, and editing. Both authors contributed to the article and approved the submitted version.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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Warming and cooling effects of local climate zones on urban thermal environment

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Understanding the thermal characteristics and contribution ranking of local climate zones (LCZs) is essential since they can help in maintaining environmental harmony. However, previous studies only considered independent effects and could not analyze the combined effects of LCZ on land surface temperature (LST). In this study, we propose a new method to establish an interaction model between LCZs. Five first-level grids with different scales from 270 to 990 m were established to calculate the area proportion of LCZ. The area proportion of LCZ was then applied in the stepwise regression model to quantitatively analyze its magnitude and direction of impact on the LST. The results suggest that the LCZ types of the study area with the highest and lowest average LST were LCZ2 (compact middle-rise building, 39.82°C) and LCZG (water body, 34.24°C), respectively. However, on most scales, the warming effect of LCZ2 was lower than that of LCZE (bare rock or paver), and the cooling effect of LCZG was lower than that of LCZD (low plants). The optimum results were obtained at a scale of 810 m. At this scale, the warming effect was in the order: LCZE (0.314) > LCZ2 (0.236) > LCZ3 (compact low-rise building, 0.135) > LCZ5 (open middle-rise, 0.084) > LCZ6 (open low-rise, 0.056); the cooling effect was in the order: LCZD (−0.272) > LCZA (dense trees, −0.104) > LCZG (−0.103). These findings can help to elucidate the unique warming and cooling effects of LCZ on the interaction condition and the construction of an urban human settlement.

KEYWORDS

land surface temperature, local climate zone, stepwise regression model, urban thermal characteristics, Shenyang

Introduction

With the continued progress of urbanization, artificial structures such as roads and houses are increasing in number and substantially changing the surface form (1). Extensive urban growth in the past has created a particular burden on the environment, thereby affecting the balance of urban climate regulation and causing numerous problems such as the heat island effect and air pollution (2–4).

Global heat exposure has risen dramatically in recent years, thus increasing the risk of extreme heat and the frequency of deaths; heat-related excess deaths are projected to rise by 2.4% in 2030 and by 5.5% in 2090 (5–9). To protect human life, the following goals have been adopted by researchers worldwide, namely: improving production, increasing living efficiency, reducing energy consumption (10–13), maintaining an ecological balance, and creating a comfortable and healthy urban thermal environment (14–16).

Land surface temperature (LST), which refers to the temperature at the intersection of the land surface and the atmosphere, affects many natural ecological processes including atmospheric circulation and energy balance. It is a critical parameter for monitoring the urban thermal environment. Remote sensing technology can provide thermal radiation information, as well as multi-temporal and synchronous LST data over large areas, for thermal environment research (17). For example, surface temperature data can be used to analyze the intensity and distribution characteristics of heat islands at different temporal and spatial scales to coordinate ecological protection and urban construction processes (18–21).

The mechanisms underlying LST change are complex. Researchers often consider the effects of urban form and landscape on LST (22–25). Variations in land surface cover often lead to temperature differences. The LSTs of natural covers such as grassland and water are usually lower than those of built-up areas (21). To quantitatively analyze the factors influencing LST, the normalized vegetation index (NDVI) and normalized water body index (NDWI) are calculated. A positive correlation has been found between the percentage of impervious surface and LST (26). The influence of factors such as building density (BD), average building height (BH), and floor area ratio (FAR) on the urban thermal environment has also been widely studied (14, 27–29). The correlation between BH and LST is weak in the daytime, but strongly positive at night. The aspect ratio of street canyons in urban core areas is negatively correlated with LST in the daytime and positively correlated during nighttime (30). Socio-economic development and human activities also affect the urban thermal environment. Based on the perspective of urban functional areas, Chen et al. (31) noted that the thermal contributions of residential, industrial, and commercial service facility lands vary significantly. However, the contribution of anthropogenic heat to the urban thermal environment is relatively weak, while solar radiation, surface type, and urban form play more critical roles (32).

To better describe the impact of urban land cover, surface morphology, and three-dimensional architectural features on the thermal environment, Oke and Stewart (33) proposed the concept of local climate zone (LCZs). This concept has been widely used (34–36) as a highly versatile urban form zoning method, which can easily analyze urban characteristics and compare multiple cities under a unified standard (37, 38).

There are numerous studies on the thermal environment using the LCZ concept (39–42). Considering the calculation of heat island intensity as an example, many limitations exist in the traditional urban–rural binary division. The introduction of LCZ improves the fuzzy division of the previous binary structure, and reduces the difficulty in analyzing heat island characteristics. The temperature differences between LCZ classes are used to better describe the spatial differentiation characteristics of heat islands, which lays a foundation for further analysis of the driving force of heat island intensity (43). Several studies have analyzed the temperature differences and characteristics within and between LCZ classes and found that the LST of building types was generally higher than that of natural types (44, 45). From the LCZ perspective, LST exhibits obvious day–night and seasonal differences (46, 47). Chang et al. (26) classified LCZ by community units and analyzed the diurnal variation characteristics of LST on different types of LCZ in downtown Xi'an by combining ECOSTRESS (ECOsystem Spaceborne Thermal Radiometer Experiment on Space Station) data. These results showed that the warming rate of low-rise compact buildings was higher than that of open high-rise buildings in the daytime, and the height effect became insignificant during nighttime (26). The influence of LCZ on the thermal environment varies in cities of different sizes; the occurrence probability is higher in large cities (48). For the impact of specific types, the subjective thermal perception of "warm" was found to be more likely observed in LCZ types with close high-rise buildings (39).

These previous studies on the impacts of different types of LCZs on LST are mostly limited to the thermal differences, and the combined effect from different LCZ types is generally ignored (49). Although some studies quantify the relationship between LCZ and LST from a statistical perspective, the connection between LCZ and LST is independent (40, 45). All these studies were based on the hypothesis that when exploring the relationship between a certain type of LCZ and LST, the changes in other LCZ types are independent and do not affect the results. This hypothesis is reasonable because changes in LCZ do not occur dramatically in a short time and they are in a relatively static state. However, it may neglect the interaction of different types of LCZ in space, and it failed to analyze how different types of LCZs synchronously affect the LST. There have been many studies using land use for reference. For example, in addition to calculating the independent impact of each factor on LST, the land use and vegetation cover types of adjacent plots have a specific interaction with the ontology, thereby affecting the changes in LST (50, 51). Given that the competition of land use types affects the urban LST, which can be calculated using regression models, this study assumed that the interaction between different LCZs is also likely to affect the changes in surface temperature. Other than calculating the effect produced by a single LCZ type, we quantified the combined effect of all LCZs on the LST.

Herein, we have created a new method to analyze the combined effects of LCZ. Firstly, we classified LCZ and calculated LST to evaluate urban thermal characteristics from the traditional perspective. Next, we created a first-level grid as a platform to analyze the joint impact of the LCZs. As LCZ is a classification concept, we used the area proportion of each LCZ to quantify the LCZ. Finally, we used correlation and regression analyses to measure the effects of different LCZs on warming and cooling, thereby showing their combined effect. The ranking of the contribution of different LCZs to LST was compared by a standardized coefficient. This study aimed to solve two problems: (1) Creating a new method to measure the combined impact between LCZs, and (2) revealing the thermal characteristics of LCZ under combined effects. We used the area within the fourth ring road of Shenyang as a case study, but this method can be extended to other areas. Our results can explain the relationship between LST and LCZ, identify the combined influence of different types of LCZs on the urban thermal environment, and provide a reference for urban renewal, planning, and future construction.

Data and methods

Study area

The study area is located in Shenyang, the capital of Liaoning Province, in northeastern China (122°25′-123°48′E, 41°12′-43°2′N). The terrain is relatively flat and mainly consists of plains. The eastern boundary extends from the hills of eastern Liaoning, and the western region comprises the alluvial plain formed by the Liao and Hun rivers. Shenyang has four distinct seasons and a temperate semi-humid continental climate with an annual average temperature of 6.2–9.7°C. Precipitation occurs mostly in summer, often in the form of torrential rains in July and August. The study area is within the Fourth Ring Road of Shenyang (Figure 1), which is the central urban area of socio-economic development in Shenyang. To balance the processes of urban development and the construction of human settlements, it is essential to study the thermal environment.

Data source

The data includes land use, Landsat-8 images, MODIS images, building vectors, and other auxiliary data. The detailed attributes and sources are listed in Table 1. A land use and cover change data including secondary classification is used. The land use data in this study have been recorded every 5 years. We used one of its pictures in 2015. To ascertain the actual land use in the study area, the land use data of 2015 were partially updated using the multi-spectral image data of Landsat-8 in 2018. Using manual visual interpretation, the green space contour of some large parks in Shenyang was extracted. Finally, potential features classified by LCZ are reclassified into seven types in the figure. The updated land use data are shown in Figure 1.

Method

We used remote sensing data, land use data and building vector data to calculate LST and divide LCZs. The concept of first-level grid was introduced to calculate the area proportion of LCZ. The correlation was calculated for area proportion of LCZ and LST. The stepwise regression model was used to analyze the warming and cooling effects of LCZ under the combined influence. The frame figure is shown in Figure 2.

LCZ classification

We combined land use and building data to classify LCZs. A 30 m grid was established for the study area, and the BD and average BH of each grid were calculated. The classification criteria are shown in Table 2 (33, 35, 38, 52). The LCZ was classified into six building coverage types comprising LCZ1–LCZ6, and seven non-building coverage types (i.e., natural surface type) comprising LCZA–LCZG.

LST calculation

In this study, the LSTs were obtained from Landsat-8 and MODIS data. We used the single-window algorithm for retrieving LST from Landsat-8 TIRS10 images (53, 54). Using Planck's formula, the LST calculated using Landsat-8 T_S is as per formula (1):

$$T_s = \frac{K_2}{ln\left(1 + \frac{K_1}{B(T_S)}\right)} \quad (1)$$

$B\,(T_S)$ represents black body radiance, $K_1 = 774.89$, and $K_2 = 1{,}321.08$.

Further, to eliminate the influence of outliers that may exist in single-day data, the average was calculated using synthetic MOD11A2 (acquired on 28 July and 13 August, 2018). MOD11A2 is an 8-day composite LST product of MODIS, including daytime and nighttime data. We select daytime data whose collection time is consistent with Landsat-8. MOD11A2 was selected and all data were resampled to 30 m resolution. Finally, the average value of Landsat LST and MODIS LST was calculated as the ultimate LST of the study area in August, with a resolution of 30 m.

Thermal contribution calculation

Based on the method of calculating the area proportion of land use types, this study established a numerical relationship

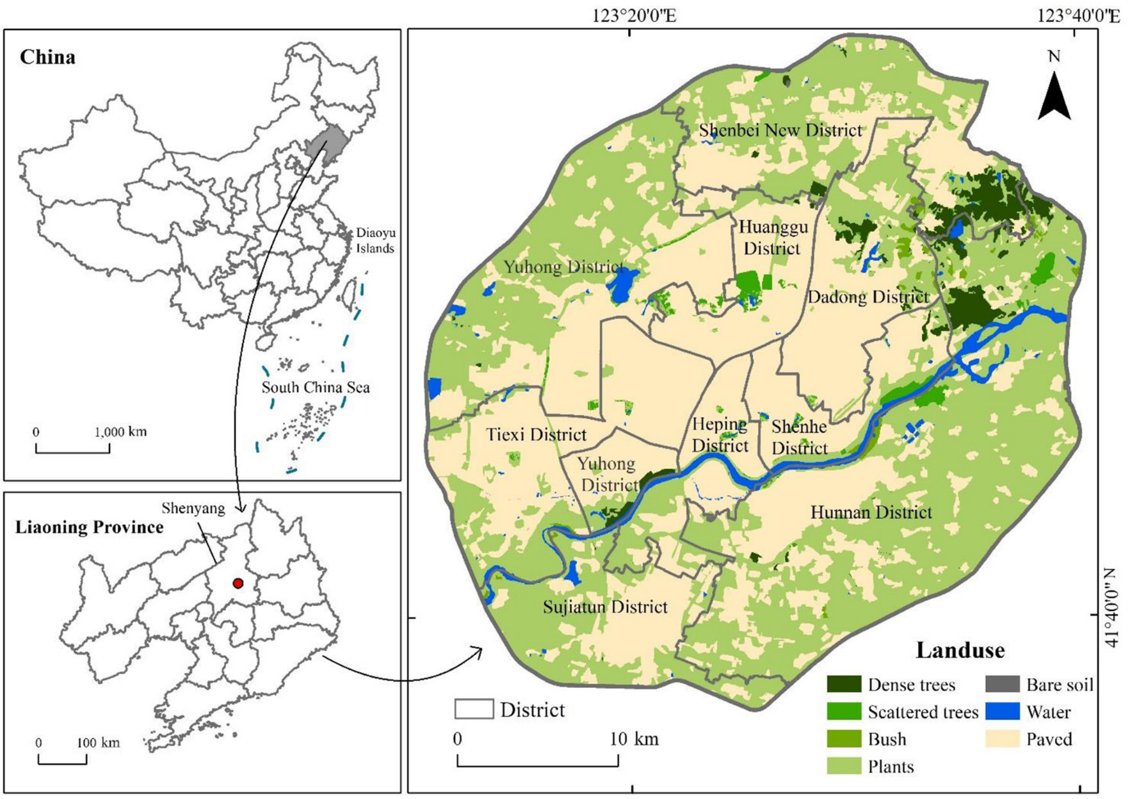

FIGURE 1
Location of the study area.

TABLE 1 Research data and sources.

Data	Description	Source
Raster	Land use and cover change data, (30 m, 2015)	www.resdc.cn
Remote sensing data	MOD11A2 Ts production, 1,000 m, (28 July, 2018, 13 August, 2018)	USGS
	Landsat-8, (30 m, 12 August, 2018)	gscloud.cn
Building data	Building profile data, (2018)	map.baidu.com
Auxiliary data	Study area vector data	webmap.cn

between the area proportion of LCZ and LST (51). To quantitatively represent the LCZ and study the relationship between different LCZs, five levels of first-level grids were created as statistical units (50). The first-level grid refers to the basic unit used to calculate the area proportion of LCZ. Within the scope of each first-level grid, the total area proportion of various LCZs is 1, and can be regarded as the impact of the competition between LCZs on the LST of the first-level grid. The combined effect is shown as the warming and cooling effect of LCZ. Therefore, the concept of first-level grid can be used to assess the combined effect of LCZ on LST. It remains uncertain which scale the combined effect of LCZ is more significant, hence this study used a variety of scales of the first-level grid. The cell sizes of the grids were 270, 450, 630, 810, and 990 m. Figure 3 shows the case of a 990 m grid covering the study area. When a first-level grid was located covering the entire study area as shown in Figure 3A, the sample was adopted. The total qualified grids were: 16,624, 5,904, 2,977, 1,776, and 1,177. Figure 3B shows the LCZ range covered by the five first-level grids. We then calculated the proportions of various LCZs and average LSTs under the first-level grid cells using ArcGIS 10.8 tools, such as intersection and summarization.

Next, Pearson correlation analysis was conducted to investigate the presence of significant correlations between LCZ variables and LST. A stepwise regression model was established to analyze the combined impact of different LCZ and LST types and the contribution of each type of LCZ to LST. The stepwise regression model can select the most important variables and analyze the specific dependence between independent variables (the area proportion of LCZ) and dependent variables (LST). This stepwise regression tested the significance and contribution by introducing independent variables individually and removing independent variables that did not meet the standard. We

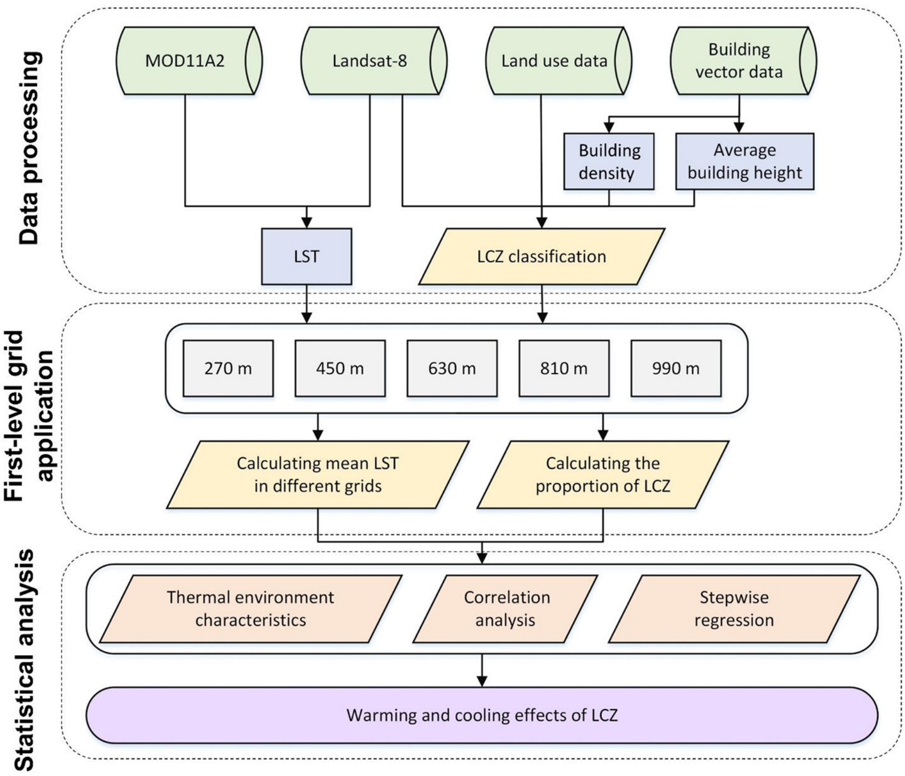

FIGURE 2
Research framework.

used the F-value to express the conditions for entering the independent variable model. When $F < 0.05$, the independent variable can enter the model, while $F > 0.1$ indicates that the independent variable is removed. The stepwise regression model was constructed using IBM SPSS statistics 26. The process was repeated until no independent variables remained to enter or be removed from the model (55). The best linear regression model was established by considering LST as the dependent variable and LCZ area proportion as the independent variable. In this case, all variables in the regression model were significant. The final regression model was as follows:

$$LST = \beta_1 \times LCZX_1 + \beta_2 \times LCZX_2 + \ +\beta_n \times LCZX_n + b \cdot (2)$$

where LCZX_n represents the proportion of LCZ1–G; β_n is the regression coefficient of LCZX_n; b is a constant term.

We normalized $\beta_1 - \beta_n$ to compare the contribution of different types of LCZ to the LST. The standardized coefficients were used to measure the direction and relative size of the contribution of different LCZs to the LST at different scales. A positive standardized coefficient indicates that the LCZ type has a warming effect on the LST, and a negative standardized coefficient indicates a cooling effect. The higher the value, the higher the actual contribution rate of the LCZ type to the LST under the same area proportion.

TABLE 2 Classification criteria of LCZs.

LCZ	Description	LCZ	Description
LCZ1	Compact high-rise	LCZA	Dense trees
LCZ2	Compact middle-rise	LCZB	Scattered trees
LCZ3	Compact low-rise	LCZC	Bush, scrub
LCZ4	Open high-rise	LCZD	Low plants
LCZ5	Open middle-rise	LCZE	Bare rock or paver
LCZ6	Open low-rise	LCZF	Bare soil or sand
		LCZG	Water

Results

Thermal environment characteristics from the LCZ perspective

LCZ classification results of the study area are shown in Figure 4A. The study area contained 12 of the total 13 LCZ types,

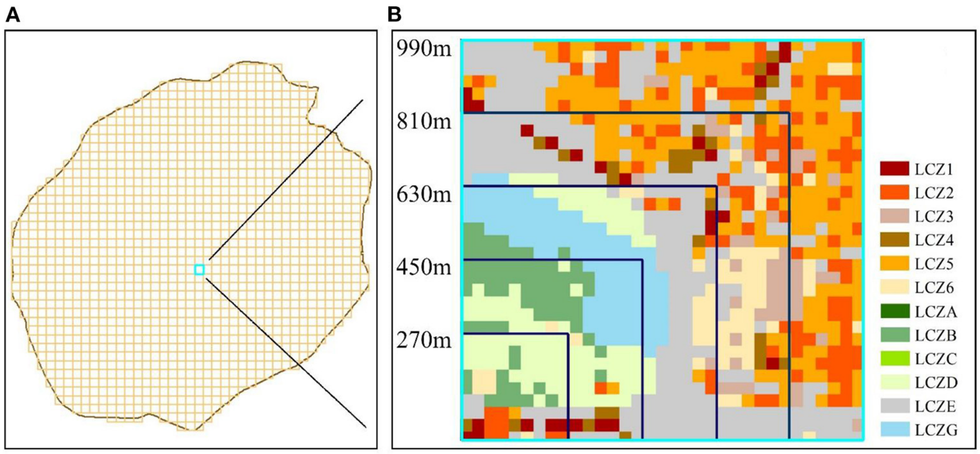

FIGURE 3
Division of the first-level grid; **(A)** 990 m grid covering the study area. **(B)** Number of LCZ covered by grids of different scales.

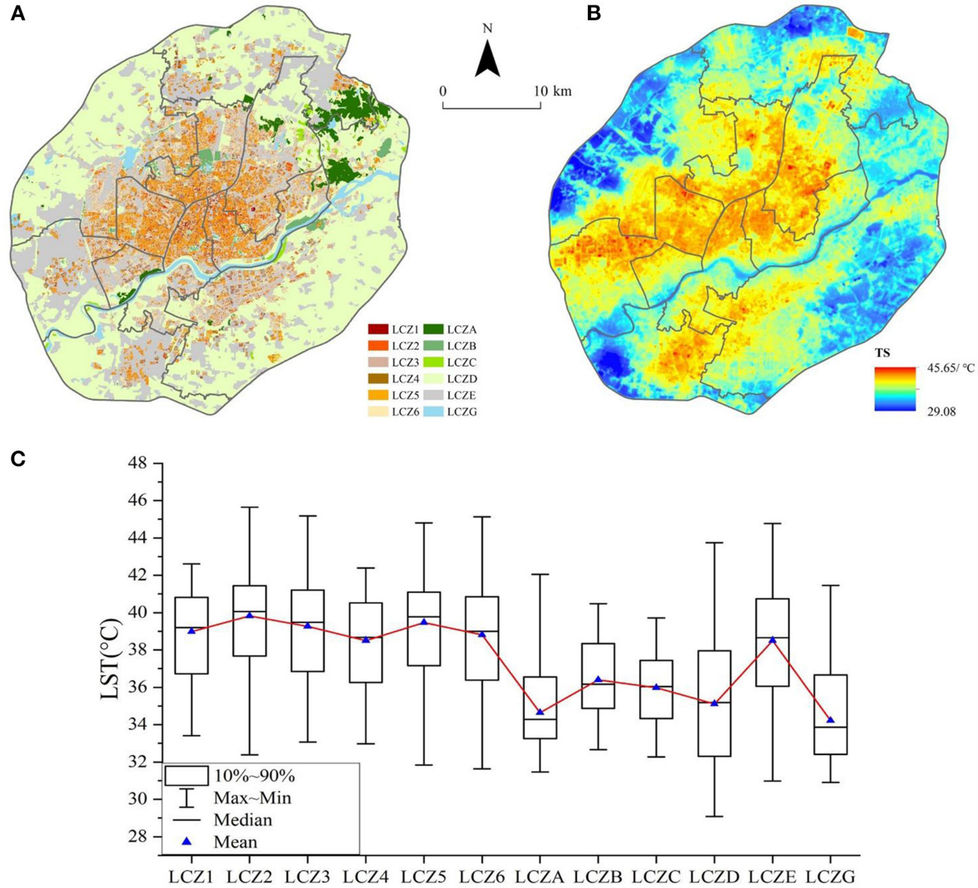

FIGURE 4
Thermal characteristics of the LCZ; **(A)** LCZ classification results; **(B)** Inversion results of land surface temperature in the study area; **(C)** Boxplot of LST distribution under LCZ.

excluding the category of LCZF (bare soil or sand). Overall, for the construction area: the overall proportion of LCZ1–LCZ6 was 19.3%, and the overall proportion of LCZA–LCZG was 80.7%. The proportion of all LCZs, from high to low, was as follows: low plants LCZD (44.4%) > bare rock or paver LCZE (30.0%) > open middle-rise building LCZ5 (5.8%) > open low-rise building LCZ6 (5.0%) > compact low-rise building LCZ3 (3.5%) > compact middle-rise building LCZ2 (3.2%) > water LCZG (2.5%) > dense trees LCZA (2.4%) > open high-rise building LCZ4 (1.2%) > scattered trees LCZB (1.0%) > compact high-rise building LCZ1 (0.6%) > bush and scrub LCZC (0.4%).

The calculated LSTs of the study area are shown in Figure 4B. In the summer of 2018, the LST in the urban area within the Fourth Ring Road of Shenyang was between 29.08 and 45.65°C, and the average LST was 36.88°C. Approximately 95% of the pixels were at temperatures within the range of 31.54–41.2°C, with few extreme temperature pixels.

Figure 4C shows the temperature characteristics of various LCZs. In the LCZ category of the built-up area, the average surface temperature (TsMean) was higher than 38°C. The LCZ type with the highest TsMean was LCZ2 compact middle-rise building (39.82°C) and that with the lowest TsMean was LCZ4 open high-rise building (38.51°C). The highest statistical range of the inter-class mean surface temperature in the LCZ of the built-up zone was 13.5°C, corresponding to LCZ6. In the natural area LCZs, the highest TsMean type was LCZE (38.51°C) and the lowest was LCZG water body (34.21°C), which also had the lowest average surface temperature among all LCZ types.

In the case of building class LCZ, the low- and middle-rise building classes (LCZ2, LCZ3, LCZ5, and LCZ6) had maximum and average temperatures higher than that of the high-rise buildings (LCZ1 and LCZ4) because tall buildings tend to cast shadows, which reduces the surface temperature; this is consistent with the findings of other studies (56). However, the minimum temperature of the high-rise buildings was higher than that of the middle- and low-rise buildings, under the corresponding BD, which may be due to the relatively high warming effect of LCZ types with high average BHs. The LCZ type with a high BD contributes more to the LST, and the warming effect is more pronounced.

Correlation between LCZ proportion and LST

Calculation of LCZ proportion at different grid scales

We calculated the proportion of different LCZ types in each grid. Table 3 lists the quantitative characteristics of the LCZ area proportion calculated under the first-level grids of different scales. As the area and spatial distribution patterns of different LCZ types were different, the area proportion calculated for some first-level grids might be zero. In Table 3, the first line represents the actual number of grids where the calculated area proportion was greater than zero. The second line represents the average area proportion after removing the zero terms.

For example, the area proportion of LCZ1–3 at scales of 450 and 990 m are shown in Figure 5. With the increase in grid scale, the maximum ratio of LCZ1–3 gradually decreased. At the 450 m scale, the maximum ratio of LCZ1 was 0.347; at the 990 m scale, it decreased to 0.156.

Correlation analysis

The correlation between the LCZ area proportion and the corresponding mean LST at each scale is shown in Figure 6. For built-up zones, the area proportions of LCZ1–6 showed a significant positive relationship with LST at all scales. Among them, LCZ2 showed the highest correlation, followed by LCZ5; LCZ4 showed the lowest correlation. This is consistent with the average temperature characteristics described in section 3.1. For natural areas, LCZA, LCZD, and LCZG showed significant negative correlations with LST, with LCZD having the strongest negative correlation. Among the natural area LCZs, LCZE was the only variable that showed a significant positive correlation with LST. The correlations of LCZB and LCZC with LST were weak with low significance. Therefore, in further discussions, the contributions of LCZB and LCZC to the LST and their combined effect will not be considered. The correlations of other variables were significant at 0.01 level.

With the increase in first-level grid scales, although the maximum proportion of built-up area gradually decreased, the correlation between the maximum area proportions of LCZ1–6, and LST showed an increasing trend. For natural area LCZA–G, the correlation increased with increasing grid scale. However, at 450 m, the correlation of LCZA, LCZE, and LCZG showed a decreasing trend. In built-up area LCZs, the correlation between LCZ and LST was more affected by grid scale.

LCZ thermal contribution ranking analysis

Parameters and adjusted R^2 values of optimal stepwise regression model

According to the results of the correlation analysis, 10 variables were selected for a stepwise regression analysis, which included LCZ1, LCZ2, LCZ3, LCZ4, LCZ5, LCZ6, LCZA, LCZD, LCZE, and LCZG. At each scale, the final independent variables and their adjusted R^2 values used in the model are shown in Table 4.

The first-level grids of different scales are used to measure the sensitivity of the combined effects of different types of LCZs to changes in distance. This limits the influence range of each LCZ grid from the geographical distance. When the primary grid scale is small, most LCZs can significantly affect

TABLE 3 The quantitative characteristics of the LCZ area proportion.

Type	270 m	450 m	630 m	810 m	990 m	Implication
LCZ1	2,086	1,234	824	595	454	Valid item count
	0.050	0.030	0.023	0.019	0.017	Average area proportion
LCZ2	4,803	2,270	1,372	938	694	
	0.113	0.086	0.072	0.064	0.058	
LCZ3	5,635	2,693	1,550	1,023	735	
	0.105	0.079	0.070	0.064	0.060	
LCZ4	2,462	1,375	905	633	483	
	0.079	0.051	0.039	0.034	0.029	
LCZ5	5,296	2,459	1,452	993	722	
	0.185	0.143	0.123	0.109	0.100	
LCZ6	6,656	2,958	1,679	1,086	771	
	0.128	0.104	0.093	0.087	0.082	
LCZA	833	411	257	198	142	
	0.482	0.349	0.279	0.219	0.203	
LCZB	623	352	254	187	157	
	0.279	0.177	0.126	0.102	0.082	
LCZC	204	121	79	56	46	
	0.356	0.216	0.164	0.141	0.111	
LCZD	10,368	4,127	2,225	1,381	957	
	0.701	0.619	0.574	0.546	0.521	
LCZE	10,499	4,283	2,357	1,539	1,061	
	0.479	0.419	0.386	0.354	0.341	
LCZG	982	521	357	264	213	
	0.424	0.284	0.210	0.169	0.139	

the LST, which shows that there are more variables entering the model. With the increased first-level grid scale, the influence scope of some LCZs becomes smaller, which means that they cannot enter the stepwise regression model. As the grid scale increases, the number of independent variables entering the model decreases. At 270 and 450 m scales, 9 LCZs were included in the optimal model. At 630 and 810 m scales, there were 8 LCZ types included in the model. However, there were only 6 types at 990 m. Although LCZ4 showed a significant positive correlation with LST, it failed to enter the model at all scales, indicating that the current LCZ4 distribution in Shenyang cannot significantly increase or decrease the LST. Similarly, with the increase in grid scale, the number of LCZ types that can affect the LST in Shenyang gradually decreases. The adjusted R^2 value of the regression model was >0.5 at all scales after considering the combined effects of the LCZs, and the interaction between them. Using the proportion of LCZ within a fixed range as an independent variable can explain more than 50% of the variation in LST of the dependent variable. The adjusted R^2 of the regression models at different scales listed in Table 4 shows that overall, the larger the first-level grid, the greater the model significance, and the higher the explanatory power of the LCZ for surface temperature changes. At the 270 m scale, the adjusted R^2 of the model was 0.608; it increased to 0.724 at the 990 m scale, increasing the explanatory power by 19.1%. At the 450 m scale, the adjusted R^2 was less than all other scales.

Effect of LCZ warming and cooling

The contribution of various LCZs to LST can be quantitatively compared by comparing the magnitude of the standardized coefficients. Thus, we can easily analyse which LCZs have significant impacts on the LST changes, and the direction of their impact at different grid scales, as shown in Figure 7. Overall, the LCZ types that played a positive role in warming were LCZE, LCZ2, and LCZ3. The LCZs that played a negative cooling role were LCZD, LCZA, and LCZG. LCZ1, LCZ5, and LCZ6 increased the temperature by small scales, such as 270 m. However, with the increase in grid scale, their warming effect was not significant in the model, therefore they were excluded.

At different grid sizes, the heating and cooling effects of LCZ were different. For example, at the 270 m scale, the warming effect from high to low was LCZE (0.298) > LCZ2 (0.200) > LCZ3 (0.137) > LCZ5 (0.135) > LCZ6 (0.100) > LCZ1 (0.015). At the 990 m scale, the warming effect of LCZ2 exceeded that of

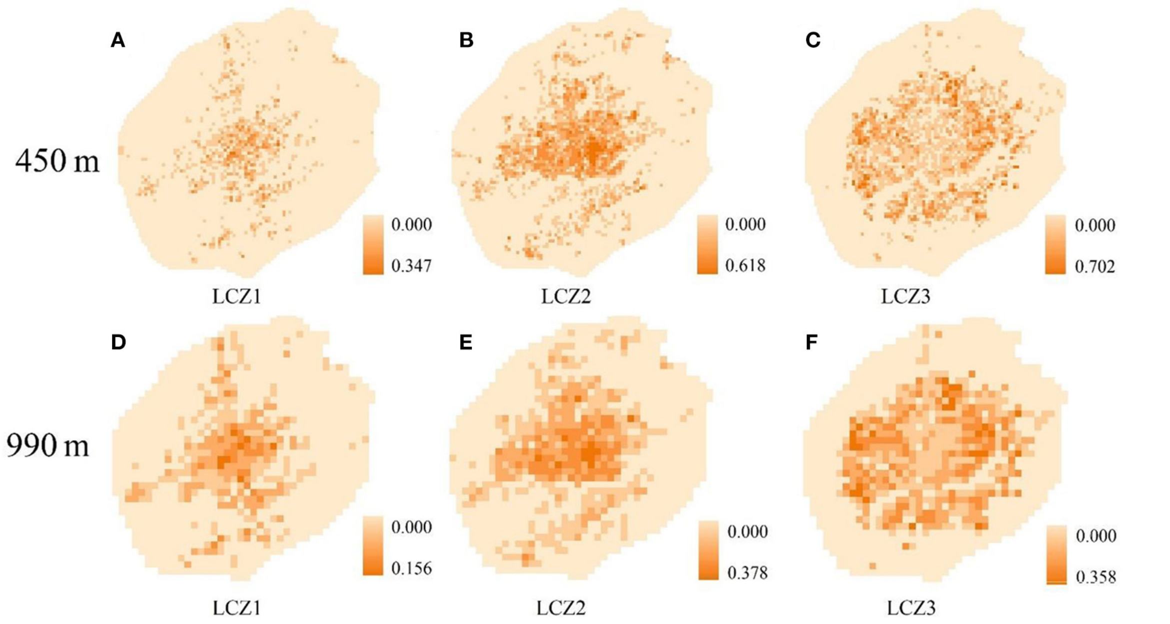

FIGURE 5
Proportion of LCZs in different scales; **(A–C)** distribution of LCZ1–3 at a scale of 450 m; **(D–F)** distribution of LCZ1–3 at a scale of 990 m.

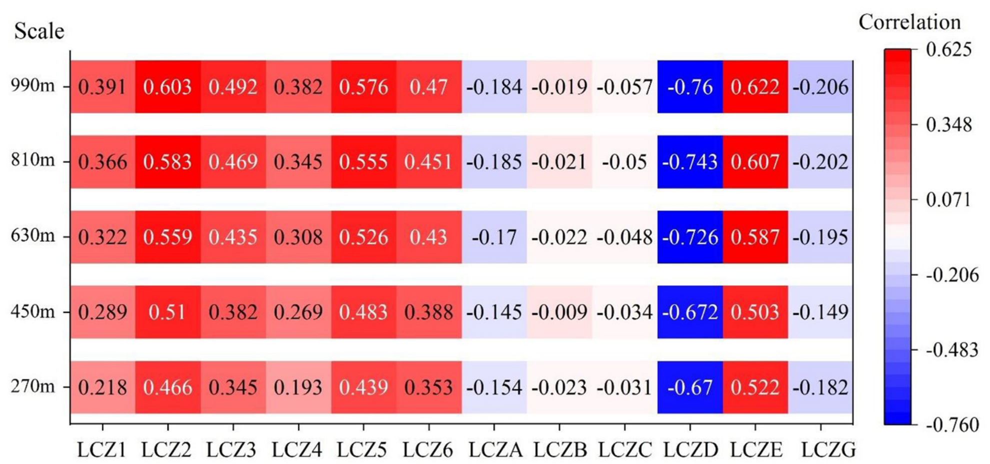

FIGURE 6
Correlation coefficients between LCZ and LST at different first-level grid scales.

LCZE. Only three LCZs significantly affected the increase of LST: LCZ2 (0.261) > LCZE (0.242) > LCZ3 (0.143). At the 270 m scale, the cooling effect was in the order of: LCZD (−0.254) > LCZG (−0.123) > LCZA (−0.101). However, at other scales, the order of cooling effect was LCZD > LCZA > LCZG.

In our study, 810 m was the most suitable scale for the calculation of LCZ contribution in Shenyang. When R^2 was >0.7, we considered that the model was reliable. The calculation of contribution requires that the simultaneous action of as many LCZ types as possible is considered, as the number of effective independent variables entering the model is important. An increase in scale leads to a decrease in the number of independent variables entering the model. When the model scale increased from 810 to 990 m, only 6 LCZ types could be considered. This means that 10.8% of the LCZ area was ignored but R^2 was only improved by 3.5%. Therefore, the 810 m scale, at which the model showed a high adjusted R^2 value with more independent variables entering the model, was considered

TABLE 4 Adjusted R^2 of stepwise regression model.

Scales	Input variables (listed in order of entry)	Adjusted R^2
270 m	LCZD, LCZG, LCZA, LCZ2, LCZ3, LCZE, LCZ5, LCZ6, and LCZ1	0.608
450 m	LCZD, LCZA, LCZG, LCZ2, LCZ3, LCZE, LCZ5, LCZ6, and LCZ1	0.576
630 m	LCZD, LCZA, LCZG, LCZ2, LCZ3, LCZE, LCZ5, and LCZ6	0.680
810 m	LCZD, LCZA, LCZG, LCZ2, LCZ3, LCZE, LCZ5, and LCZ6	0.704
990 m	LCZD, LCZA, LCZG, LCZ2, LCZ3, and LCZE	0.724

the best scale. At 810 m, the warming effect was in the order of: LCZE (0.314) > LCZ2 (0.236) > LCZ3 (0.135) > LCZ5 (0.084) > LCZ6 (0.056). The cooling effect was in the order of: LCZD (−0.272) > LCZA (−0.104) > LCZG (−0.103). The results show that the method of calculating the area ratio of LCZ and incorporating it into the stepwise regression equation can measure the combined influence of LCZ and explain about 70% of LST changes. At the same time, compared with the traditional perspective, the contribution of LCZ considering the combined impact to the surface temperature is different. This shows that it is necessary to consider the actual contribution of the LCZ under the combined influence.

Discussion

Interaction between LCZs

To establish the relationship between LCZ and the thermal environment, the average temperatures within LCZs are usually used to estimate the thermal characteristics (32). We also applied this method to analyze the thermal environment characteristics of Shenyang in summer, as described in section 3.1. Previous studies show that many factors within the LCZ can be quantified, such as NDVI, BH, the proportion of impervious water surface, and the average tree height using this method (26, 41). These studies elucidated the influence of internal characteristics of LCZ on LST. However, they estimated the impact of each type of LCZ on LST in an independent state. Therefore, when the correlation between LCZ1 and LST is analyzed, the area and location of other LCZs, such as LCZ2 and LCZB, do not have any impact on the correlation results. But in fact, LCZs do not exist independently in the city; they are adjacent to, or intersect with, other LCZs. Therefore, an important but unanswered question was whether LCZs had combined or competitive influence on LST. To answer this question, we proposed to use the area proportion to describe LCZs. In this method, we demarcated a series of first-level grids and calculated the area proportion of LCZs.

As the area proportion is competitive, all LCZs are no longer independent LST-related variables, but their changes are closely related to other LCZs. They are placed in an environment with a total of "1," competing for influence on the LST. The results of the calculated area proportion are described in section 3.2. However, the relevant analysis method is independent and does not reflect the competition and combined influence of LCZs. Therefore, the ranking of thermal characteristics measured by average temperature is consistent with the correlation. As all LCZs were included in the regression model, they required a simultaneous impact on LST, and the results changed. We found that the warming effect of LCZE and the cooling effect of LCZG might have been underestimated due to the neglect of the combined and competitive effects of LCZs in the past. It should be noted that these results apply only to the current LCZ configuration in Shenyang. However, the method of using area proportions to analyze the combined effect of LCZs on LST can be applied to other regions to explore the factors that have been neglected in the independent analysis.

A new perspective on understanding urban thermal environment

We can find that the influence of different LCZ categories on the LST, calculated by a stepwise regression (section 3.3), is not completely consistent with their thermal characteristics (i.e., the corresponding average LST of each LCZ category; section 3.1), or the degree of correlation (section 3.2). The average temperature ranking of LCZ was a description from a regional perspective not involving the interaction between LCZ categories. The combined effect emphasized that LCZ impacts LST at the same time, considering the interaction between different categories. The differences reflected from the two perspectives suggest the presence of combined effect. This may be associated with the change in heat storage capacity caused by the arrangement of LCZ. Although LCZ2 has the highest mean surface temperature, the regression results show that LCZE has a higher warming effect on LST than LCZ2 across the four scales from 270 to 810 m. Previous studies focused on the heat generated by building coverage LCZs to the urban thermal environment. The strong warming effect produced by LCZE has not been discussed. Meanwhile, despite the low surface temperature of LCZG, it failed to produce a sufficient cooling effect in the stepwise regression model. A different perspective on the LST contribution can explain this contradiction. The average temperature of an LCZ shows its thermal state, which cannot be used to estimate the actual contribution to urban surface temperature because its area and distribution are not considered. The standardized coefficient obtained by stepwise regression

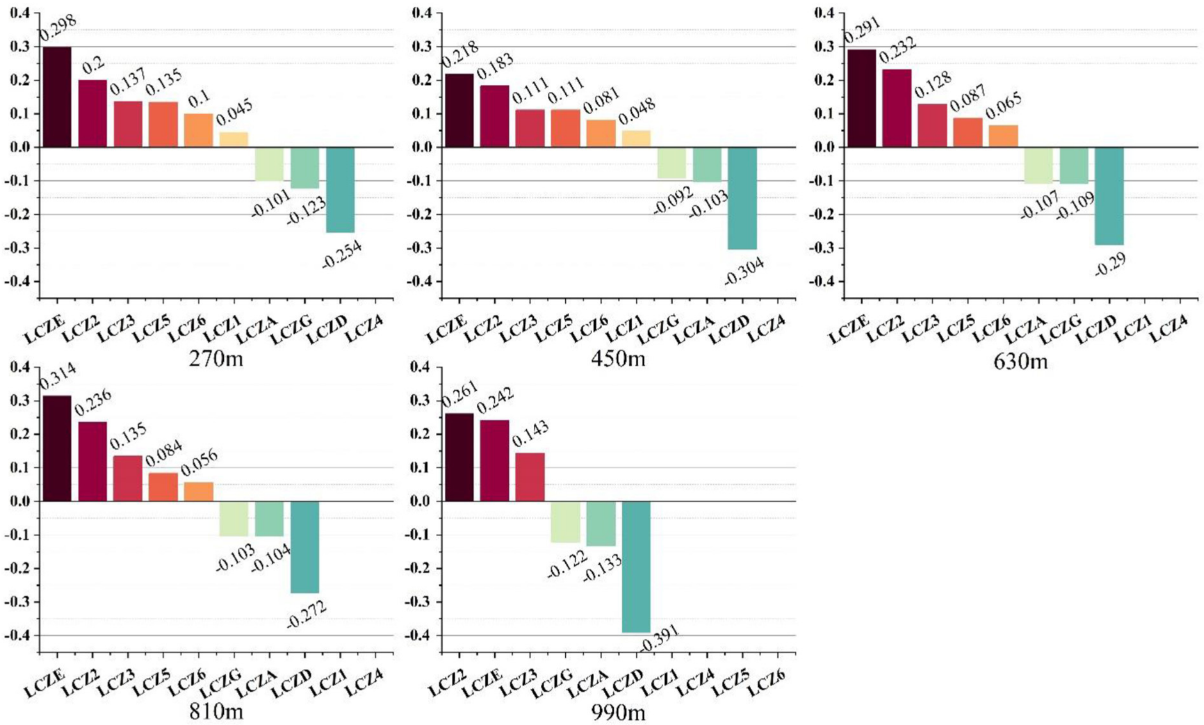

FIGURE 7
Normalized coefficients of various LCZ and LST regression models under the combined influence.

modeling represents a relative state and is used to calculate the degree of LST change caused by LCZ. Combining the two factors can better analyze the urban thermal environment. The cooling of the city alone cannot explain the local minimization; instead, it is essential to consider the combined influence of various factors to achieve the optimal effect.

Strategies for cooling cities

To achieve the goal of urban cooling, many studies have been conducted on land use adjustment, planning, and construction (15, 57). For example, in China's Beijing-Tianjin-Hebei, Pearl River Delta, and Yangtze River Delta urban agglomerations, the LST of the compact medium- and high-rise buildings is high, which is not conducive to urban cooling (40). However, green spaces and water bodies can be added to compact high-rise buildings to meet the cooling requirements (58). Optimizing ventilation corridors and increasing the area of green space and water bodies can cool the city (59–61).

This study provides some new cooling ideas based on the contribution of LCZ to LST. The thermal characteristics (i.e., average LST) and their ranking based on temperature-increasing ability (i.e., standardized coefficient) of different LCZs were determined. For LCZ types with high average temperatures, such as building-type LCZs and LCZE, measures should be taken to reduce their LST. Increasing the greening between buildings and optimizing roof materials or ground paving materials may play a cooling role. To alleviate the influence of high-temperature, reduce the LST, and achieve the purpose of cooling the city, we should explore the cooling potential of trees in the city (62, 63). For LCZs with a strong warming effect, such as LCZ2, LCZ3, and LCZE, the excessive increase should be avoided in the process of urban planning. Simultaneously, a database on the variation of the warming effect of different LCZs in cities should be established. The thermal characteristics and warming effect of LCZs should be recorded and analyzed regularly to provide a reference for the thermal environment background of future urban construction.

For the study area, the main central high temperature area is continuous. This is similar to the distribution trend of LCZE. Therefore, in the future urban planning of Shenyang, we proposed building greenways, increasing LCZD and reducing the combined warming effect caused by impervious surface. On a smaller scale, especially in the built-up areas of the city center, including Shenhe, Heping, and Huanggu Districts, we propose the construction of pocket parks to improve the cooling capacity.

Limiting factors

To facilitate the calculation of LCZ area proportion, we preferentially choose the 30 m LCZ division, which may cause the spatial discontinuity of LCZs. With respect to the classification of LCZs in this study, there is still room for the improvement in classification accuracy owing to the timeliness and availability of data (64). Results can be improved by optimizing the LCZ classification and area proportion calculation methods.

Using only the area proportion as a measure of LCZ cannot reflect the spatial location attributes of LCZ and the intra-type differences of LCZ. Our study could not reveal whether the spatial distribution of LCZs affects LST, which requires some new models or perspectives to be considered, such as the geographic weighted regression model and landscape pattern index (65, 66).

Finally, although we could quantify the relative contribution, the causes have not been identified. It may still be necessary to consider the mutual relationship and competitive impact between LCZs, which will be addressed in future research.

Conclusion

This study analyzed the spatial distribution characteristics of LST based on different types of LCZs in Shenyang City. The proposed method used stepwise regression analysis to quantify the contribution of LCZ area proportion to LST. The main conclusions are as follows:

The study area was classified into 30 m LCZs. The LCZs of the building and natural areas accounted for 19.33 and 80.67% of the units, respectively. The proportion of natural species was the highest in LCZD (44.34%) and lowest in LCZC (0.4%). Construction accounted for the largest proportion of units in LCZ5 (5.8%) and the least in LCZ6 (0.6%). In terms of spatial distribution, construction LCZ presented a spatial pattern of staggered intermixed distribution, whereas natural LCZ was more concentrated and independent. There was a significant heat island effect in the study area. The high-temperature area was concentrated in the urban built-up area, and the average LST was 36.88°C. The highest average LST of 39.82°C was observed in a LCZ2 middle-level compact building and the lowest average LST of 34.24°C was observed in the LCZG water body.

Five first-level grids with different scales were established to calculate the area proportion of LCZ. The LCZ1–6 and LCZE showed a significant positive correlation with LST, while LCZA, LCZD and LCZG showed significant negative correlations with LST. LCZB and LCZC showed weak correlations with LST. With the increase in the first-level grid scale, the correlation between LCZ and LST generally exhibited an upward trend. In the case of building areas, the correlation between LCZ and LST was more affected by grid scale.

From 270 to 990 m, the LCZs entering the stepwise regression model were different. As the grid scale increased, the independent variables entering the model decreased. The adjusted R^2 values of stepwise regression models at different grid scales were 0.608 (270 m), 0.576 (450 m), 0.680 (630 m), 0.704 (810 m), and 0.724 (990 m). The influence of LCZ on LST was determined by calculating the standardized coefficients. The most suitable scale for the calculation of LCZ contribution in Shenyang was 810 m. The warming effect was in the following order: LCZE (0.314) > LCZ2 (0.236) > LCZ3 (0.135) > LCZ5 (0.084) > LCZ6 (0.056); the cooling effect showed the following order: LCZD (−0.272) > LCZA (−0.104) > LCZG (−0.103). Unlike the average LST, this method determined the effect on the LST change considering the interaction between LCZs.

Data availability statement

The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding authors.

Author contributions

RZ: data curation, software, and writing—reviewing and editing. JY and DS: conceptualization, methodology, and reviewing and editing. XM, XX, and JX: writing—reviewing and editing. WY: data curation and reviewing and editing. All authors contributed to the article and approved the submitted version.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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Street centrality and vitality of a healthy catering industry: A case study of Jinan, China

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In the context of an overall improvement in the national economy, residents' demand for nutrition and health has been increasing. An industry that provides healthy eating plays an increasingly important role in urban development. Few studies, however, have focused on the relationship between the urban road network structure and the vitality of the healthy catering industry (VHCI). Based on social media data and urban traffic network data, in this study, we explored the impact mechanism of street centrality on the VHCI through a case study of Jinan, China, using geographic detectors and multiscale geographically weighted regression (MGWR) methods. The results show the following: First, the vitality of the catering industry in the main urban area of Jinan has multicore spatial distribution characteristics, and the high-value areas of the vitality of the catering industry are highly matched with the main business districts in the city in space. Second, we found clear spatial differences in street centrality between the walking and driving modes. With an increase in the search radius, the trend of high-value areas closely gathering in the urban center became clearer. The distribution of betweenness was observed from sheet to grid, and the multicenter structure of straightness was more prominent. Third, differences in the residents' perception of the road network structure caused by different travel modes affected their choice of dining places. In the driving mode, betweenness and straightness had a greater impact on the vitality of the catering industry, and the effect of closeness in the walking mode was more obvious. Fourth, the influence of street centrality on the vitality of the healthy catering industry had obvious spatial heterogeneity. In the walking mode, the spatial heterogeneity of straightness was the strongest, followed by betweenness, and closeness was the weakest; in the driving mode, the spatial heterogeneity of closeness was the strongest, followed by straightness, and betweenness was the weakest. From the perspective of residents' travel, the results of this study revealed the influence mechanism of urban road network characteristics on the VHCI. This information can aid planning for urban space optimization and improve residential living quality.

KEYWORDS

healthy catering industry, street centrality, vitality, geographical detectors, multiscale geographically weighted regression

Introduction

The concept of "vitality" originated from biology and ecology, which originally meant vigorous vitality. Jacobs first proposed the concept of "urban vitality" and believed that the process of interweaving people's activities and living places constituted the diversity of urban life and enabled the city to obtain vitality (1). Gehl noted that urban vitality comes from the people and the activities of the people in the urban space (2). Based on previous studies, Montgomery proposed that the components of urban vitality include "activity," "transactions," and "diversity" (3). With the development of society and the economy, this theory of "vitality" has been introduced gradually into various fields of urban life, such as industrial development (4, 5), public health (6), and criminology (7). Today, the consumer economy has shifted gradually from products to services, and the significant demand generated by consumers has become an important force driving economic and social development (8). As an important part of the urban service industry, the catering industry has shown strong development potential and has become a dynamic source of urban vitality (9). In recent years, the emphasis on high-quality life has led people to pursue healthy green diets (10). Nutrition, health, and wellness have become the major trends in the development of the catering industry (11). Therefore, in the context of the construction of "Healthy China" (China's development strategy to improve national health policies and provide people with all-round and full-cycle health services), researching restaurants that provide healthy diets from the perspective of urban vitality not only is conducive to promoting the green development of the catering industry but also can satisfy people's ever-growing needs for a better life.

The study of urban catering industry has always been one of the focuses of urban geography and urban planning. According to the gravitational model, traditional research has analyzed the location characteristics of the urban catering industry, emphasizing the role of centrality and distance (12, 13). With the improvement of the convenience of spatial data acquisition, research on the urban catering industry has continued to deepen. From the perspective of research methods, the existing research mainly obtains spatial location data of catering outlets through network technology, by combining ArcGIS software and measurement models to analyze the spatial layout characteristics and influencing factors of the catering industry (14–16). For example, Girish et al. used a gravity model to assess the factors influencing restaurant development (17); Lu et al. (18) analyzed the spatial distribution characteristics of urban economic and geographical elements using methods such as location entropy and nearest neighbor index; and Zhang et al. (19) quantitatively analyzed the hierarchical hotspots and spatiotemporal structures of catering services in Chongqing, China, based on kernel density estimation (KDE) method. From these research results, most scholars believe that the distribution of urban catering merchants generally presents a circular divergence law from the urban central business district to the surrounding areas. The interior of each area appears to form a combination of clustered agglomeration and banded distribution (20, 21). The rise of big data has provided new opportunities for the research of the urban catering industry (22, 23). In addition to the research on the geographical distribution and influencing factors of the catering industry, this research has gradually extended to include the online word-of-mouth effect of the catering industry (24, 25), local population catering preferences (26), catering consumption behavior (27), and other aspects. For example, Xu et al. established a word-of-mouth evaluation index system based on network big data to study the spatial pattern of the catering industry in Nanjing, China (28), and Tian et al. revealed the interaction between residents' dining activities and urban space through the mining and analysis of social media data (29). Overall, the current research results on the urban catering industry have been relatively rich, but few studies have examined healthy catering. In particular, the research on the urban healthy catering industry from the perspective of vitality needs to be further strengthened.

Transportation is an important factor affecting the development of the catering industry. The synergistic relationship between urban transportation and the catering industry has always been the focus of scholars (30). In terms of the relationship between transportation and catering, typical research has included the following: Li et al. (31) analyzed the layout of the catering industry in Lhasa based on ArcGIS software and found that catering outlets tend to be concentrated in areas with high traffic integration; and Njomo analyzed the spatial distribution of catering outlets in Nairobi County, Kenya, and found that a convenient road network could bring more customers to restaurants and increase profits (32). In recent years, with the introduction of complexity science and the advancement of digital information technology, the network characteristics of transportation elements have become a consensus. Street centrality is an effective means to interpret the spatial characteristics of the transportation network (33)—that is, the better the centrality, the better the location conditions. Therefore, the relationship between the distribution of urban social activities and economic activities and street centrality has received considerable attention. The multiple centrality assessment (MCA) model is an important method used for centrality evaluation. This method introduces the real distance of the road network into the road network model, and it reflects the node centrality by measuring the importance of the node in the road network, which has strong practical significance (34). At present, the MCA model has been used widely in many aspects of urban life, such as land space optimization (35, 36), traffic orientation detection (37), and traffic flow analysis (38). In addition, many studies have proved that street centrality has an important influence on the creation of urban vitality. For example, Rui et al. used the MCA model to study the

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relationship between street centrality and land use, and they found that different street centrality indicators could reflect different human activity patterns (39). Kang studied the impact of urban road networks on residents' travel and found that the characteristics of road network structures that are attractive to residents' walking vary with travel scales (40). Sarkar et al. studied the comprehensive impact of urban greening and road network intermediary on residents' activities, and they found that the higher the road network intermediary, the stronger the willingness of residents to walk (41). These studies have explored the connection between urban vitality and street centrality; however, some limitations persist. First, research is lacking on the relationship between urban street centrality and the vitality of the catering industry; second, residents' perception of the road network structure is different because of different travel scales, and therefore, the role of the street centrality index in different travel modes of residents should be further explored; and, third, most of the studies have conducted global modeling of the relationship between street centrality and economic activities but have lacked local modeling analysis. As a result, the local characteristics of the relationship between street centrality and residents' activities has been ignored.

According to this analysis, this study promotes the development of the existing literature in the following three ways: first, we focused on restaurants that provide healthy meals and explore their vitality; second, based on the MCA model, we calculated the street centrality of residents' travel under different traffic modes (walking and driving) and compared the differences in the impact of road network structure on the VHCI; and third, using a MGWR model, we revealed that the spatial heterogeneity of street centrality affects the VHCI. Specifically, we selected Jinan, China, as the research area. We selected restaurants that meet the standards of healthy eating and used the number of restaurant comments on Dianping.com to characterize their vitality. Then we analyzed the spatial characteristics of the vitality of the catering industry and street centrality. Finally, using Spearman's correlation coefficient, geographic detectors, and the MGWR model, we analyzed the influence mechanism of street centrality on the vitality of the catering industry under different travel modes. This study deepens our understanding of the relationship between road network structure and urban economic activities and provides policy guidance for the optimization of urban dining space and improvements in residential quality of life.

Materials and methods

Study area

Jinan is located in the central and western parts of Shandong Province, China, with Mount Tai in the south and the Yellow River in the north. The terrain is high in the south and low in the north. Restricted by geographical conditions, the old city of Jinan expands in an east–west direction, forming a long and narrow urban space from east to west. As the provincial capital of Shandong Province, Jinan is the political, economic, and cultural center of the province, and it is also an important meeting point between the Bohai Rim economic zone and the Beijing-Shanghai economic axis. Thus, it is one of the most important transportation hubs in eastern China. The development of Jinan's catering industry has reached a significant level in China in terms of market size, industrial structure, and richness. In this study, we selected the main urban area of Jinan as the research area (Figure 1), with an area of about 197.5 km^2. With convenient transportation and dense catering outlets, the main urban area is the primary carrier of population and economic activities in Jinan. Therefore, it is suitable to conduct research on the street centrality and the vitality of the catering industry in Jinan.

Data sources

The traffic road network data in the main urban area of Jinan were obtained from the National Geographic Information Public Service Platform. Combined with the research content and the actual situation, the road vector data were preprocessed. Excluding non-research objects, such as roads in parks and communities, the study area has 5,089 roads and 3,479 traffic nodes. The catering industry data came from Dianping.com and were collected from December 2020. According to the health management items in the Chinese National Standard "green hotels" (GB/T 21084-2007), we selected restaurants that can provide a safe, healthy, nutritious, and balanced diet. Selected restaurants had more than 20 dishes. We obtained 4,935 restaurant datasets, and the data for each restaurant included coordinates, merchant name, classification, score, and comment number. To exclude the influence of other factors, such as spatial location differences, on the vitality of the catering industry, we selected the intensities of various types of land, the number of bus stops, and the distance from downtown as the control variables (Table 1). Comprehensively consider the selection of influencing factors and the size of the study area, we used ArcGIS software to create a 500 × 500 m fishing net. A total of 870 grids were obtained, which were used for geographic detection and MGWR analysis.

Research methods

Street centrality

According to the "Jinan 15-min Community Life Circle Planning" issued by the Jinan municipal government, we assume that the average travel distance of walking and driving is 1,500 m and 7,500 m, respectively when residents go out to eat.

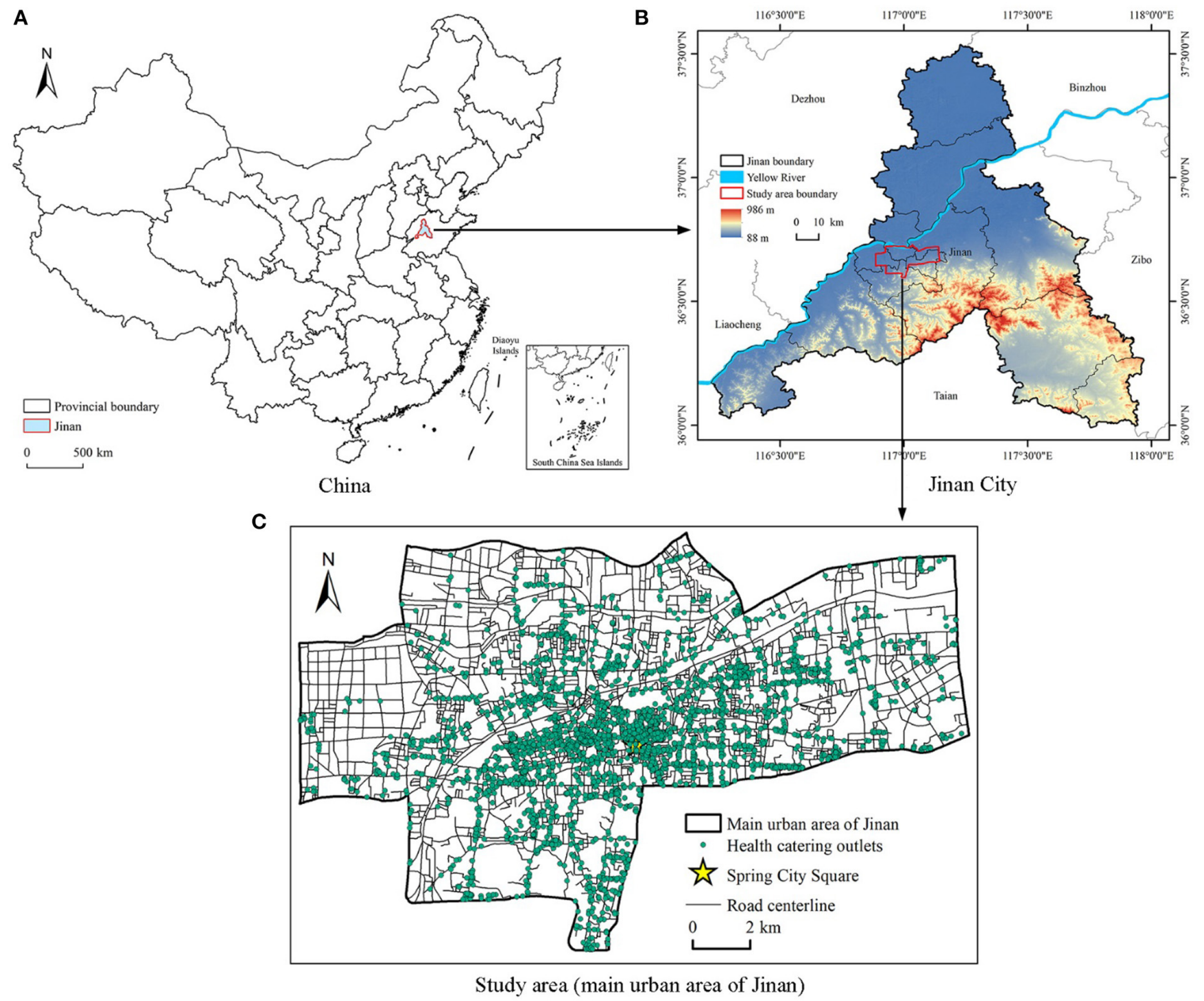

FIGURE 1
Study area and geographical location of Jinan. **(A)** China. **(B)** Jinan City. **(C)** The main urban area of Jinan.

Based on the MCA model, we calculate the street centrality when the search distance threshold is 1,500 m and 7,500 m, to simulate the road network structure characteristics of walking and driving modes. Based on ArcGIS software, we selected the three indicators of closeness, betweenness, and straightness, and measured the street centrality of the main urban area of Jinan under the two travel modes. The definitions and calculation method for each indicator are described in what follows.

Closeness refers to the proximity of a node to all other nodes, which reflects the relative accessibility of the node in the transportation network. The formula is as follows (42):

$$C_i^c = (N-1) / \sum\nolimits_{j=1, j \neq i}^{N} d_{ij}, \tag{1}$$

where C_i^C represents the closeness of node i, N represents the total number of nodes, and d_{ij} represents the shortest distance of the actual route from node i to node j.

According to the concept of betweenness, there is a shortest path connecting any two nodes in the transportation network, and the more shortest paths pass through a certain area, the better the betweenness of the place. The betweenness can reflect the traffic volume passing through a node—that is, the higher the betweenness value, the greater the traffic volume passing through the node. The formula is as follows (43):

$$C_i^B = \frac{1}{(N-1)(N-2)} \sum\nolimits_{j=1, k=1, j \neq k \neq i}^{N} \frac{n_{jk}(i)}{n_{jk}}, \tag{2}$$

where C_i^B represents the betweenness of node i, N represents the total number of nodes, n_{jk} represents the number of shortest paths from node j to node k, and $n_{jk}(i)$ represents the number of paths passing through node i in the shortest path from node j to node k.

TABLE 1 Variable descriptions.

Variable properties	Variable names	Variable symbols	Quantitative standards	Variables explained
Dependent variable	Vitality of the catering industry	Lif	KDEs of healthy restaurants based on the number of online comments	The activity level of a healthy catering industry in the region
Core explanatory variables	Closeness	Cos	Centrality value of closeness	The proximity of an area to other areas
	Betweenness	Bet	Centrality value of betweenness	The regional traffic transfer capacity
	Straightness	Str	Centrality value of straightness	The regional traffic efficiency
Control variables	Intensity of industrial land	Ind	KDEs based on floor area ratio	Land use intensity of industrial land
	Intensity of commercial land	Com	KDEs based on floor area ratio	Land use intensity of commercial land
	Intensity of public service land	Pub	KDEs based on floor area ratio	Land use intensity of public service land
	Intensity of residential land	Res	KDEs based on floor area ratio	Land use intensity of residential land
	Number of bus stops	Bus	KDEs based on number of bus stops	Accessibility to public transport
	Distance from downtown	Dis	Straight line distance from the restaurant to spring city square	Location of catering outlets in the city

Straightness is an effective means to measure the traffic efficiency of a node. The smaller the ratio of the distance of the shortest path between the two nodes to the distance of the straight line (i.e., the smaller the deviation of the shortest path from the straight line), the higher the traffic efficiency between the two nodes. The formula is as follows (44):

$$C_i^S = \frac{1}{N-1}\sum\nolimits_{j=1, j\neq i}^{N} \frac{d_{ij}^{Eucl}}{d_{ij}}, \tag{3}$$

where C_i^S represents the straightness of node i, N represents the total number of nodes, d_{jk} represents the shortest distance of the actual route from node j to node k, and d_{ij}^{Eucl} represents the Euclidean distance from node i to node j.

Geographical detectors

Geographical detectors are a set of statistical methods that reveal the comprehensive interaction characteristics behind multi-factor-driven differentiation through the influence measurement of different factors based on the spatial stack and spatial collection of geographic information. We used geographic detectors for differentiation and factor detection, and we investigated the extent to which each influencing factor explained the spatial differentiation of the vitality of the catering industry. To measure the influence of each detection factor on the vitality of the catering industry, the expression is as follows (45):

$$q = 1 - \frac{\sum_{h=1}^{L} N_h \sigma_h^2}{N\sigma^2}, \tag{4}$$

where h is the stratification of the impact factor; N_h and N are the number of units in the stratum h and the whole area, respectively; and σ_h^2 and σ^2 are the variance of the vitality of the catering industry in the stratum h and the whole area, respectively. The value range of q is [0,1], and the smaller the value, the smaller the explanatory power of the factor X to the dependent variable Y. When $q = 1$, the factor X determines the spatial distribution of the dependent variable Y, and when $q = 0$, the factor X does not affect the dependent variable Y at all.

Multiscale geographically weighted regression

According to the first law of geography, the closer the distance between two things, the greater the connection. The geographically weighted regression (GWR) model shows the natural connection between items by giving higher weights to the observations in the neighborhood of the sample points. The structural equation of the classical GWR model is as follows (46, 47):

$$Y_i = \beta_0(u_i, v_i) + \sum\nolimits_k \beta_k(u_i, v_i) X_{ik} + \varepsilon_i, \tag{5}$$

where Y_i is the dependent variable at point i; $\beta_0(u_i, v_i)$ is the intercept; $\beta_k(u_i, v_i)$ is the value of the continuous function $\beta(u_i, v_i)$ at point (u_i, v_i); X_{ik} is the value of the k_{th} predictor at point i; and ε_i is the residual.

Compared with traditional regression models, such as ordinary least squares (OLS), the classical GWR model takes into account the spatial heterogeneity of influencing factors to a certain extent by means of local regression. It uses a single kernel function and bandwidth, however, to calculate the weights, which results in the same scale characteristics for the spatial variation of all parameter estimates (48, 49). In contrast, each regression coefficient of the MGWR model is obtained based on local regression, and the bandwidth is specific, which can explain the spatial scale effect of socioeconomic phenomena (50). The

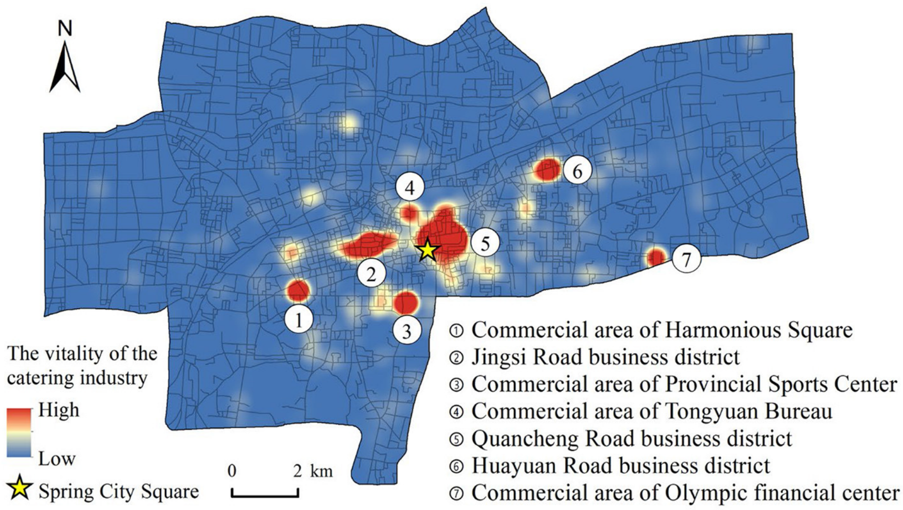

FIGURE 2
Main business districts and KDEs of the catering industry.

linear regression equation for the MGWR is as follows (51):

$$Y_i = \sum\nolimits_{k=1}^{q} \beta_0 X_{ik} + \sum\nolimits_{k} \beta_{bwk}\left(u_i, v_i\right) X_{ik} + \varepsilon_i, \quad (6)$$

where *bwk* represents the bandwidth used by the k_{th} variable regression coefficient. We used the Gaussian function method as the weight function and select the Akaike information criterion (AIC) to optimize the bandwidth.

Results and discussions

Spatial differentiation characteristics of the VHCI and street centrality

Taking the number of comments as the weight, we conducted the KDEs of healthy catering outlets and obtained a spatial distribution map of the vitality of the catering industry (Figure 2). Using road intersections and endpoints as nodes for street centrality analysis, we created a road network dataset in the study area. The street centrality was measured using the urban network analysis tool (Figure 3).

As shown in Figure 2, the spatial distribution of the vitality of the catering industry in Jinan presents an obvious multicenter structure with two large high-value areas. The first is the area with Quancheng Road business district as the core. This area is the center of Jinan, and it not only has famous scenic spots, such as Daming Lake and Baotu Spring, but also popular streets for snacks, such as Furong Street and Kuanhouli, which handle dense crowds and feature a dynamic catering industry. The second is the area with Jingsi Road business district as the core. This area is the traditional leisure and entertainment center of Jinan. The catering industry developed earlier in this center and the consumer market is huge. It features five smaller high-value areas, namely, the commercial area of Harmony Square, the commercial area of the Provincial Sports Center, the commercial area of Tongyuan Bureau, the Huayuan Road business district, and the commercial area of the Olympic Financial Center. In general, the vitality of the catering industry in the main urban area of Jinan is extremely uneven in spatial distribution. Areas with high vitality values are spatially clustered and are distributed near the main business district or commercial area in the central area of the city, whereas the catering vitality in other areas is relatively low.

In order to more clearly show the characteristics of the street centrality, we used the closeness, betweenness, and straightness as the weights to perform KDE on the nodes (Figure 4). We observed a clear spatial difference in the street centrality between the walking mode and the driving mode. From the perspective of closeness (Figures 4A,B), in the walking mode, areas with high closeness were distributed mainly at the edge of the study area and were highly discrete. This reflected the fact that at the local scale, although the number of nodes in the peripheral area was less than that in the central area, the average distance between nodes was shorter and had higher closeness. In the driving mode, the areas with high closeness gathered from the edge area to the central area. Areas with higher closeness, such as the Quancheng Road business district and the commercial area of Tongyuan Bureau, had higher values for the vitality of the catering industry.

From the perspective of betweenness (Figures 4C,D), the high-value areas of betweenness in the walking mode presented a large flaky distribution, which was concentrated in the old town in the west of Spring City Square. In the driving mode, the high-value area of betweenness expanded along the main

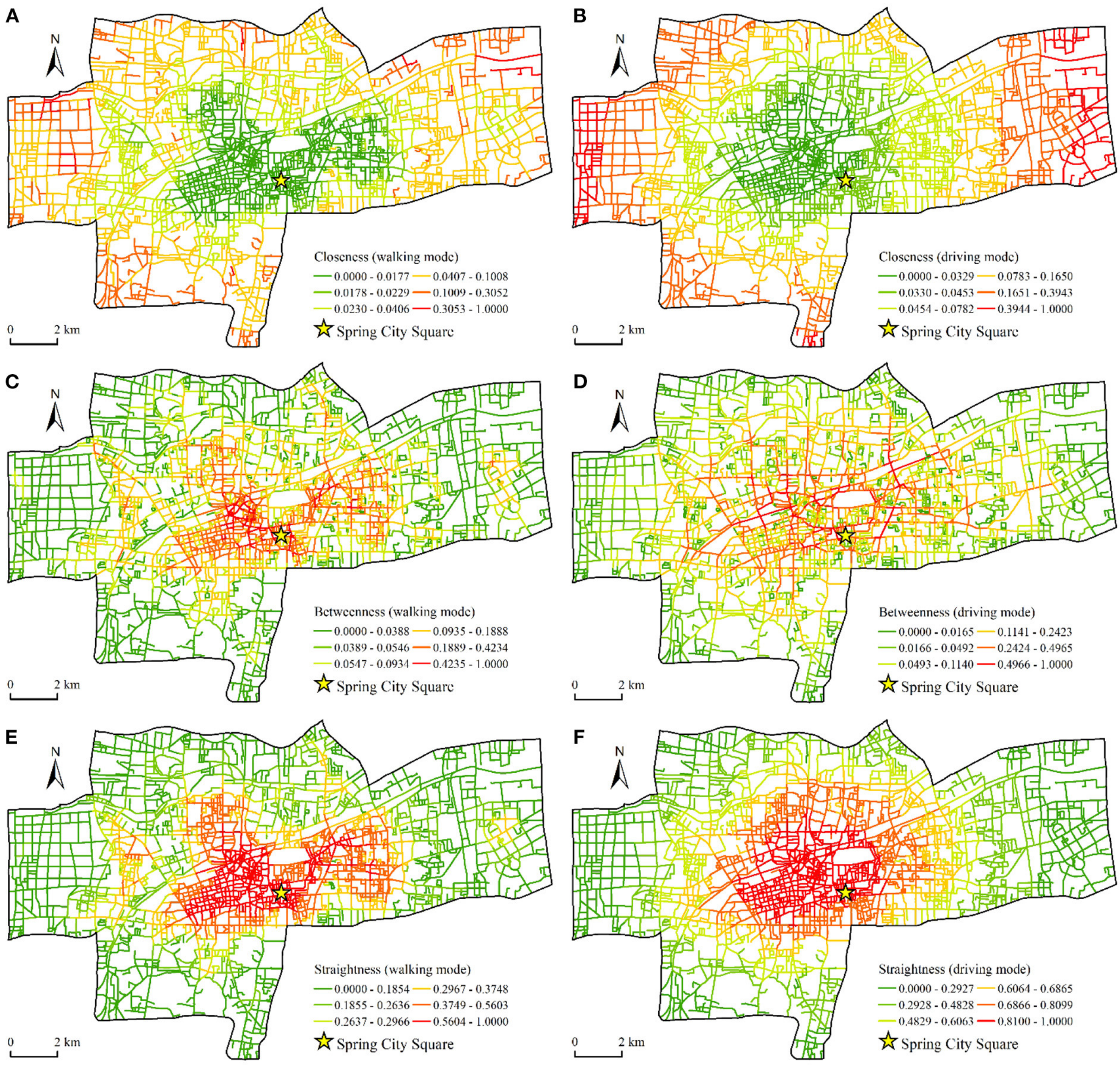

FIGURE 3
Spatial pattern of street centrality. **(A)** Closeness of walking mode. **(B)** Closeness of driving mode. **(C)** Betweenness of walking mode. **(D)** Betweenness of driving mode. **(E)** Straightness of walking mode. **(F)** Straightness of driving mode.

traffic road and formed an obvious grid structure. The areas with high betweenness have played an important role in connecting and transiting between urban roads. This result indicated that the traffic nodes in these areas had large traffic flow and high commuting degree.

From the perspective of straightness (Figures 4E,F), the spatial distribution characteristics of straightness in walking mode were similar to betweenness, which showed that in the walking range of residents, the more the shortest paths between traffic nodes passed through an area, the straighter the route was in the area. In the driving mode, the straightness near the intersection of the roads has become larger, indicating that the urban traffic nodes have played a greater role in the long-distance travel of residents, and the ratio of the actual distance to the straight line between the nodes has become smaller. We found significant differences in the spatial pattern of street centrality from the perspective of these two travel modes. According to the principle of street centrality measurement, all nodes in the traffic network search for the number of nodes within a certain threshold along a road and obtain a centrality value through calculation. In the walking mode, the number of searched nodes was small, and the morphological structure of the local road network had a significant influence on the measurement of centrality; in the driving mode, the road

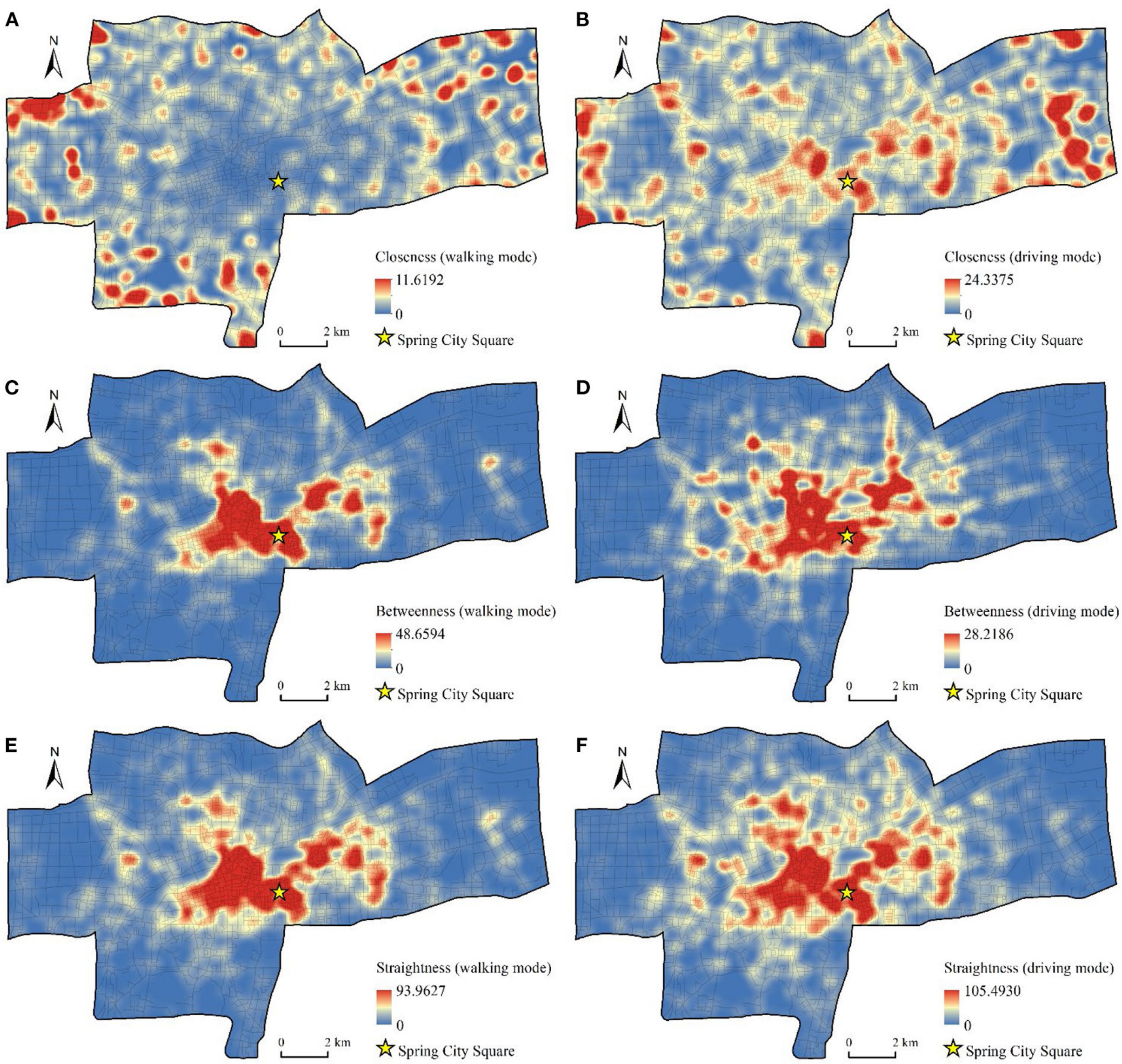

FIGURE 4
KDEs of street centrality. **(A)** Closeness of walking mode. **(B)** Closeness of driving mode. **(C)** Betweenness of walking mode. **(D)** Betweenness of driving mode. **(E)** Straightness of walking mode. **(F)** Straightness of driving mode.

search radius increased, which revealed a wider range of road structure characteristics.

Influence of street centrality on the VHCI

We used Spearman's correlation coefficient to preliminarily analyze the correlation between the centrality of the road network and the vitality of the catering industry under the two modes of travel (Table 2). The results showed that the correlation between straightness and the vitality of the catering industry in the walking mode was not significant, and other street centrality indicators were significantly positively correlated with the vitality of the catering industry at the 5% significance level. Specifically, betweenness had the strongest correlation with the vitality of the catering industry in both travel modes. This result was the same as the research of Lin et al. on the retail industry in Guangzhou, China (52). The betweenness reflected the passing degree of the transportation network (53), the high-value area of betweenness was densely populated, and the vitality of the catering industry was prosperous. The correlation between straightness and the vitality of the catering industry in driving mode was greater than closeness, which means that the catering industry in areas with high traffic efficiency is more dynamic at a larger spatial scale. Among the control variables, the vitality of the catering industry was significantly negatively correlated with the intensity of industrial land and was positively correlated with the intensity of other types of land use. We found a strong positive correlation between the number of bus stops and the vitality of the catering industry, and the distance between restaurants and the downtown area had a strong negative correlation with the vitality of the catering industry.

Spearman's correlation coefficient represents the linear relationship between variables, but it does not reflect the impact of street centrality on the vitality of the catering industry. Therefore, we used geographic detectors to further analyze the extent to which street centrality explains the spatial differentiation of the vitality of the catering industry (Figure 5). The q statistic of the geographical detection showed the following: In the walking mode, Distance from downtown (0.2592) > Straightness (0.1941) > Betweenness (0.1835) > Number of bus stops (0.1324) > Intensity of commercial land (0.1099) > Intensity of residential land (0.0756) > Closeness (0.0619) > Intensity of public service land (0.0366) > Intensity of industrial land (0.0026). In the driving mode, Distance from downtown (0.2592) > Straightness (0.2341) > Betweenness (0.1962) > Number of bus stops (0.1324) > Intensity of commercial land (0.1099) > Intensity of residential land (0.0756) > Intensity of public service land (0.0366) > Closeness (0.0078) > Intensity of industrial land (0.0026).

The results of geographical detectors showed that the impact of the street centrality index on the vitality of healthy catering industry under the two travel modes was significantly different. After considering the spatial effects of independent and dependent variables, straightness had the greatest impact on the vitality of the catering industry, followed by betweenness and closeness. This meant that the degree of deviation between the shortest path and the straight path between nodes in the area had the greatest impact on the vitality of the catering industry, the number of the shortest paths between nodes had a secondary impact on the vitality of the catering industry, and proximity had the least impact on the vitality of the catering industry. This result was different from the conclusion of Scopa et al. on the relationship between the distribution of commercial facilities and street centrality in Buenos Aires (54). The reason for this is that the street centrality index plays a different role in the road network structure of different cities. Catering outlets are greatly affected by the traffic network. To obtain greater benefits and meet the needs of more consumers, these outlets tend to be distributed in areas with superior traffic conditions (55). At the same time, the goal-oriented travel habits of urban residents have made the regional catering industry with high traffic efficiency and strong transit ability more dynamic (56). The straightness represents traffic efficiency, and the betweenness represents transit capacity. These two factors have had a significant impact on the vitality of the catering industry in the driving mode, which has demonstrated that the road network plays a greater role in a wider range of spatial scales (57). Road sections with strong transfer capacity often have large traffic flow and are prone to traffic congestion. At the same time, residents are more inclined to choose straight roads with low time cost and high safety (58). Therefore, the impact of betweenness on the vitality of the catering industry was less significant than that of straightness. The difference in the impact of betweenness and straightness on the vitality of the catering industry was more obvious in the driving mode because traffic congestion had a greater impact on driving than on walking. The influence of closeness on the vitality of the catering industry in the walking mode was higher than that in driving mode. When residents drove out of the urban center, the attractiveness of the neighboring areas was weaker because of the more convenient travel. Among the control variables, Distance from downtown, Number of bus stops, and Intensity of commercial land had the greatest impact on the vitality of the catering industry. These results showed that the distance between the restaurants and the downtown area, the convenience of public transportation, and the concentration of business have greatly affected the spatial distribution of the vitality of the catering industry.

Spatial heterogeneity analysis

The global Moran's I test is used to test whether there is a non-equilibrium spatial distribution of each variable (Table 3). The results showed that both the dependent variable and the independent variable had a positive spatial correlation. Intensity of industrial land, Intensity of residential land, and Number of bus stops passed the significance test at the 5% level, and other factors passed the significance test at the 1% level. This result indicated that both the core variable and the control variable had spatial clustering between similar values, which was suitable for local regression analysis. We conducted the MGWR analysis using MGWR 4.0 software, selected the Gaussian fixed kernel as the kernel type, and selected the AIC_C method as the model bandwidth. We selected the AIC_C and adjusted R^2 to compare the fitting results of OLS, GWR, and MGWR (Table 4). The MGWR model had the smallest AIC_C and the largest adjusted R^2, and therefore, the MGWR model had a best fitting effect. The statistical description of the coefficients of each variable of MGWR is shown in Table 5.

Walking mode

According to the results in Table 5, the closeness coefficient was less discrete in the walking mode. This result explained that the influence of closeness on the vitality of the catering industry varied slightly in different locations. As shown in Figure 6A, the spatial distribution of the closeness coefficient was in the "core-periphery" mode, with the northern area of Spring City Square as the core, and gradually decreased to the periphery. The closeness coefficient in the western area of the main urban area was the smallest. The closeness coefficient for the high-value areas was

TABLE 2 Spearman's correlation coefficient and significance test.

Variable	Walking mode			Driving mode			Ind	Res	Pub	Com	Bus	Dis
	Clo	Bet	Str	Clo	Bet	Str						
Lif	0.106**	0.663**	−0.028	0.436**	0.667**	0.658**	−0.151**	0.724**	0.625**	0.609**	0.738**	−0.640**

**means the confidence level is 95%.

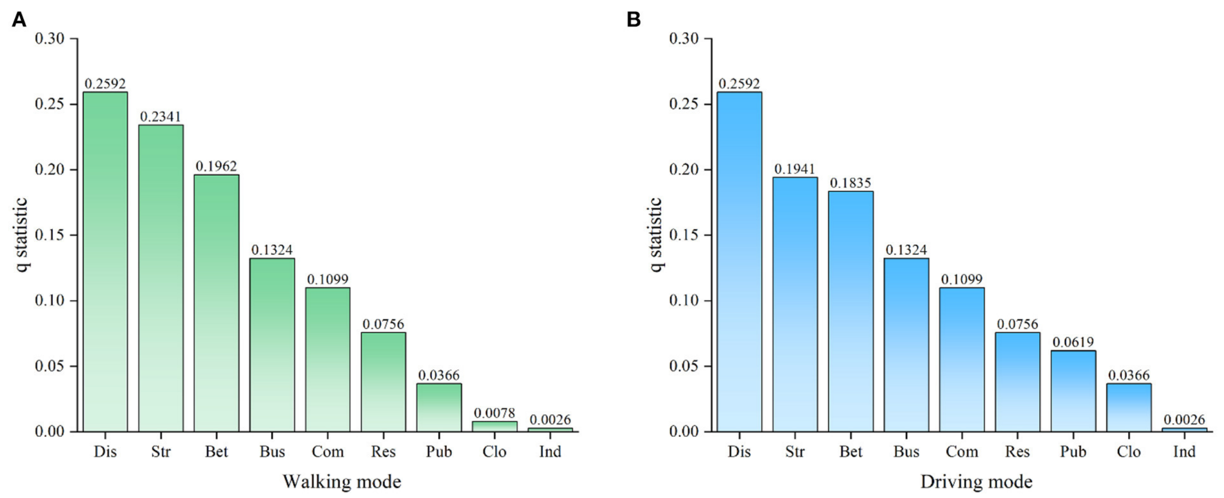

FIGURE 5
Influence of street centrality and control variables on the vitality of the catering industry. **(A)** q statistics of walking mode. **(B)** q statistics of driving mode.

TABLE 3 Spatial correlation test results of variables.

Variable	Walking mode			Driving mode			Ind	Res	Pub	Com	Bus	Dis
	Clo	Bet	Str	Clo	Bet	Str						
Moran's I	0.949***	0.345***	0.848***	0.692***	0.530***	0.856***	0.849***	0.455**	0.696**	0.631***	0.626***	0.676**

**means the confidence level is 95%, and ***means the confidence level is 99%.

TABLE 4 Comparison of goodness of fit of OLS, GWR, and MGWR models.

	OLS		GWR		MGWR	
	AIC_C	Adjusted R^2	AIC_C	Adjusted R^2	AIC_C	Adjusted R^2
Walking mode	2255.598	0.227	1921.585	0.608	1641.858	0.691
Driving mode	2284.233	0.201	1977.065	0.543	1735.088	0.651

concentrated in the city center, because residents in this area have a tense life rhythm. Therefore, they pay more attention to the accessibility of a destination to save traffic time. The degree of dispersion of the betweenness coefficient was relatively high, which showed that the influence of betweenness on the vitality of the catering industry varied greatly in different locations. Figure 6B shows that the spatial pattern of the betweenness coefficient had a multicenter structure. The high-value areas were mostly business gathering areas or tourist scenic areas, and many business people and tourists came from other places. The directness coefficient had the highest degree of dispersion, which indicated that the directness had the greatest impact on the vitality of the catering industry in different locations. Figure 6C shows that the spatial pattern of the straightness

TABLE 5 Statistical description of the coefficients of each variable in MGWR.

Walking mode	Mean	STD	Min	Median	Max	Driving mode	Mean	STD	Min	Median	Max
Clo	0.145	0.161	−0.005	0.083	0.722	Clo	0.446	0.373	0.002	0.344	1.949
Bet	0.382	0.268	−0.175	0.304	1.404	Bet	0.102	0.245	−0.579	0.109	1.150
Str	−0.577	0.288	−1.288	−0.563	0.180	Str	−0.677	0.309	−1.574	−0.732	0.042
Ind	0.012	1.041	−7.016	−0.084	4.707	Ind	−0.012	0.001	−0.013	−0.012	−0.011
Com	0.253	0.132	0.020	0.255	0.471	Com	0.212	0.130	−0.013	0.193	0.446
Pub	−0.092	0.054	−0.252	−0.083	−0.008	Pub	−0.108	0.088	−0.395	−0.081	−0.011
Res	−0.079	0.002	−0.082	−0.079	−0.077	Res	−0.065	0.002	−0.067	−0.064	−0.063
Bus	0.036	0.003	0.030	0.037	0.040	Bus	0.023	0.004	0.015	0.025	0.029
Dis	−0.961	0.915	−2.787	−1.328	0.151	Dis	−1.099	0.896	−3.060	−1.453	0.032

coefficients also presented a multicenter pattern. The regression coefficient in the western part of the main urban area generally was higher. These areas are located far from the downtown, and the catering outlets have to attract a wider range of consumers. Because residents pay more attention to the traffic efficiency of the destination when they travel long distances, straightness has a greater impact on the vitality of the catering industry (57). The distribution of the remaining four high-value areas basically coincided with the betweenness coefficient for the high-value areas. This result showed that betweenness and straightness, as important indicators to measure the convenience of transportation, both had an important impact on consumers' choice of dining places. The straightness coefficients in the north and southwest of the main urban area were negative. The vitality of the catering industry in this area may be greatly affected by other factors. Among the control variables, the influence of the intensity of industrial land on the vitality of the catering industry had the greatest difference in the different locations. From the perspective of the spatial distribution of the regression coefficients, the regression coefficients for the main urban areas where the distribution of industrial land is concentrated were mainly negative, which indicated that the industrial land in this area would have a certain negative impact on the vitality of the catering industry. The regression coefficient in the central area of the city was positive, because the industrial production process in this area is more environmentally friendly and the industrial land area is small, which had no obvious negative impact on the vitality of the catering industry.

Driving mode

According to the results in Table 5, the spatial difference of the impact of street centrality on the vitality of the catering industry was greater in the driving mode than in the walking mode. In the regression coefficient of the street centrality index, the closeness coefficient had the highest degree of dispersion. Under the driving mode, the influence of closeness in different locations on the vitality of the catering industry had the most obvious difference. As shown in Figure 7A, compared with the walking mode, the distribution of the closeness coefficient exhibited a ring-layer structure that gradually decreased from the center to the periphery, but the high-value area extended from the center to the southwest. The two core areas were the Quancheng Road business district and commercial area of Harmonious Square. This indicated that the increase in travel distance changed the local characteristics of the influence of closeness on the vitality of the catering industry. As shown in Figure 7B, the degree of dispersion of the betweenness coefficient was small, which indicated that the influence of betweenness on the vitality of the catering industry was not very different in different regions. As an important indicator to measure the convenience of transportation, betweenness had an important influence on the vitality of the catering industry in most areas. The commercial area of Harmonious Square, the commercial area of the Provincial Sports Center, and the Quancheng Road business district together constitute the high-value areas of the betweenness coefficient. Compared with the walking mode, the betweenness coefficient of the urban central area became smaller, and the edge coefficient of the study area became larger. The public transportation in the central area is developed, and residents can travel by bus or subway. The influence of betweenness on the vitality of the catering industry has been weakened. Conversely, public transportation is inconvenient in the fringe areas and the proportion of private car trips is relatively large, and thus areas with high betweenness have greater transportation advantages. The degree of dispersion of the straightness coefficient was higher than betweenness and was secondary to closeness. As shown in Figure 7C, the straightness coefficient in the driving mode was also in a multicore mode, and the distribution characteristics of the high-value areas were similar to those in the walking mode. Judging from the absolute value of the coefficient, the impact of straightness on the vitality of the catering industry west of the main city was particularly prominent. The road network in this area is relatively sparse, and choosing restaurants with high straightness saves travel time. Among the control variables, the distance from downtown was

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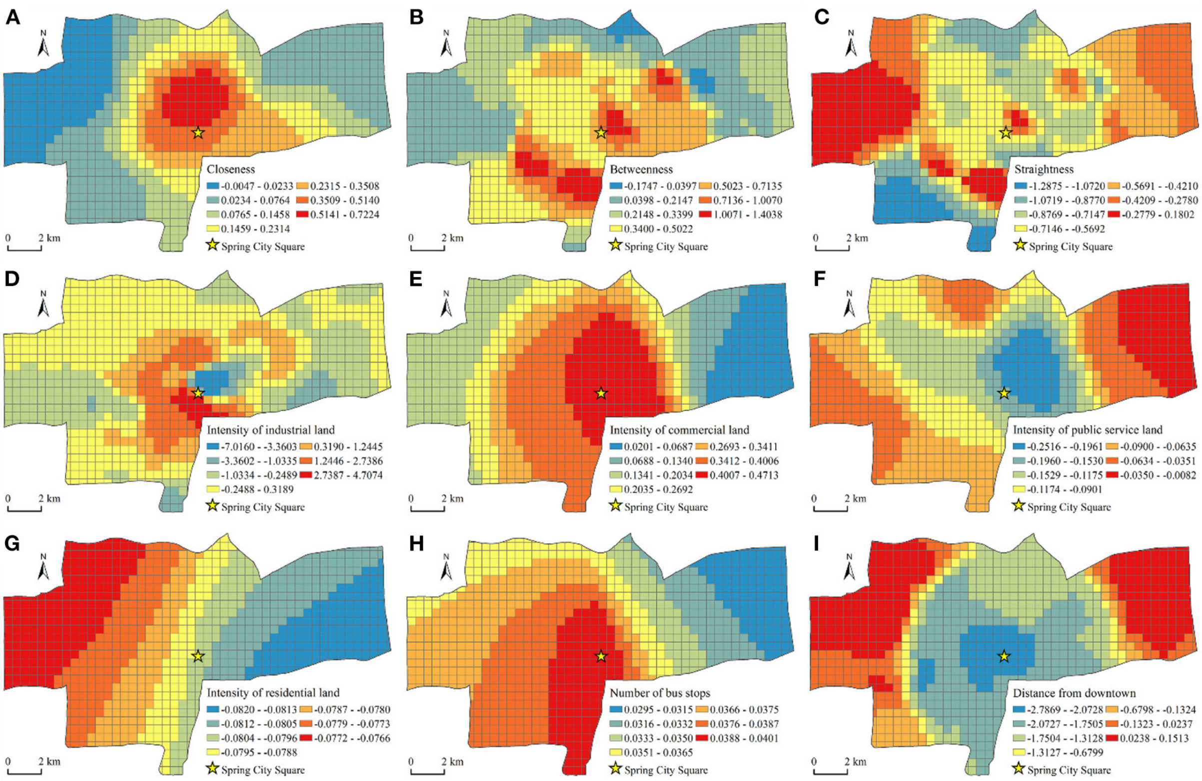

FIGURE 6
Spatial pattern of regional coefficients of MGWR variables in the walking mode. **(A)** Closeness. **(B)** Betweenness. **(C)** Straightness. **(D)** Intensity of industrial land. **(E)** Intensity of commercial land. **(F)** Intensity of public service land. **(G)** Intensity of residential land. **(H)** Number of bus stops. **(I)** Distance from downtown.

the biggest factor affecting the spatial difference of the vitality of the catering industry. The regression coefficient gradually increased from Spring City Square to the periphery, which indicated that the promotion effect of the city center location on the vitality of the catering industry weakened with an increase in distance. The absolute values of the coefficients on the western and eastern edges of the main urban area were relatively small. For restaurants, the location advantage of the downtown existed only within a certain distance threshold. After the distance threshold was exceeded, the attractiveness of the central location decreased rapidly.

Conclusion and planning implications

Major findings

By analyzing the relationship between street centrality and the vitality of healthy catering industry, the following conclusions can be drawn:

First, the vitality of the catering industry in the main urban area of Jinan presented a multicore spatial distribution model. We identified two cores, the Quancheng Road business district and Jingsi Road business district, and five subcenters, but most of these areas had low or no vitality. The high value areas of vitality coincided with the main business districts of the city in terms of spatial distribution. We found obvious differences in the spatial pattern of street centrality in the walking and driving modes. As the measurement scale of street centrality became larger, a wider range of traffic road network characteristics was revealed. The high-value area of closeness tended toward the downtown area from the edge of the study area, the betweenness was distributed from sheet to grid, and the multicenter structure of straightness was more protruded.

Second, street centrality affected the vitality of the catering industry by affecting regional traffic flow and traffic efficiency. In general, straightness had the greatest impact on the vitality of the catering industry, followed by betweenness and closeness. Changes in residents' travel patterns led to differences in the perception of the road network structure, which in turn affected destination choices. On the large-scale spatial scale, betweenness and straightness had a greater impact on the vitality of the catering industry, and closeness was more obvious on the small spatial scale.

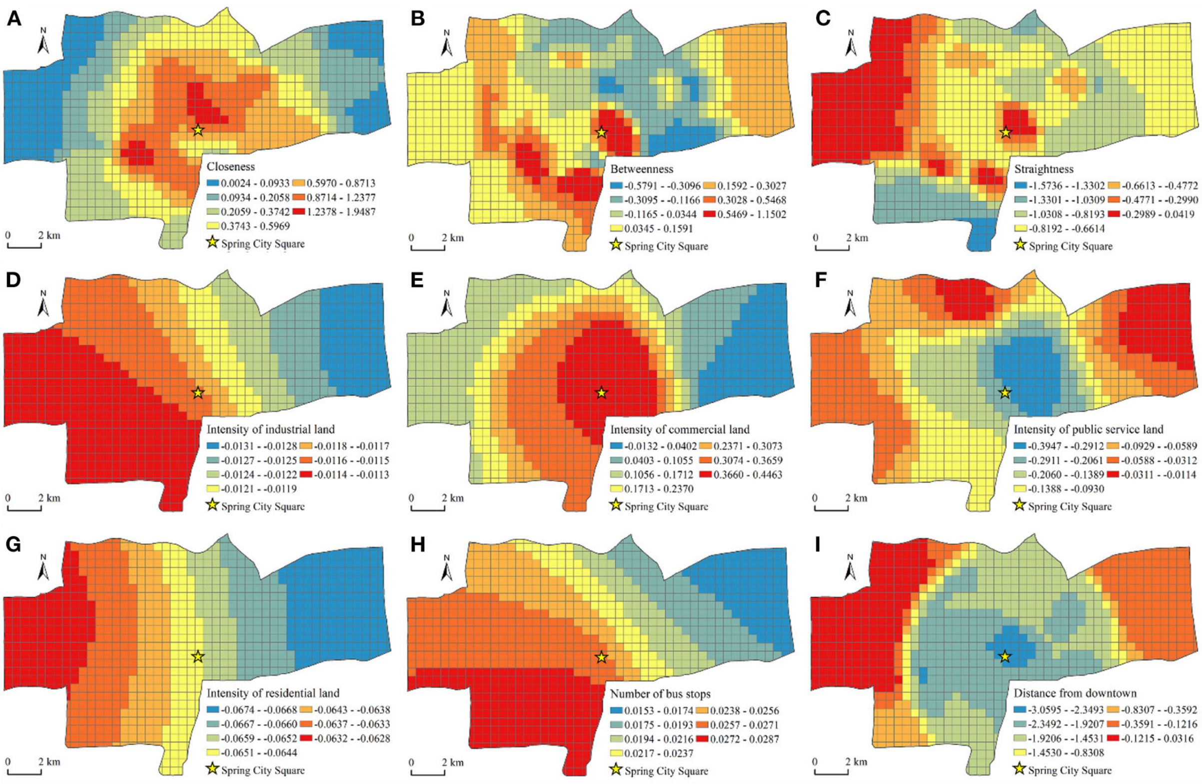

FIGURE 7
Spatial pattern of expression coefficients of MGWR variables in the driving mode. **(A)** Closeness. **(B)** Betweenness. **(C)** Straightness. **(D)** Intensity of industrial land. **(E)** Intensity of commercial land. **(F)** Intensity of public service land. **(G)** Intensity of residential land. **(H)** Number of bus stops. **(I)** Distance from downtown.

Third, residents' different living conditions, travel habits, and travel needs also affected the choice of restaurants. Street centrality of the two travel modes had different influences on the vitality of the catering industry in different locations. In the walking mode, the straightness had the strongest spatial heterogeneity, the betweenness was the second, and the closeness was the weakest. In the driving mode, the closeness had the strongest spatial heterogeneity, the straightness was the second strongest, and the betweenness was the weakest.

Planning implications

The findings of this study have policy implications for the key role of road network structure in the healthy living environment of urban residents. First, the overall positive spatial connection between street centrality and VHCI shows that the spatial features of human activities, such as geographic location, are necessary for scientific urban planning (57). Authorities should make use of the location advantage of the road network, the construction of the urban business districts and the planning of the living circle to guide the design of a healthy urban environment, provide a beneficial location for restaurants that provide healthy food, and actively guide the green and healthy development of the catering industry. Second, urban designers and planners should realize that the advantages of a street network configuration cannot be determined on a single scale. On the contrary, various travel modes should be considered, taking into account the healthy dietary needs of different groups of people, and promoting the improvement of urban quality (59). The results of our study indicate key factors that need to be considered in the construction of a healthy urban environment, and provide a useful reference for urban space optimization. However, residents' travel habits and dietary preferences vary from region to region, so further research is needed to determine the specific impact of different regions. With more evidence, it is easier to extend the findings of one region to others and provide information for healthy urban planning in China and other countries (60).

Limitations

Influenced by data sources, analysis models, and methods, this study will be further improved in the following two ways: First, the influence of road grade, width, and other factors was not considered when calculating the street centrality, which may have caused the deviation between the calculation results and the actual situation. Second, because of data acquisition limitations, this study analyzed the impact of street centrality on the vitality of the catering industry based on cross-sectional data and failed to reflect the dynamic characteristics of the vitality of the catering industry and its influencing factors. In the future, data for different types of cities in different years will be collected, and a spatiotemporal dynamic analysis of street centrality and the vitality of healthy catering will be conducted.

Data availability statement

The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding author.

Author contributions

Conceptualization, formal analysis, and methodology: YC and YH. Data curation and software: YH. Funding acquisition and project administration: GY. Supervision and writing—review and editing: GY and YH. Writing—original draft: YC. All authors contributed to the article and approved the submitted version.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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Spatio-temporal effect of provincial technological innovation on environmental pollution in China

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The relationship between technological innovation (TL) and environmental pollution (EP) and its action mechanisms are complex and controversial aspects of discussion. Using the spatial autocorrelation analysis, standard deviation ellipse analysis, kernel density function, spatial econometric model, this study analyzed the spatial distribution, evolution characteristics, and influencing factors of the EP and TL from 2000 to 2020 in China. Results found there was a significant spatial autocorrelation between the EP and TL in 2000–2020. The standard deviation ellipse of EP was broadly distributed in the "southwest-northeast" direction, indicating that EP presented a trend of concentration in the direction of "southwest-northeast." The moving trajectory of the center of gravity for the EP in 2000–2020 was essentially moved from the northeast to southwest. Overall, the national level of TL exhibited a "north-south change, high in the east, and low in the west" trend. Regional differences were gradually expanding, and the polarization was evident. Regardless of using least squares method (OLS) or quantile regression (QR) models, TL, human capital (HC), and industrial structure (IS) all had an inhibitory effect on the EP at the effective significance level. Total population (TP), foreign direct investment (FDI), and local fiscal expenditure (LFE) were positively related to the EP.

KEYWORDS

technological innovation, environmental pollution, space effect, quantile regression, China

Introduction

With the rapidly development of global economy and industrialization, the global environmental sustainability is constantly threatened, which has aroused extensive attention (1, 2). Water pollution (3, 4), air pollution (*via* gaseous emissions) (5, 6), soil pollution (7), and air pollution (*via* other industrial pollutant emissions) have a significant influence on environmental stability (8). With the societal advancements, an awareness of the destruction of the natural environment has emerged (9–11). The book "Silent Spring" focuses on scientific information regarding environmental risks (12). Research has indicated that disparities in economic development levels could trap regions in environmental inequality problems such as environmental restriction policies

(13), industrial structure layouts (14), and research & development (R&D) investment in green technology innovation (15, 16). Developed nations have a higher income level encouraging them to prioritize high-quality environmental development at an early stage. During the later stages of economic development, there was a progressive decline in environmental pollution as the economic development level increased (17). Environmental inequality intensifies the contradiction between economic development and pollution discharge in some regions, and key industrial emissions such as sulfur dioxide, soot, wastewater, and solid waste are significantly correlated in a spatial context (18–21). Although the geographical environment or climatic conditions influences environmental pollution, anthropogenic factors such as excessive use of fossil fuels, increased population densities, rapid urbanization, and industrialization remain the primary causes of environmental pollution and degradation (22–24).

Technological innovation (TL) is often considered the driving force behind economic growth, and it can play an important role in strengthening the competitiveness of enterprises and enhancing the national economy as a whole (25). Because of regional heterogeneity and asymmetry, TL has become a research hotspot for solving environmental pollution problems by developing a sustainable industrial structure (IS) (26). About the relationship between the environment and TL, during the previous studies, there is no research-based consensus on the relationship between TL and the environment pollution, with three main viewpoints existing. First, TL can effectively improve environmental quality in accordance with sustainable development goals (27). Second, TL can degrade environmental quality in the short term, but this trend can be reversed as an investment in core R&D technologies grows (28). Third, there is no influence or a non-linear relationship between TL and environmental quality (29). However, as research has progressed, the majority of researchers currently agree that TL is the most effective method to reduce environmental pollution under the guidance of reasonable policies. Despite the fact that TL cannot directly reduce the carbon emission intensity, it can indirectly reduce the carbon emission intensity by supporting the adjustment and optimization of IS, as demonstrated by a number of research findings (30). The industry-based economy has begun to minimize pollution through transformation and TL because of the progress in industrialization (31).

Researches concerning the reduction of environmental pollution by TL in the world are growing. Various studies have been conducted in domestic and foreign. Many international scholars have conducted research in succession (32–34). Such as, Mughal et al. (35) analyzed the panel data of five South Asian countries (Bangladesh, Bhutan, India, Maldives, and Pakistan) from 1990 to 2019 to examine the impacts of TL, EP, energy consumption, and economic growth in these countries. The results demonstrated that the development of TL within the context of policies on sustainable development had eased the consumption of energy, but the resultant consumption levels were still significant. Omri and Hadj (36) examined data from 23 emerging economies and found that most developing countries could effectively reduce carbon dioxide emissions through TL and solid environmental governance. Iqbal et al. (37) used data on the consumption of renewable energy in 37 Organization for Economic Co-operation and Development (OECD) member countries and the enhanced mean group (AMG) method to examine and conclude that renewable energy and TL could contribute to environmental improvement.

As the largest developing country globally, the rapid industrialization and high-quality economic development of China have led to an increase in its income level and heightened concern for EP. Chen et al. (38) analyzed the impact of enterprise TL on air pollution using large enterprise-level data sets from 1998 to 2012. The results showed that TL could significantly reduce the pollution from emissions of enterprises. The sulfur dioxide emissions of industries could be reduced by 2.71% if patent authorizations were increased by 1%. Following further analysis, it was determined that the industrial sector, geographical location, and ownership type influenced the reduction in air pollution *via* TL. Hao et al. (29) examined the impact of TL on EP from the perspective of the quantity and quality of foreign direct investment (FDI) using panel data between 2006 and 2016 for 30 Chinese provinces. The findings revealed that there was a complex non-linear relationship between TL capacity and environmental pollution. When the level of FDI increased from a low to a high level, TL could improve the quality of the environment. However, when the level of FDI went beyond a certain threshold, this beneficial impact would diminish. The ability of TL to have a positive impact on environmental pollution may improve as the quality of FDI grew. Xin and Lv (39) utilized a geographically weighted regression model to analyze the regional differences and impact mechanisms of TL on environmental pollution using data from 285 cities in China. The results indicated that both TL and environmental pollution exhibited significant spatial agglomeration, with urban TL having a detrimental effect on environmental pollution. Economic development, human capital, FDI, environmental regulation, and other factors jointly affected the pollution improvement effect of TL, which indirectly reduced environmental pollution by optimizing IS *via* technological progress.

Therefore, it can be deduced that besides TL, there are also many other factors have the most significant effects, such as the acceleration of economic development, the modification of IS, the improvement of environmental pollution-control policies. Therefore, the impact of TL on EP is unpredictable and limited by numerous factors, and different regions have distinct geographical characteristics. Existing studies have discussed the mechanism of TL affecting EP, but most of them are qualitative analysis. There is a lack of quantitative research on

TABLE 1 Variable setting.

Variable type	Variable definition	Variable description	Data source
Explained variable	Environmental pollution (EP)	Comprehensive index of industrial wastewater discharge, industrial SO_2 discharge, and industrial smoke (powder) dust discharge	"China Statistical Yearbook," statistical yearbook of each province
Explanatory variable	Technological innovation (TL)	Number of green invention patent applications	China national intellectual property administration (https://www.cnipa.gov.cn/)
Control variable	Total population (TP)	Total regional population	"China statistical yearbook"
	Gross domestic product (GDP)	Regional gross domestic product	"China statistical yearbook"
	Human capital (HC)	Number of college students per 10,000 people	"China statistical yearbook"
	Foreign direct investment (FDI)	Regional foreign direct investment	"China statistical yearbook"
	Ratio of added value of secondary and tertiary industries (IS)	Added value of secondary industry/added value of tertiary industry	"China statistical yearbook"
	Environmental regulation (ERS)	The intensity of environmental regulation is measured by the comprehensive index of expenditure and regulatory indicators	"China statistical yearbook," "China environmental statistics yearbook"
	Local fiscal expenditure (LFE)	Local fiscal expenditure	"China statistical yearbook"

the degree of interaction among various influencing factors at the spatial level.

In view of the research deficiency above, this study aimed to analyze the interaction between TL and EP by focusing on 31 provinces in China, taking into account various driving factors, such as TP, GDP, IS, FDI, HC, ERS, and LFE among other factors. By analyzing this mechanism, this study could facilitate a better understanding of the specific mechanisms of inter-provincial TL capacity and environmental pollution and provide a theoretical basis for the Chinese government to formulate innovative incentive policies and environmental pollution control measures that are reasonable and effective. Moreover, it served as a scientific reference for coordinating the development capacity of TL between provinces and enhancing environmental governance.

Data sources and variables selection

The sample interval of this study was set as 2000–2020, owing to data availability, and the total scope of the research covered 31 provinces (including municipalities and autonomous regions, excluding Hong Kong, Macao, and Taiwan). In view of the previous researches (39–41), based on the principles of objectivity, impartiality and data availability, on the premise that the explanatory variable and the explained variable are determined, this study selected the main control variables. Data sources of the variables can been in Table 1.

Explained variables

Environmental pollution (EP) index: environmental deterioration is mainly caused by industrial pollution. Numerous researches utilize industrial emission indicators to quantify the level of environmental pollution. Accordingly, this study selected three indicators, namely, industrial wastewater discharge, industrial SO_2 discharge, and industrial smoke (powder) dust discharge, calculated their weights using the entropy method, and calculated a comprehensive index of environmental pollution for each province using weighted summation.

Explanatory variables

Technological innovation level (TL): this study considered the number of invention patent authorizations as an indicator to measure the level of TL.

Control variables

In addition to TL, other factors affect the ecological environment. The following control variables were selected in this study based on their comparability and the availability of data:

(1) Gross domestic product (GDP): the total GDP is a measure of the amount of economic development.

(2) Total regional population (TP): the TP of the region represents the population scale of the region.

(3) Industrial structure (IS): as an important link between human economic activities and the ecological environment, IS defines the types and quantities of pollution emissions and has varying degrees of impact on the ecological environment. Comparatively, the secondary industries have a far greater coercive effect on the ecological environment than primary and tertiary industries. However, owing to the advancement of information technology, the tertiary industry has gradually assumed a dominant position in the IS. This study measured the IS by the ratio of the added value of the secondary industry to that of the tertiary industry, taking into account the environmental impact of the secondary industry and the change in the IS.

(4) Foreign direct investment (FDI): as an important expression of economic globalization, it is debatable what impact FDI has on the environment, but its impact is undeniable. This study used the quantities of FDI to measure its environmental impact.

(5) Human capital (HC): human capital is the carrier of knowledge and technology, as well as an indispensable aspect for analyzing the environmental effects of HC. Once human capital attains a high level, HC can benefit the local environment *via* technology spillover. The academic community has not established a consensus on human capital measurement indicators. This study was constrained by the availability of provincial data provided references to prior research to measure the amount of human capital using the number of college students per 10,000 people.

(6) Environmental regulation (ERS): the majority of existing studies estimate the intensity of environmental regulation from the perspectives of environmental input and environmental performance. The former consists of pollution control investments, government environmental protection fiscal expenditures, and emission reduction costs, whereas the latter comprises pollution discharge fees, pollution discharge taxes, and pollutant disposal rates. This study covered economic-environmental regulation because it was simpler to internalize external environmental costs *via* economic-environmental regulation (42). Based on the consistency and availability of data, this study employed a comprehensive index of expenditure and regulatory indicators to assess the intensity of environmental regulation. The expenditure index focused on governance expenditures, which were measured by the ratio of industrial pollution control expenditures to industrial added value. The regulatory indicators are based on the monitoring of government departments in implementing the environmental regulation system and policies, following the practice of existing research (43, 44), and using the revenue from domestic sewage charges as the regulatory indicators. In this study, the min-max standardized method was used to calculate the comprehensive index of environmental regulation variables. The formula used was as follows:

$$ERS_{ij} = \frac{ERSM_{ij} - \min(ERSM_i)}{\max(ERSM_i) - \min(ERSM_i)} + \frac{ERRI_{ij} - \min(ERRI_i)}{\max(ERRI_i) - \min(ERRI_i)}$$

$$(i = 1, 2, \ldots, 21; j = 1, 2, \ldots, 31) \tag{1}$$

Where ERS_{ij} represented the comprehensive index of environmental regulation of the *j*th province in the *i*th year, $ERSM_{ij}$ and $ERRI_{ij}$ were the proportions of investment in environmental regulation and the average income of environmental regulation of the *j*th province in the *i*th year, respectively. The $\max(ERSM_i)$ and $\min(ERSM_i)$ represented the maximum and minimum values of the proportion of environmental regulation investment in each province of the country in the *i*th year, respectively. The $\max(ERRI_i)$ and $\min(ERRI_i)$ represented the maximum and minimum of the average income of environmental regulation in each province of the country in the *i*th year, respectively.

(7) Local fiscal expenditure (LFE): the local financial expenditure was used to represent the level of concern for local financing of public goods.

Methods

Spatial autocorrelation analysis

(1) Global spatial autocorrelation. Spatial correlation of variables is the premise of using spatial econometric models. In this study, Moran's index (Moran's *I*) was used to test the spatial autocorrelation of core variables (45). If the sample range of the spatial correlation test was set to encompass the whole research scope of this study, the global Moran index could be utilized to reflect the spatial distribution pattern state of variables across the entire region (i.e., determining whether a clustering distribution existed). Formula (2) demonstrates the calculation method:

$$I = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} W_{ij}(Y_{ij} - \overline{Y})(Y_j - \overline{Y})}{S^2 \sum_{i=1}^{n}\sum_{j=1}^{n} W_{ij}} \tag{2}$$

where $S^2 = \frac{\sum_{i=1}^{n}(Y_i - \bar{Y})}{n}$ represented the sample variance, W_{ij} represented the spatial weight matrix, and Y_i and Y_j were the observed values of area *i* and area *j*, respectively. The value range of Moran's *I* index was $-1 \leq$Moran's $I \leq 1$. If the *I* value was >0, it indicated a positive spatial autocorrelation; when the *I* value was <0, it indicated a negative spatial autocorrelation; when *I* was equal to 0, there was no spatial autocorrelation.

(2) Local spatial autocorrelation. Global Moran's index can only characterize the cluster status of core variables within a

provincial scope and is incapable of accurately locating and distinguishing the specific spatial correlation patterns of the region (45). The local spatial correlation index LISA could describe whether the aggregation distribution between a region and its surrounding areas was a high- or low-value aggregation. The calculation method is shown in formula (3):

$$I_i = \frac{(Y_i - \overline{Y}) \sum_{j=1}^{n} W_{ij}(Y_j - \overline{Y})}{S^2} \tag{3}$$

where $S^2 = \frac{\sum_{j=1, j \neq i}^{n} Y_j - \overline{Y}}{n-1}$; I_i is the local spatial autocorrelation coefficient of the ith province; Y_i represents the observation value of the ith province; and W_{ij} represents the spatial weight matrix. Based on the local Moran's I index, the LISA agglomeration map can be drawn up, which classifies the local spatial connection forms into High-High cluster, Low-Low cluster, Low-High cluster, and High-Low cluster.

Standard deviation ellipse analysis

The standard deviation ellipse derived from spatial statistics can accurately reveal the spatial distribution characteristics of geographical elements (46). The model primarily represents the shape, orientation, distribution range, and other characteristics of the spatial distribution of attribute values of the research scope *via* the long axis, short axis, center of gravity, and rotational angle (47). The formula is as follows:

$$\overline{X_w} = \frac{\sum_{i=1}^{n} w_i x_i}{\sum_{i=1}^{n} w_i} \qquad \overline{Y_w} = \frac{\sum_{i=1}^{n} w_i y_i}{\sum_{i=1}^{n} w_i} \tag{4}$$

$$\tan\theta = \frac{(\sum_{i=1}^{n} w_i^2 \Delta x_i^2 - \sum_{i=1}^{n} w_i^2 \Delta y_i^2) + \sqrt{\sum_{i=1}^{n} w_i^2 \Delta x_i^2 - \sum_{i=1}^{n} w_i^2 \Delta y_i^2) + 4 \sum_{i=1}^{n} w_i^2 \Delta x_i^2 \Delta y_i^2}}{2 \sum_{i=1}^{n} w_i^2 \Delta x_i \Delta y_i} \tag{5}$$

$$\sigma_x = \sqrt{\frac{\sum_{i=1}^{n} (w_i \Delta x_i \cos\theta - w_i \Delta y_i \sin\theta)^2}{\sum_{i=1}^{n} w_i^2}}$$

$$\sigma_y = \sqrt{\frac{\sum_{i=1}^{n} (w_i \Delta x_i \sin\theta - w_i \Delta y_i \cos\theta)^2}{\sum_{i=1}^{n} w_i^2}} \tag{6}$$

$$S = \pi \sigma_x \sigma_y \tag{7}$$

where (x_i, y_i) indicates the geographical coordinates of province i in the study area, and w_i represents the weight. (X_w, Y_w) represents the weighted average geographical center coordinates of the study area; θ is the azimuth angle of the ellipse $(\Delta x_i, \Delta y_i)$; represents the deviation between the geographical location of province i in the study area and the weighted average geographical center coordinates of the study area; σ_x and σ_v represent the standard deviation values along the X-axis and Y-axis, respectively; and S is the area of the ellipse.

Trend surface analysis

Trend surface analysis is based on spatial data and uses mathematical analysis methods to simulate spatial surfaces, depict the spatial distribution law of geographical elements, and consequently investigate the spatial change trend of geographical elements. It has significant utility in spatial analyses (48). In this study, we used coupled co-scheduling as the observation value, and we simulated the spatial differentiation characteristics of TL of provinces in China using trend surface analysis. If (x_i, y_i) is the spatial position of the ith province, then Z (x_i, y_i) represents the trend function of the ith province, where the X-axis depicts the east-west direction, and the Y-axis depicts the north-south direction.

Dynamic evaluation analysis model

To further investigate the spatiotemporal dynamic characteristics of the EP, the kernel density function was employed to analyze its temporal characteristics. The kernel density function method analyzes the overall spatial change and evaluates the overall difference by adjusting the convergence degree and range of the function curve. The kernel density function is as follows:

$$f(x) = \frac{1}{nh} \sum_{i=1}^{t} K\left(\frac{x_i - x}{h}\right) \tag{8}$$

where n is the total number of samples and h is the set window width, where $lim\ n \to \infty$, $h(n) = 0$. In this study, the Gaussian kernel function is used for estimation, and its expression is:

$$K(x) = \frac{1}{\sqrt{2\pi}} \exp\left[-\frac{x^2}{2}\right] \tag{9}$$

By combining the distribution form and the kernel density function diagram, we could effectively judge the change of the EP across various observational periods and then characterize its dynamic characteristics.

TABLE 2 Regional division of China.

Region	Provinces
Eastern China	Beijing, Tianjin, Shanghai, Liaoning, Jiangsu. Zhejiang, Fujian, Shandong, Guangdong.
Central China	Hebei, Shanxi, Jilin, Heilongjiang, Anhui, Jiangxi, Henan, Hubei, Hunan, Hainan.
Western China	Inner Mongolia, Guangxi, Chongqing, Sichuan, Guizhou, Yunnan, Xizang, Shaanxi, Gansu, Ningxia, Qinghai, Xinjiang.

The driving factors based on the quantile regression model

The least squares method is the most commonly used method of fitting a regression curve to given data (49). The basic notion is as follows:

$$f(x) = \alpha_1\varphi_1(x) + \alpha_2\varphi_2(x) + ... + \alpha_m\varphi_m(x) \quad (10)$$

where $\varphi_k(x)$ is a predetermined set of linearly independent functions; α_k is an undetermined coefficient (k = 1, 2,..., m, m < n); and the fitting criterion is to minimize the square sum of the distance ∂_i between y_i (i = 1, 2,..., n) and $f(x_i)$, also known as the least square criterion.

Traditional regression models emphasize the influence of explanatory variables on the conditional expectations of the explained variables, depicting a concentrated trend while frequently disregarding the coefficient changes resulting from the conditional random probability distribution. To remedy this flaw, Koenker and Bassett Jr. (50) developed the QR model. This model excludes the interference of outliers more effectively than other models and does presume that the data follow a normal distribution. It can examine the influence of explanatory variables on explained variables in different quartiles in an effective manner (51). The formula for the panel data is as follows:

$$Q_{Y_{it}}(\tau|X_{it}) = \alpha_i + {X_{it}}^T\beta(\tau), (i = 1, 2, \ldots, n; \; t = 1, 2, \ldots, T) \quad (11)$$

where Q_{Yit} is the conditional quantile function; i is the individual of different samples; t is the sample observation period; n is the sample size; T is the study period; τ is the quantile set in this study, and the value range is (0, 1); α_i is a constant term; and $\beta(\tau)$ is the influence coefficient at the τ quantile, which isoften estimated using weighted least squares β.

$$\beta(\theta) = \min_{(\alpha,\beta)} \sum_{k=1}^{q}\sum_{i=1}^{n}\sum_{t=1}^{T} w_k\rho_{\tau_k}\left[Y_{it} - \alpha_i - X_{it}^T\beta(\tau_k)\right] \quad (12)$$

where $\beta(\theta)$ represents the influence coefficient; k is the kth group of quantiles; q represents the number of quantile arrays; w_k is the weight coefficient of the k quantile; $\rho_{\tau k}$ represents the quantile loss function; and $\beta(\tau_k)$ is the influence coefficient of the k quantile.

In order to clearly express regional differences, the Table 2 shows the specific divisions of the eastern, central and western provinces in China.

Results

Spatial autocorrelation analysis

The global spatial autocorrelation, as measured by the global Moran's I index, can reflect the interdependence of core variables in various regions in the global range. Table 3 depicts Moran's I index of the spatial distribution of environmental pollution and TL under the conditions of a geographical adjacency matrix from 2000 to 2020. In the majority of provinces, the results indicated there is a significant spatial autocorrelation between EP and TL, which could be utilized for subsequent spatial effect measurements and estimation.

For further analysis, this study further uses LISA scatterplot to characterize the EP clustering distribution of the area and its surrounding areas (Figure 1). Figure 1 shows that, except for insignificant areas, there were four spatial clustering types of EP: High-High cluster, Low-Low cluster, Low-High cluster, and High-Low cluster. Quantitatively, the positive spatial correlations of High-High cluster and Low-High cluster are predominated. Among them, from 2000 to 2020, High-High cluster of EP agglomerations are mainly distributed in the central and northern areas, which may be due to the fact that the technological innovation and industrialization of these cities are at a high level, and the negative impact of industrialization on the EP is greater than the positive effect of technological innovation, and technological innovation activities are not enough to improve the EP in the surrounding areas; Low-High cluster of EP agglomerations are mainly located in the central and southern areas of China (Hubei, Anhui), indicating that these areas have a low level of EP themselves and a high level of EP in the surrounding areas.

TABLE 3 Global Moran's *I* index of each core variable from 2000 to 2020.

Year	Variable	*I*	Year	Variable	*I*	Year	Variable	*I*
2000	TL	0.0980**	2007	TL	0.0064*	2014	TL	0.0077*
	EP	0.0281*		EP	0.7720*		EP	0.1229**
2001	TL	0.0442**	2008	TL	0.0375*	2015	TL	0.0264**
	EP	0.0387*		EP	0.0756*		EP	0.1012**
2002	TL	0.0382**	2009	TL	0.0456*	2016	TL	0.0340**
	EP	0.0403*		EP	0.0735*		EP	0.1051**
2003	TL	0.2299*	2010	TL	0.0449*	2017	TL	0.0012*
	EP	0.0574*		EP	0.0989**		EP	0.1298**
2004	TL	0.0504*	2011	TL	0.0394*	2018	TL	0.0033*
	EP	0.0725*		EP	0.1283**		EP	0.0789*
2005	TL	0.0054*	2012	TL	0.0249*	2019	TL	0.0241*
	EP	0.0651*		EP	0.1352**		EP	0.0606*
2006	TL	0.0092*	2013	TL	0.0125*	2020	TL	0.0069*
	EP	0.0628*		EP	0.1325**		EP	0.1090**

*, **, and *** Mean significant correlation at the level of 10%, 5%, and 1%, respectively.

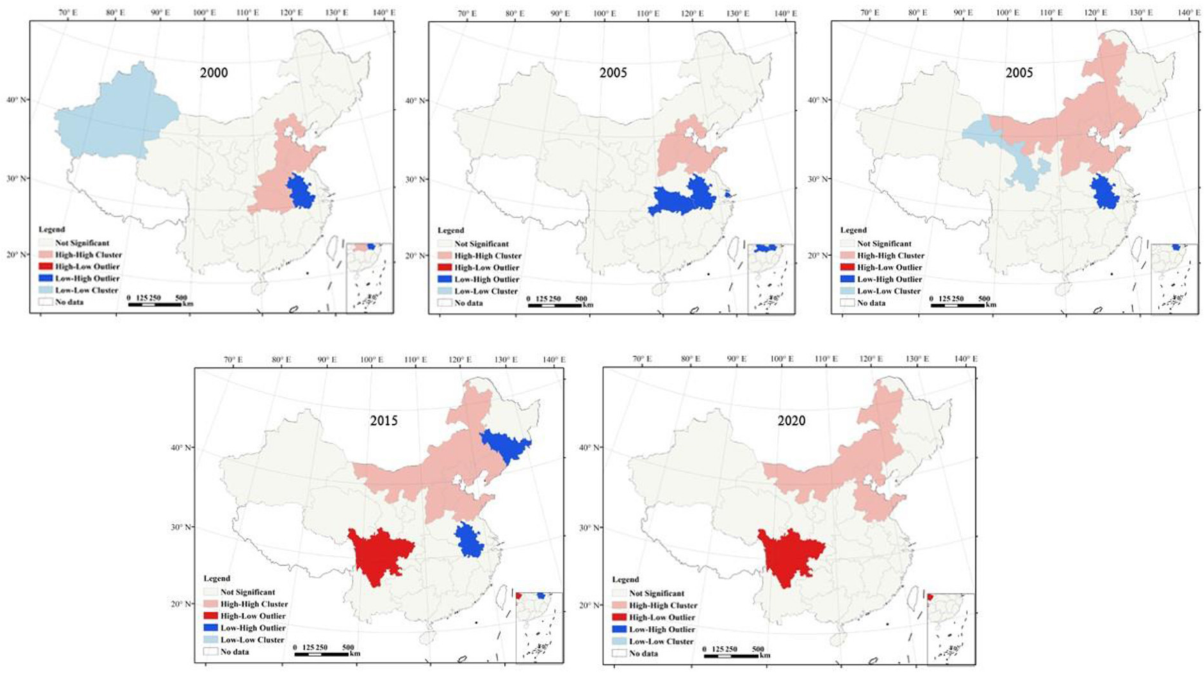

FIGURE 1
LISA cluster diagram of EP in 2000–2020.

Trend analysis

Trend analysis of core explanatory variables

The spatial distribution direction and dynamic characteristics of the comprehensive EP at the national and provincial scales were investigated using the standard deviation ellipse analysis tool of ArcGIS 10.3 software (Environmental Systems Research Institute), as listed in Table 4 and Figure 2.

The results show that the following: (1) the standard deviation ellipse was generally positioned in the eastern China. The circumference of the ellipse showed a "first increasing and then decreasing" trend; it increased from 58.23 km in 2000 to 63.87 km in 2015 and then decreased to 63.77 km in 2020. (2)

TABLE 4 Basic information of standard deviation ellipse analysis.

Year	Circumference of the ellipse (km)	Elliptical area (km^2)	Longitude	Latitude	X-axis length (km)	Y-axis length (km)	Direction
2000	58.23	255.86	113.46	33.11	7.47	10.91	56.53°
2005	59.75	274.33	113.55	33.31	8.02	10.89	57.30°
2010	61.24	289.14	113.45	33.50	8.30	11.10	60.05°
2015	63.87	313.05	113.20	34.00	8.54	11.67	68.54°
2020	63.77	314.11	113.01	33.55	8.68	11.52	65.95°

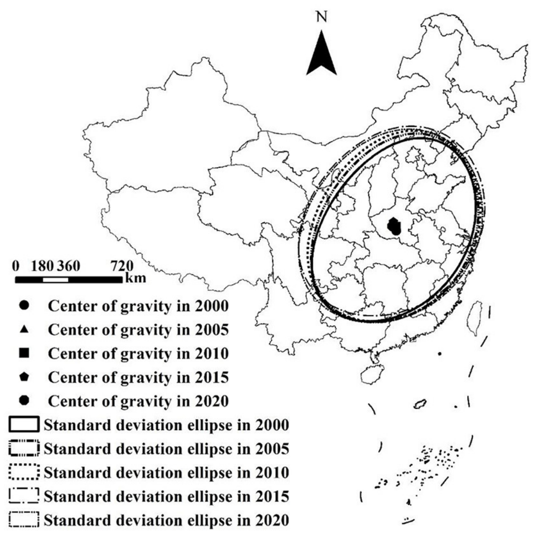

FIGURE 2
Standard deviation ellipse and center of gravity movement trajectory of China's environmental pollution index (EP) from 2000 to 2020.

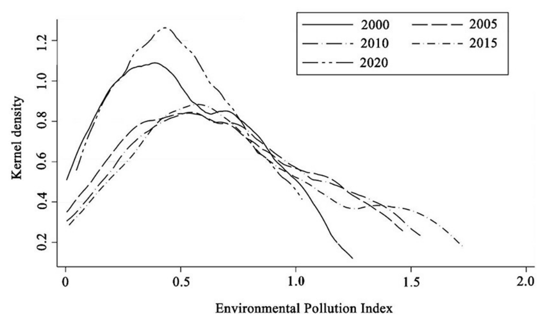

FIGURE 3
Dynamic evolution of the national EP from 2000 to 2020.

The area of the ellipse showed a "continuous increase" trend; it increased from 255.86 km^2 in 2000 to 314.11 km^2 in 2020, indicating that the EP of cities outside the ellipse was higher than that of cities inside the ellipse during 2000–2020. During the study period, the EP in the central region had a spatial distribution characteristic of "continuous expansion." (3) There was a clear difference between the long and short axes of the standard deviation ellipse, indicating that the spatial distribution of the national EP was directional. The standard deviation ellipse was broadly distributed in the "southwest-northeast" direction, indicating that EP presents a trend of concentration in the direction of "southwest-northeast." (4) The rotational angle of the standard deviation ellipse increased from 56.53° in 2000 to 68.54° in 2015 and then decreased to 65.95° in 2020. It revealed that the ellipse first rotated counterclockwise and subsequently slightly clockwise, indicating that the EP in the southwest or northeast changed rapidly. (5) The moving trajectory of the center of gravity of the EP from 2000 to 2020 was as follows: from 2000 to 2005, it moved to the northeast; from 2005 to 2015, it continued to move to the northwest; and from 2015 to 2020, it moved to the southwest. Henan Province was always the center of gravity of the EP from 2000 to 2020 (Figure 2).

To better elucidate the dynamic characteristics of regional differences in the EP, this study used the Gaussian kernel density function and growth distribution chart to depict the evolution trend of regional differences in the EP. The data for 2000, 2005, 2010, 2015, and 2020 were selected, and the dynamic evolution process of the national and provincial EPs was plotted using Stata 15 software (Computer Resource Center) (see Figure 3).

Overall, the peak of the kernel density curve of the national and provincial EPs slowed down progressively. In 2005, the center of the density function shifted to the right compared to 2000, and the peak declined, indicating that the regional differences were increasing. In 2010 and 2015, the center of the density function shifted to the right by a substantial margin, the peak slowed, and the width significantly widened, indicating that the disparity between regions in the EP expanded with time. In 2020, the peak value of the kernel density function of the EP abruptly increased, and the center of the function shifted to the left, indicating that the polarization of the regional EP had weakened.

Trend analysis of explained variables

The trend surface analysis was used to process and analyze the national TL level from 2000 to 2020 to analyze the changing

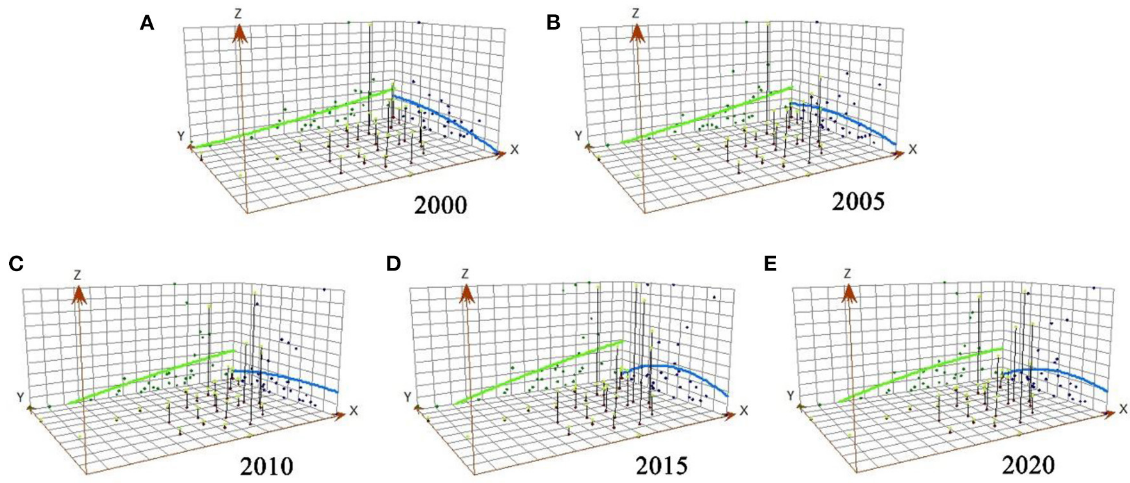

FIGURE 4
(A–E) Trend surface analysis results of provincial technological innovation (TL) levels in China.

TABLE 5 Least squares method (OLS) and quantile regression (QR) estimation results.

Variable	OLS	QR								
		0.10	0.20	0.30	0.40	0.50	0.60	0.70	0.80	0.90
ln TL	−0.078***	−0.056***	−0.046***	−0.046***	−0.052**	−0.051**	−0.057***	−0.062**	−0.089***	−0.110***
	(0.013)	(0.012)	(0.01)	(0.011)	(0.016)	(0.017)	(0.018)	(0.024)	(0.026)	(0.024)
ln TP	0.337***	0.236***	0.276***	0.303***	0.329***	0.361***	0.373***	0.410***	0.354***	0.362***
	(0.023)	(0.022)	(0.018)	(0.019)	(0.027)	(0.03)	(0.032)	(0.042)	(0.045)	(0.041)
ln HC	−0.112***	−0.067*	−0.100***	−0.123***	−0.139***	−0.163***	−0.155***	−0.200***	−0.139*	−0.080*
	(0.03)	(0.029)	(0.024)	(0.025)	(0.036)	(0.041)	(0.042)	(0.057)	(0.06)	(0.055)
ln FDI	0.044***	0.030***	0.031***	0.035***	0.040***	0.038***	0.033***	0.045***	0.051***	0.044**
	(0.007)	(0.007)	(0.006)	(0.006)	(0.009)	(0.01)	(0.01)	(0.014)	(0.015)	(0.013)
ln IS	−0.248***	−0.184***	−0.203***	−0.220***	−0.245***	−0.281***	−0.270***	−0.290***	−0.324***	−0.287***
	(0.028)	(0.027)	(0.022)	(0.023)	(0.034)	(0.038)	(0.039)	(0.052)	(0.055)	(0.051)
ln LFE	0.176***	0.132***	0.124***	0.126***	0.140***	0.150***	0.145***	0.188***	0.209***	0.210***
	(0.016)	(0.015)	(0.013)	(0.013)	(0.019)	(0.022)	(0.022)	(0.03)	(0.032)	(0.029)
_cons	−2.951***	−2.200***	−2.372***	−2.519***	−2.739***	−2.903***	−2.834***	−3.315***	−3.025***	−3.006***
	(0.172)	(0.164)	(0.138)	(0.141)	(0.206)	(0.23)	(0.239)	(0.319)	(0.336)	(0.31)

Values in parentheses are *t*-test values; ***, **, and * represent significance at a confidence level of 1, 5, and 10%, respectively.

trend and distribution law of TL at the national and provincial levels. The X-axis signifies the due east direction; the Y-axis represents the due north direction; the blue curve shows the change fitting line of the national TL in a north-south direction; and the green curve represents the change fitting line in an east-west direction (Figure 4). Figure 4 demonstrates that the national green technology innovation index in its entirety exhibits a trend of "north-south change, high in the east, and low in the west".

Based on the north-south trend of the curve, the level of TL in 2000–2005 displayed a clear north-south spatial distribution, with high levels in the north and low levels in the south (Figures 4A,B). However, from 2010 to 2020, it gradually transformed into a significant spatial distribution characterized by low values in the north and high values in the south. The northeast showed evident spatial characteristics of "high in the east and low in the west." While, the gap between the east and the west slightly widened, indicating that the gap of TL level at the provincial level in China was steadily widening in an east-west direction. The level of TL among regions had developed to varying degrees, and the regional gap was deepening (Figures 4C–E).

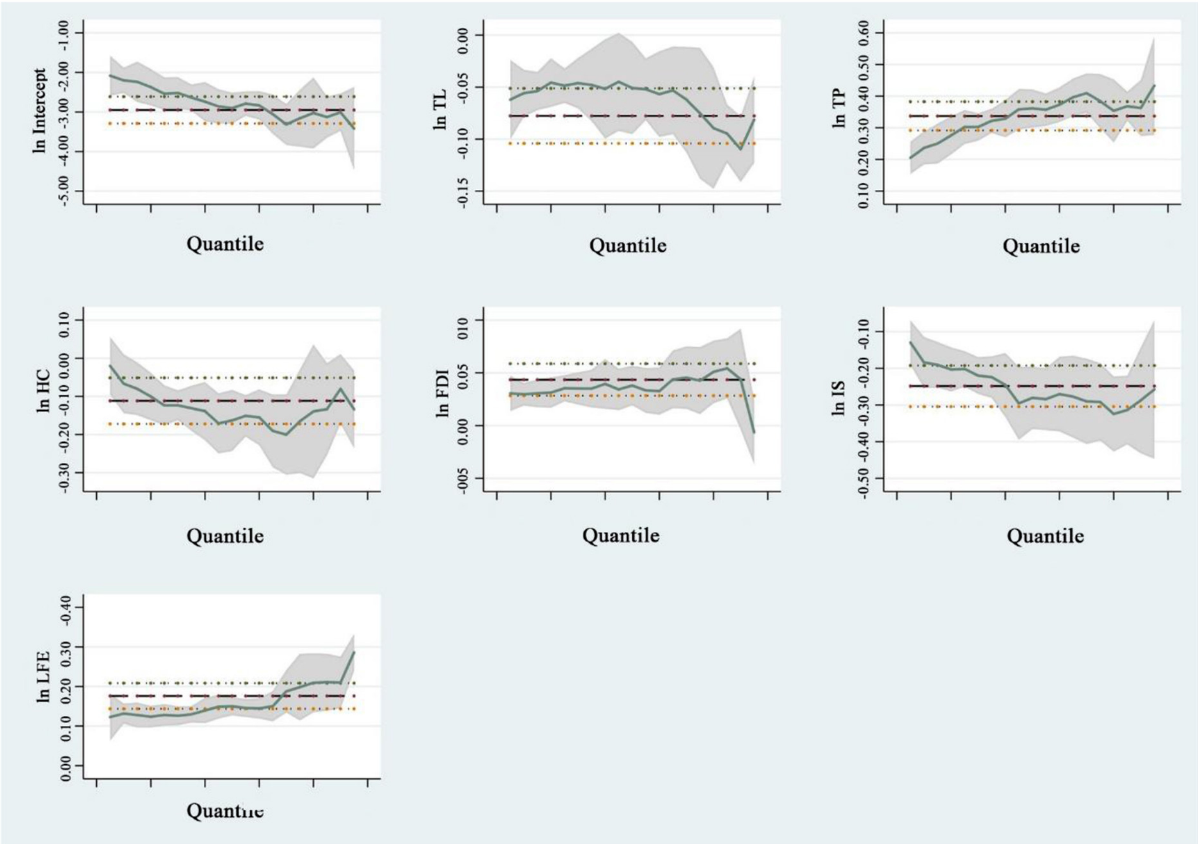

FIGURE 5
Distribution of the regression elasticity coefficient of influencing factors of the environmental pollution index (EP) in China.

Influencing factors of green technology innovation level

Existing research indicates that the degree of EP differs at various stages of economic development, and the impact of different stages of TL on the EP varies as well. Compared with the ordinary least square regression, the QR model gave a novel perspective on the basis of compensating for the biases and outliers in the data, which could not fulfill the presupposition of mean regression: when the independent variable was determined, more data were mined at different levels of the dependent variable to effectively portray the dynamic relationship between different and dependent variables. Therefore, this study estimated the dynamic relationship between the EP and TL using equations (10) and (11). There was potential for multicollinearity among variables. Based on the QR, the process was as follows: take the logarithm of the primary term of the control variable, conduct a multicollinearity test, eliminate variables with possible collinearity, and finally retain TL, TP, HC, FDI, IS, and LFE. To compare the mean regression coefficient of the traditional panel data model, the OLS model was initially generated. To enhance the evaluation effect, this study utilized nine quantile indexes (i.e., 0.10, 0.20, 0.30, 0.40, 0.50, 0.60, 0.70, 0.80, and 0.90) to evaluate the relationship between various influencing factors and the distribution of the EP under variable conditions. Table 5 lists the panel QR results for different variables, whereas Figure 5 depicts the elasticity coefficient distribution for various variables.

Table 5 demonstrates that the regression coefficients (regression curve slopes) of different variables in different quartiles vary; that is, the degree of influence and the effect of different variables on the marginal effects for EP in various quartiles differ. From the perspective of core explanatory variables, regardless of OLS or QR, the impact of TL on the EP was negative at the level of effective significance, and the overall trend initially increased and then decreased with the increase in quantile, indicating that TL had a negative impact on the EP. This indicated that all provinces in the country were in the initial stage of cost saving and that TL support, such as technology improvement and management mode optimization, was poor. Innovation compensation could hardly compensate for the high production costs caused by environmental regulation, and matching funds and policies could hardly demonstrate the impact of environmental pollution levels, making it difficult to offset the negative impact of TL on the crowding-out effect of innovation input. The results showed that TL was the primary contributor to the EP, and that the inhibitory effect of TL on EP was more significant in the middle quartile provinces than that in the high quartile provinces.

Regarding the control variables, the TP, HC, FDI, IS, LFE, all had a significant impact on the EP at the effective significance level. Specifically, the TP had a significant positive correlation with the EP, and the positive effect fluctuated with an increase in the quantile, which generally exhibited a trend of "initially increasing and then decreasing." The specific realization was that the regression coefficient exhibited an ascending trend in the low and middle quartiles (0.10–0.70) and a descending trend in the high quartiles (0.80–0.90). This showed that increasing the total population would aggravate the level of environmental pollution to a certain extent, because population growth would result in the aggregation and development of various industrial resources, which will aggravate the degree of environmental pollution to a certain extent.

HC had a significant inhibitory effect on the EP, which fluctuated as the quartile increased. Specifically, the regression coefficient revealed an increasing trend in the low and middle quartiles (0.10–0.50), followed by a fluctuating trend in the high quartiles (0.60–0.90). This was because HC reflected the educational level and consciousness of environmental protection of local populations, which is conducive to regional environmental protection.

FDI had a significant positive effect on the EP at the middle and low quartile levels, with a clear inverted "m" - shaped rising trend with an increase in the quartile. This indicated that the influence of FDI on regions with a low EP was evident, whereas the effect of FDI on regions with a high EP was weaker.

IS had a significant inhibitory effect on the EP, which fluctuated with an increase in quantiles. Particularly, the regression coefficient revealed an ascending trend in the low and middle quartiles (0.10–0.50), followed by a fluctuating trend in the high quartiles (0.60–0.90). This indicated that the inhibitory effect of IS in regions with a low EP was minimal, whereas in regions with a high EP, the inhibitory effect of increased IS was amplified.

The positive effect of local LFE on the EP fluctuated with an increase of the quantile. Generally, it showed an "*n*" type fluctuating trend with an increase of the quantile. The specific performance is that in the low and middle quantiles (0.10–0.60), the regression coefficient was low, and the positive effect on the EP was weak. Moreover, it was at a high level in the high quartile (0.70–0.90), and it had a strong positive effect on the EP. This demonstrated that the regression coefficient of LFE increased as the quantile increased. The positive effect of LFE gradually increased, indicating that the degree of environmental pollution could effectively be reduced by increasing LFE during the transition process of provincial EP from low to high.

The aforementioned results demonstrated that each variable had different effects on the EP at various quantile levels. On this basis, the confidence interval diagram of the QR curve of the various quantiles was produced to investigate the impact of different variables on the EP (Figure 5). The regression elasticity coefficient distribution of variables demonstrated that the influence of social and economic factors on the level of green TL was phased. The upper and lower limits of OLS estimation coefficients and their confidence intervals are represented as horizontal lines, and their coefficients and confidence intervals remain unchanged as quantiles change. For the regression coefficient of the QR model, with a change of quantile conditions (Figure 5), it was discovered that the regression coefficient significantly changed with a high EP.

The TP, HC, FDI, IS, and LFE had a significant influence on the EP at the effective significance level, regardless of whether OLS or QR was used. In particular, the regression coefficients and confidence intervals of the TP, FDI, and LFE were all >0, indicating a positive effect on the EP. The confidence intervals of the TP and FDI were gradually widening, indicating that the standard deviation of the coefficient and its volatility were gradually increasing.

The promoting effect of TP and TS on the EP of low and middle quartile provinces was greater than that of high quartile provinces; FDI had a more substantial role in promoting the improvement of the EP of high-ranking provinces than other variables. The regression coefficients and confidence intervals for TL, HC, and IS were <0, indicating a negative impact on the EP.

Furthermore, the coefficient estimates for different quantiles of each variable fell outside the coefficient confidence interval of the mean regression model, indicating that the mean regression model was partially irrational and the QR model could better explain the relationship between variables. However, compared to the results of panel QR, the TP, HC, FDI, IS, and LFE estimated by OLS fixed-effect regression were the same at the level of effective significance, regardless of whether it was OLS or QR.

Conclusion and policy recommendations

This study analyzes the spatial distribution pattern of the national EP and TL, explores its spatiotemporal evolution trend, and then quantitatively evaluates the effect of the influencing factors on the EP. It ensures a thorough understanding of the specific mechanisms of inter-provincial TL capacity and environmental pollution in China, as well as promoting the formulation of innovative incentive policies and environmental pollution control measures that are reasonable and effective by the Chinese government. This study found there is a significant spatial autocorrelation between the EP and TL. Overall, the spatial distribution of the EP was directional, being concentrated in the southwest and northeast. TL showed a "north-south change, high in the east, and low in the west" trend. Regional differences and the phenomenon of polarization were clearly visible. Regardless of using OLS or QR, TL, HC, IS all had a constraining effect on the EP at the effective significance level, whereas the TP, FDI, and LFE were positively correlated to the EP.

Certainly, there were some shortcomings in this study. Factors were used which were difficult to quantify, such as environmental awareness and policy control, which may affect the research results. Future research should use appropriate methods to incorporate the aforementioned factors into the analysis of influencing factors, enhancing the accuracy. In additional, the research scale should be more refined.

Based on the findings above, the following recommendations can be proposed: Firstly, we should completely understand the complex relationship between TL and EP, and then we should formulate a positive strategic plan for green industrial development. We should maximize the role of TL in industrial production and increase investment in green technology R&D to advance environmental protection technologies. Secondly, in the context of high-quality economic development, we should actively encourage the optimization and upgrading of the industrial sector, especially the secondary and tertiary industries. To achieve the optimization and upgrading of the IS during industrialization. Thirdly, we should strengthen policy support and environmental regulation for the development of regional TL by enhancing the green policy framework. Finally, we should optimize the market competition environment, strengthen the legislative framework for the innovation of green technology by enterprises, and enhance the system of environmental regulations and standards.

Data availability statement

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

Author contributions

CW and XG: conceptualization, methodology, writing—review, editing, and formal analysis. CW: software, investigation, writing—original draft preparation, and data curation. All authors have read and agreed to the published version of the manuscript.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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Calculation of inter-provincial differences in the appropriate proportioning of land transfer income to support rural revitalization

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This research examined the suitability and regional differences of the distribution ratio of land transfer income aimed at supporting rural revitalization by calculating the distribution ratio of 31 provincial-level administrative divisions (abbreviated as 31PLAD), while providing a reference template for land transfer incomes. Herein, we collated and calculated the fiscal expenditure of five dimensions of each province (city, district) in 2005, 2010, 2015, and 2020, and then predicted the situation of the next period (that is, 2025) using GM (1, 1). Further, we used a time series to calculate the land transfer income of each province in 2025. After combining these two, the possible support of land transfer income in all dimensions of rural revitalization across the 31PLAD in 2025 was calculated. Then, according to the Dagum Gini coefficient method, the regional differences of each dimension across the 31PLAD were observed. The financial expenditure of the 31PLAD across the five dimensions studied revealed that the expenditure of industrial prosperity and its proportion is higher, followed by the dimensions of ecological livability and rural civilization. The expenditure of the other dimensions, except for that of affluence in Regions I and II, is better than that of the same dimension in the region. The overall differences among the 31PLAD represent low industrial prosperity, high affluent life, similar overall differences between rural civilization and effective governance, and relatively large differences in ecological livability. Our findings provide relevant suggestions that would help support rural revitalization effectively. After focusing on the first four dimensions of rural revitalization, we suggest measures to promote the development of other dimensions within industrial prosperity and the linkage and cross-development of all dimensions so as to achieve complete rural revitalization. Further, we specify local policies and regulations for using land transfer income to make overall plans and proper arrangements. According to the industrial development and changes found among the 31PLAD, the necessary support path ahead is clear. According to the forecast trend and changes in the income difference found in this study, the PLAD could use these to plan objectives, clarify fund management, establish relevant supervision systems, and develop policy communication methods, among other measures.

KEYWORDS

land transfer income, rural revitalization, proportion is suitable for distribution, regional differences, PLAD

1 Introduction

During the 14th Five-Year Plan period, the sustained and rapid revitalization of rural areas requires a variety of methods with which to achieve its goals. That is, villages that have been successfully influenced by urbanization can lead to revitalizing the overall market, with the saved financial resources being transferred to those that have not yet been urbanized (Liu, 2018a; Yao and Shi, 2020; Yang et al., 2021). Further, according to their advantages, these urbanized villages could also explore endogenous power (Liu and Li, 2020; Guo and Liu, 2021), promote industrial reform, and actively connect with the surrounding areas of the local city for further development. Under these conditions, both the urbanization and modernization of He Xuefeng are essentially completed, meaning that China's rural revitalization plan can progress to the stages involving strong and rich construction (He, 2021). Herein, future research needs to focus on the mutual feedback mechanism and regional model of urban-rural integration development and rural revitalization (Long and Chen, 2021).

Rural revitalization is an indispensable strategic choice needed to solve the current lack of endogenous motivation (Wang and Su, 2017; Huang, 2018); that is, China has begun to implement the "land finance" policy intended to promote rural and agricultural development. The more traditional financial system tends to develop cities and industrialization in the initial redistribution of national income, while most farmers have to continue to undertake more burdensome tasks involved in their less advanced accumulation of capital, which is one key motive for the formation of the "three rural issues" (Xu, 2019). The National Rural Revitalization Strategic Plan (2018–2022) states that it is "continuing to adhere to the financial priority guarantee" (Chen et al., 2018; Guo et al., 2018; Tan and Luo, 2018), while the Opinions of the Ministry of Finance on Implementing the Rural Revitalization Strategy (2018) outline the overall requirements of financial support needed for rural revitalization and the multi-input guarantee system. Existing research states that finance is the basic element needed for implementing this rural revitalization strategy, with the modern rural financial systems needing to cover all fields of rural revitalization, the fiscal expenditure needing to assign priority to agriculture and rural areas (Xiao, 2020), and the rural methods of pluralistic governance needing to be constructed through the use of more detailed financial guidance (Yan and Bao, 2019a). In terms of "improving the multi-input guarantee mechanism," the second article of the National Rural Revitalization Strategic Plan (2018–2022) states that, after "continuing to adhere to the financial priority guarantee," it is "increasing the proportion of land transfer income used for agriculture and rural areas." The Opinions of the General Office of the CPC Central Committee and the General Office of the State Council on Adjusting and Perfecting the Use Scope of Land Transfer Income and Giving Priority to Supporting Rural Revitalization (2020) (hereinafter referred to as the Opinions [2020]) state that, for a long time, the proportion of land value-added income directly used in agriculture and rural areas is low. During the first year of the "14th Five-Year Plan," more than 10.0% of the land transfer income was used in both agriculture and rural areas. At the end of this plan, the proportion of land transfer income used in agriculture and rural areas reached more than 50.0%. However, the actual proportion of specific support areas in the PLAD has not been well researched. The five-dimensional development of rural revitalization showcases that developing the industry is the fundamental policy of rural revitalization (Liu and Wang, 2020; Guo and Lu, 2021), ecological livability is the more realistic requirement and key content of rural revitalization (Kong and Lu, 2019), rural civilization is the soul and guarantee of rural revitalization (Tang and Li, 2019; Liu and Chen, 2020; Zhao et al., 2021), effective governance is the most effective way of ensuring rural revitalization, as well as that affluent life is the ultimate goal of rural revitalization. Fiscal expenditure has a long history of rural development (Yan and Bao, 2019b), with insufficient current research on fiscal expenditure from these five dimensions. The structure and proportion of financial support for agriculture have constantly been adjusted according to the development of each stage (Li and Qian, 2004; Ju, 2005). In this regard, scholars have concluded, from different levels, that the internal use of finance for rural revitalization and the construction/management of related institutional mechanisms can exist within the wider financial support strategy for rural revitalization (Liu, 2021; Shi and Jin, 2021), while also giving guidance for the problems that occur in the actual development of rural revitalization (Zhang and Ouyang, 2021). Previously, most of the land value-added benefits came from rural collectives (Liu and Song, 2020; Zou et al., 2021), despite these collectives lacking the right to distribute the benefits generated by land development rights, while cities can enjoy these benefits (Peng, 2016). As such, scholars provide answers from different angles on the fair, effective, and reasonable distribution of land value-added income. Some scholars believe that after land-losing farmers get due land compensation, the land value-added income should belong to the state (Zhang and Yue, 2016; Liu and Hu, 2017; Hai and Chen, 2019). Conversely, some researchers think that farmers have complete land income rights, meaning that they and the state can rationally distribute land value-added income according to the given situation (Yang, 2015).

In the new journey of modernization during the 14th Five-Year Plan period, the construction of new countryside is very important for socialist modernization. Existing policies mention that rural development pays attention to rural farmland water conservancy and hydropower construction and promotes rural multi-industry linkage development, cultural construction, education, etc. To ensure rural development, the rural financial input mechanism should be diversified. At present, the policy orientation of land transfer income is used for the development of rural undertakings (Liu, 2014). Studying the possible support of land transfer income can not only scientifically guide the use of land transfer income but also have certain reference significance for other kinds of funds to invest in rural construction.

In different areas of China, there is no uniform structure for the use and distribution of land transfer fees due to their characteristics. The current guidelines on land transfer income mention that the resulting income funds are to be used for the key implementation of state support under rural revitalization. As such, this study explains the mechanism of land transfer income that supports rural revitalization, reveals the different laws involved in the proportion of different fields in rural revitalization, predicts the trend in the next fifth year, allocates the proportion in various fields, and puts forward reasonable proportional countermeasures of possible land transfer income that would support rural revitalization in various provincial-level administrative divisions (PLAD).

2 Materials and methods

2.1 Scope of study

The research data are selected from 31PLAD. The selected time nodes are 2005, 2010, 2015, and 2020, and each dimension meets the data described by each dimension index. There are 34 provincial administrative units in China, including 23 provinces, five autonomous regions, four municipalities directly under the Central government, and two special administrative regions. Different from other provinces' land systems, Hong Kong, Macao, and Taiwan are not included in current policies, with their data on land transfer income and related rural construction not being easy to obtain. As such, we did not include these three regions in our sample.

2.2 Dimensions and indicators of rural revitalization

The five dimensions of industrial prosperity, ecological livability, rural civilization, effective governance, and affluent life were all selected for use in this study. The selection principles were objective, reasonable, and relevant, with the universality and suitability of these dimensions being measured as accurately as possible. In addition to matching the relevant content of the Rural Revitalization Strategy from 2018 to 2022 and the Guiding Opinions, these indicators were also selected based on the key direction of future expenditure of land transfer income and in combination with the consistent direction of previous agricultural support. The focus of the expenditure direction in each stage is constantly changing, while some statistics are inconsistent. The selected indicators herein cover the rural expenditure direction in each planning stage as much as possible, allowing us to calculate this part of the data to observe its specific expenditure. Many domestic scholars have evaluated rural revitalization (Lv and Cui, 2021; Tian et al., 2021; Wang et al., 2022). From this perspective, we chose to measure the effectiveness that is highly related to fiscal expenditure. Table 1 shows the selection of indicators.

Herein, we calculated the key and related expenditures under the five dimensions of rural revitalization while observing and predicting the differences in the distribution ratio of rural revitalization in various fields of PLAD. Additionally, the total effect of the 5-year expenditure was planned using a 5-year time series. This time series is the same as the 5-year schedule outlined in China's national economic plan. According to the 5-year planning schedule, the node data from 2005, 2010, 2015, and 2020 were selected for our analysis. These data are continuous at the same time point. This time point is selected to observe the specific development results of each stage under the 5-year plan, and it is difficult to obtain continuous annual data under more statistical indicators. Statistical indicators of the same type are consistent every year. Table 1 explains the specific indicators, showing the statistical indicators and specific connotations of each dimension. The data of each PLAD are from various statistical yearbooks, as shown in Table 1. Among them, the surveyable data of Tibet in some dimensions are blank. As such, we were able to quantitatively predict the possible expenditure ratio and quota of various fields in the next phase of this 5-year plan—that is, 2025—and analyzed the developmental trends of the next five fields under the guidance of existing environmental, system, and internal policies, as well as observe its environmental evolution and the effectiveness of policy implementation. Further, after using the data of land transfer income combined with the five-dimensional fiscal expenditure ratio, this study calculated the future possible use direction and degree of land transfer income that provides a possible basis for developing future policies.

The Dagum Gini coefficient method was used to observe the regional differences in fiscal expenditure for rural revitalization. According to the degree of rural revitalization, we divided the dataset into a series of regions (Mao, 2021; Zhang et al., 2021; Lu et al., 2022), with the regional division shown in Table 2.

2.3 Research methods

After comprehensively analyzing various options, we chose a time series prediction model. A time series is simple, with its

TABLE 1 Selection of indicators of each dimension.

Dimensions	Indicator selection and content	Content interpretation	Data source
Prosperous industry	Expenditure on agriculture, forestry and water affairs	Highly related to the content of industrial prosperity are the financial expenditure related to agriculture, forestry, animal husbandry and fishery and the related parts of agricultural science and technology, including agricultural machinery, farmland water conservancy and hydropower constructionetc.	China Financial Statistics Yearbook
Ecological livability	Expenditure on commercial and health construction, investment in ecological restoration or forestry, expenditure on environmental pollution control, and expenditure on rural development	Social environment includes local commercial medical and other public facilities construction expenditure, self-environment includes related forestry investment and environmental pollution control expenditure, and artificial environment includes gas, central heating, roads and bridges or drainage sanitation treatmentetc.	China Rural Statistical Yearbook Statistical Yearbook of Urban and Rural Construction in China China Environmental Statistics Yearbook China Statistical Yearbook
Rural civilization	Financial expenditure of various rural schools and financial expenditure of rural cultural institutions	Same as left	Statistical Yearbook of Education Expenditure in China Statistical Yearbook of Chinese Culture and Tourism China Social Statistics Yearbook
Effective governance	Expenditure on rural administration and public utilities construction and possible local administrative expenses	Same as left	Statistical Yearbook of Urban and Rural Construction in China China Financial Statistics Yearbook
Rich life	Expenses related to rural housing or other housing	Same as left	China Rural Statistical Yearbook

TABLE 2 Classification table of four regions of 31PLAD.

District Ⅰ-Areas with strong rural revitalization	District II-an area with strong rural revitalization	District III-an area with a general degree of rural revitalization	District IV-An area with backward rural revitalization
Beijing, Tianjin, Shanghai, Jiangsu, Zhejiang and Guangdong	Hebei, Fujian, Shandong, Hubei and Hunan	Heilongjiang, Anhui, Jiangxi, Henan, Hainan, Chongqing and Ningxia	Shanxi, Inner Mongolia, Liaoning, Jilin, Guangxi, Sichuan, Guizhou, Yunnan, Tibet, Shaanxi, Gansu, Qinghai and Xinjiang

numerical value only relating to time, which avoids the influence of any other factors on the index while having a good degree of accuracy. Under the premise of a stable environment, the numerical value also has a certain reference significance. The one disadvantage is that it depends solely on time. This paper selects the Holt model, simple linear regression model, and AMIMA model for the data of each PLAD.

There are only four fiscal expenditure data periods of rural revitalization in the current statistics, with the amount of data being small overall; as such, the grey system prediction model was selected. The GM (Yao and Shi, 2020) model is one of the most widely used grey dynamic prediction models in grey system theory, which is composed of a single variable first-order differential equation. Specifically, it is suitable for forecasting with less data. Generally, only four data sources are needed. The integrity and reliability of the sequence are low, while the essence of the system can be fully excavated by differential equations with high precision. Further, it can generate irregular original data to obtain regular generation sequences, which is simple in operation and convenient for inspection, without considering distribution law and change trends. Herein, only the data from the later period are needed, which belongs to the short-term forecast and is suitable for the application. The operation of the GM (Yao and Shi, 2020) model was carried out by Matlab in this research.

The Dagum Gini coefficient was used to study regional differences. When measuring regional differences, the Gini coefficient is classified into three parts according to the subgroup decomposition method: intra-regional difference contribution, inter-regional difference contribution, and super-variable density contribution. These represent the sources of developmental differences in various dimensions within each region, as well as the overlapping effects of the various regions.

$$G = G_w + G_{nb} + G_t \tag{1}$$

The Gini coefficient is then calculated as follows:

$$G = \frac{\sum_{j=1}^{k}\sum_{h=1}^{k}\sum_{i=1}^{n_j}\sum_{r=1}^{n_h}\left|Y_{ji} - Y_{hr}\right|}{2n^2\bar{Y}} \tag{2}$$

$$G_{jj} = \frac{\frac{1}{2\bar{Y}}\sum_{i=1}^{n_j}\sum_{r=1}^{n_j}\left|Y_{ji} - Y_{jr}\right|}{n_j^2} \tag{3}$$

$$G_{jh} = \frac{\sum_{i=1}^{n_j}\sum_{r=1}^{n_k}\left|Y_{ji} - Y_{hr}\right|}{n_j n_h\left(\bar{Y}_j + \bar{Y}_h\right)} \tag{4}$$

$Y_{ji}Y_{hr}\bar{Y}$ Among them, N is the number of PLAD and K is the number of regions. Further, the 31PLAD in China is divided into four regions according to their degree of rural revitalization. They are divided into regions with a strong revitalization degree, those with a general revitalization degree, and those with a backward revitalization degree. Therefore, k is four, and nj (nh) is the number of regional introspection (cities, districts) of j (h). Further, Y_{ji} (Y_{hr}) is the size of the fiscal expenditure of any province (city, district) in the j (h) region. Herein, it is the average value of fiscal expenditure in this dimension of all PLAD in China.

G_w is used to calculate the difference contribution within each region:

$$G_w = \sum_{j=1}^{k} G_{ij} P_j S_j \tag{5}$$

G_{nb} is used to calculate the contributions of regional differences:

$$G_{nb} = \sum_{j=2}^{k}\sum_{h=1}^{j-1} G_{jh} D_{jh}\left(P_j S_h + P_h S_j\right) \tag{6}$$

G_t is used to calculate the contribution of the degree of supervariable density:

$$G_t = \sum_{j=2}^{k}\sum_{h=1}^{j-1} G_{jh}\left(P_j S_h + P_h S_j\right)\left(1 - D_{jh}\right) \tag{7}$$

Finally, to calculate D_{jh}, we used the following method:

$$D_{jh} = \frac{d_{jh} - p_{jh}}{d_{jh} + p_{jh}} \tag{8}$$

When defining relevant variables, we can refer to the following equations representing the relative impact of fiscal expenditure in this dimension between two regions. $P_j = n_j/n, S_j = n_j\bar{Y}_j/n\bar{Y}, D_{jk} = \frac{M_{jk}-N_{jk}}{M_{jk}+N_{jk}}$, Specifically, $M_{jh} = \int_0^{\infty} dF_j(Y)\int_0^{Y}(Y - x)dF_h(x)$ they represent the difference in fiscal expenditure in this dimension between regions, $\bar{Y}_j > \bar{Y}$, and M_{jk} as the weighted average of fiscal expenditure differences $(Y_{ji} - Y_{hr})$ in this dimension of all villages under a given condition $Y_{ji} - Y_{hr} > 0$. $N_{jh} = \int_0^{\infty} dF_h(Y)\int_0^{Y}(Y - x)dF_j(x)$, they are the supervariable first moment, $\bar{Y}_j > \bar{Y}_h$, N_{jh} representing the weighted average of all examples $(Y_{hr} - Y_{ji})$ under that condition $(Y_{hr} - Y_{ji} > 0)$. To calculate this, we used the following formula:

$$d_{jh} = \int_0^{\infty} dF_j(y)\int_0^{y}(y - x)\cdot dF_h(x) \tag{9}$$

$$p_{jh} = \int_0^{\infty} dF_h(y)\int_0^{y}(y - x)\cdot dF_j(y) \tag{10}$$

3 Results

3.1 Previous changes in land transfer income across different provinces and the future forecast

After selecting the time series model in SPSS, as well as after using the traditional model, the data values of the 31PLAD from 2002 to 2017 were used to predict those leading up to 2025; that is, the values from 2018 to 2025 were predicted. The traditional method involves selecting the most suitable model for the data characteristics of the different 31PLAD. Table 3 shows the specific model.

Furthermore, the Holt model is an advanced exponential smoothing model. This method is suitable for non-stationary series with linear trends and periodic fluctuations. The exponential smoothing method (EMA) was used to continuously adapt the model parameters to the changes of non-stationary series while predicting short-term trends. Further, we also used a simple linear regression model—that is, a unary linear regression model, when the causal variables include only one dependent and one independent variable, with its expression form being y = ax + b + ε. Here, a is the slope of the model, b is the intercept, and ε is the error. This model is easy to read and is only related to time-based data. Additionally, the ARIMA is an autoregressive moving average model, which is abbreviated as the ARIMA (P, D, Q) model. In particular, when D = 0, the ARIMA (P, D, Q) model is the ARMA (P, Q) model. When d = 1 and p = q = 0, the ARIMA (0, 1, 0) model is also called the "random walk" or the "drunk model." Most provinces under the ARIMA model are predicted using ARIMA (0, 1, 0), except for the Shaanxi Province, which is predicted by ARIMA (0, 1, 2), and the Ningxia Autonomous Region, which is predicted by ARIMA (1, 1, 0). Figure 1 shows the above predictions.

Figure 1 shows the changes in the total land transfer income of PLAD before 2017 and the changes in total land transfer income before 2025. Herein, 2018–2025 is the forecast result, meaning that the forecast period is long. Further, the results in 2025 only have a certain reference value. Different PLAD have different data conditions, while different provinces choose different methods of time series forecasting. These results show that the land transfer income in Tibet, Ningxia, and Gansu, as well as other economically disadvantaged areas, has not been significantly enhanced either before or after the forecast. In Jilin, Heilongjiang, and Liaoning, the increase in land transfer income is not obvious. A possible reason for this lies in the sharp

TABLE 3 Classification table of forecasting models used by 31PLAD.

Holt model	Simple linear regression model	ARIMA
Beijing, Tianjin, Hebei, Jiangsu, Zhejiang, Anhui, Fujian, Jiangxi, Guangdong, Hainan, Chongqing, Sichuan, Tibet, Gansu, Qinghai and Xinjiang	Inner Mongolia, Liaoning, Jilin, Heilongjiang and Yunnan	Shanxi, Shandong, Henan, Hunan, Guangxi, Guizhou, Shaanxi and Ningxia

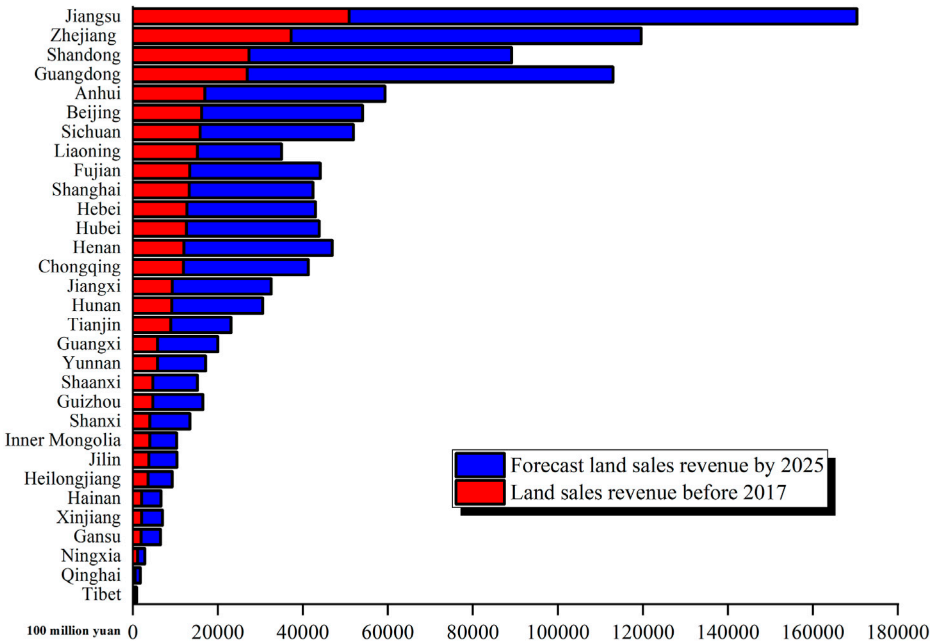

FIGURE 1
Previous and forecasted changes of land transfer income in the 31PLAD.

decline of land transfer behaviors caused by large population loss and low fertility rate. In the Guangdong, Shandong, Zhejiang, and Jiangsu regions, the economic development is good, and the geographical characteristics are wide. Although not much land can be sold, the price of land sold by units is high. In the next few years, the income from land transfer should be sufficient without considering the crises caused by external environmental epidemics or other risks.

3.2 Fiscal expenditure of PLAD in each dimension

3.2.1 Financial expenditure of the 31PLAD in each dimension

First, we looked at the expenditure of the industrial prosperity dimension and its forecast results. The key directions of fiscal expenditure in this dimension are high-standard farmland construction, farmland water conservancy construction, modern seed industry promotion, the comprehensive improvement of agricultural land, and the permanent basic protection of cultivated land. To this end, we explored the existing guidance on land transfer income that supports rural revitalization and the related description of industrial prosperity in the rural revitalization strategy. To accurately describe the financial expenditure of industrial prosperity, the indicators arising from investments in agriculture, forestry, animal husbandry, the fishery industry, and agricultural science and technology to the industrial prosperity expenditure represented by the expenditure on agriculture, forestry, and water affairs were measured. The specific values are shown in Table 4 (left).

Table 4 (left) shows that from 2005 to 2020, almost every province experienced a substantial leap forward in the fiscal expenditure of industrial prosperity, which coincides with the 11th Five-Year Plan period, with notable achievements in the

TABLE 4 Financial Expenditure on Industrial Prosperity-Ecological Livability in 31PLAD (Unit: 100 million).

Province	Prosperous industry					Province	Ecological livability				
	2005	2010	2015	2020	2025		2005	2010	2015	2020	2025
Beijing	42.64	158.64	424.78	497.33	794.95	Beijing	53.93	108.24	271.35	364.84	600.71
Tianjin	12.85	67.14	156.08	154.82	226.28	Tianjin	21.29	72.55	79.49	107.29	128.50
Hebei	63.27	312.66	712.49	988.74	1602.27	Hebei	77.15	88.09	222.16	324.59	551.39
Shanxi	46.17	201.71	394.46	653.68	1077.58	Shanxi	59.50	103.29	207.47	217.79	308.78
Inner Mongolia	72.02	281.00	675.58	867.59	1389.08	Inner Mongolia	64.60	153.91	352.46	223.66	305.73
Liaoning	70.47	289.00	446.07	504.83	664.22	Liaoning	47.10	99.11	160.41	95.57	115.41
Jilin	42.60	238.94	408.61	577.76	859.76	Jilin	32.61	72.01	133.04	162.68	235.63
Heilongjiang	61.18	338.06	681.48	914.53	1410.38	Heilongjiang	43.64	116.83	202.93	440.10	750.92
Shanghai	35.12	151.93	267.37	473.80	773.10	Shanghai	67.51	105.82	131.72	289.08	449.72
Jiangsu	97.57	489.16	1008.60	1091.25	1574.97	Jiangsu	152.63	331.33	571.09	575.68	763.31
Zhejiang	86.15	290.37	739.08	764.89	1160.99	Zhejiang	138.22	242.56	495.47	583.16	862.25
Anhui	47.65	292.52	577.74	924.29	1509.80	Anhui	69.82	158.37	276.40	432.38	673.43
Fujian	33.18	160.34	441.86	450.05	694.78	Fujian	39.93	119.56	439.27	268.41	412.02
Jiangxi	45.68	232.34	557.30	740.31	1198.72	Jiangxi	40.14	107.28	221.24	309.72	488.57
Shandong	90.11	465.98	964.42	1065.29	1549.36	Shandong	170.83	339.86	933.10	792.21	1171.19
Henan	64.14	399.19	791.63	1145.40	1806.51	Henan	37.44	145.37	261.48	388.81	600.16
Hubei	57.46	305.44	616.57	868.90	1364.83	Hubei	53.89	170.11	321.67	334.74	463.62
Hunan	71.91	322.65	676.24	987.71	1590.23	Hunan	103.58	146.27	390.96	417.61	648.30
Guangdong	111.78	325.02	811.90	1125.81	1872.22	Guangdong	83.40	212.31	318.34	688.68	1127.69
Guangxi	47.48	260.26	497.53	904.38	1525.14	Guangxi	26.69	93.50	1137.88	264.92	608.16
Hainan	12.30	87.68	164.24	268.57	434.88	Hainan	8.81	18.78	54.93	52.76	81.43
Chongqing	31.09	159.18	331.33	416.76	634.36	Chongqing	43.99	132.02	140.25	209.92	260.01
Sichuan	95.06	401.76	926.65	1339.36	2210.13	Sichuan	113.41	321.49	537.10	615.91	840.50
Guizhou	53.29	246.76	534.26	1024.31	1816.58	Guizhou	36.55	87.11	322.26	404.04	714.88
Yunnan	73.50	327.21	641.52	1100.13	1835.77	Yunnan	47.59	110.38	266.74	441.67	774.11
Tibet	9.64	89.11	200.27	415.44	756.81	Tibet	0.00	25.19	31.30	85.05	133.23
Shaanxi	62.00	267.16	520.58	742.25	1157.85	Shaanxi	42.83	133.15	226.77	278.68	392.66
Gansu	42.46	196.27	497.05	775.83	1350.37	Gansu	49.61	107.74	155.11	191.42	252.42
Qinghai	14.93	69.50	204.41	279.80	483.69	Qinghai	10.53	27.95	52.31	72.12	109.65
Ningxia	32.47	94.23	166.27	253.45	392.37	Ningxia	8.48	43.30	47.75	61.25	71.90
Xinjiang	34.14	220.50	605.34	1127.88	2121.20	Xinjiang	25.04	64.80	147.60	181.10-	280.94

development of the national economy. The financial expenditure for the prosperity of rural industries has also greatly improved. During 2010–2015 (i.e., the 12th Five-Year Plan period), the nation's economic situation underwent certain profound changes, with industrial prosperity having greatly improved across every province and their regions. However, during 2015–2020, the economy was still developing ahead of schedule, but economic development was not as rapid as that of the previous two stages. Specifically, compared with the fiscal expenditure of industrial prosperity in 2015 and 2020, the current growth situation is not as rapid as that of the previous two stages.

We further investigated the statistics of the ecological livability dimension's expenditure and its forecast results. Ecological livability measures how well residents can experience both the beauty of their environment and how much enjoyment they feel, both spiritually and materially, as a result. Spiritually speaking, residents need a clean, tidy, comfortable, and convenient living environment that is fresh and natural. From the material point of view, residents need to have an environmental area suitable for ensuring health. Health service construction and old-age care institutions belong to public buildings, which are counted as a whole in the Statistical Yearbook of Urban and Rural Construction in China, and belong to public building expenditures. Public buildings are divided into six categories: administrative, educational welfare, cultural and scientific, medical and health, commercial service, and public utilities. The medical and old-age service buildings mentioned here belong to this group of statistics. In this group, according to the nature of various public buildings, each area's contents were divided into dimensions. Administrative and public utilities construction expenditures are strongly based on public management, which is divided into effective governance dimensions. Among them, commercial service and medical and health service buildings cover the expenditure on health service construction and old-age care institutions, which are further divided into ecological livability dimensions. Cultural, scientific, educational, and welfare buildings are in line with the financial expenditure from the perspective of rural civilization and are divided within this dimension.

After access, the data related to public buildings are from rural areas. Herein, let public building expenditure be (PC_e), administrative building expenditure be (AC_e), education and welfare building expenditure be (EWC_e), cultural and scientific building expenditure be (CSC_e), medical and health building expenditure be (MHC_e), commercial service building expenditure be (BSC_e), and public utility building expenditure be (PUC_e).

The calculation is as follows:

$$PC_e = \alpha AC_e + \beta EWC_e + \gamma CSC_e + \delta MHC_e + \varepsilon BSC_e + \epsilon PUC_e \tag{11}$$

$$1 = \alpha + \beta + \gamma + \delta + \varepsilon + \epsilon \tag{12}$$

After data review and comparison, the coefficient of each region was determined to identify the specific expenditure within each. After fuzzy estimation, the coefficients of each part of the population are determined as follows:

$$\alpha + \epsilon = 0.2635\beta + \gamma = 0.3492\delta + \varepsilon = 0.4143$$

Among them. . .

It is speculated that the proportion of various expenditures in each stage always changes. It is based on economic development and changes in planning requirements in each stage. As such, we need to adjust slightly for changes in planning objectives and development results at each stage. This information comes from the Wind database and the China Fiscal Yearbook, which collates the structure of fiscal expenditure in each stage, and then extracts and re-determines its proportion according to the total of various fiscal expenditure parts.

Assuming that the 10th Five-Year Plan was from 2001 to 2005 after the reform and opening up of the national economy, the economic development mode changed, with the education level improved, the infrastructure construction improved further, and the industrial science and technology developed, which was followed by a high energy-consuming growth mode. The income gap between urban and rural areas widened, along with the high growth of secondary and tertiary industries and low employment.

During the 11th Five-Year Plan from 2006 to 2010, the deepening reform and opening of the national economy, the ever-increasing and excessive levels of heavy industrialization, high consumption of economic growth, high pollution, and rising proportion of natural assets loss (i.e., rapid economic growth and deepening of economic structure contradictions) all occurred. The development in all aspects has deepened, with the administration and public utility management having been further improved.

$$\alpha + \epsilon = 0.3059\beta + \gamma = 0.3524\delta + \varepsilon = 0.3416$$

At this point.

$$\alpha + \epsilon = 0.274\beta + \gamma = 0.444\delta + \varepsilon = 0.282$$

The 12th Five-Year Plan was from 2011 to 2015.

$$\alpha + \epsilon = 0.1975\beta + \gamma = 0.425\delta + \varepsilon = 0.3775$$

The 13th Five-Year Plan was from 2016 to 2020.

After examining the above descriptions and statistics, the specific expenditures of the six types of public buildings were obtained, with us then combining them with the other expenditures of ecological livability, rural civilization, and effective governance, which allowed us to obtain the specific fiscal expenditure results of all three dimensions. Table 3 (right) shows the effects of ecological livability.

As shown in Table 4 (right), the ecological livability of the 31PLAD experienced a leap-forward growth in some areas, while the investment in other areas increased annually along with the regional economic development. The large amount of data in Guangxi are due to the large increase in forestry investment in this region in that year. With the economic development and response to the national environmental protection policy, the overall governance and forestry investment levels in other regions have also improved.

We now present the expenditure of the rural civilization dimension and its prediction results. This section primarily includes the financial expenditure related to rural education, as well as that of various recreational institutions or activities. Table 5 (left) shows the specific statistical results.

The findings for Beijing, Shanghai, and Tianjin are not significant, which may be due to their high urbanization levels, their relatively few rural areas, and their superior overall development compared with the state of rural development in other regions, with their expenditure on rural education and culture thus not being significant. For Shandong and Henan, with large populations and wide rural areas, the expenditure on rural education and culture is larger than that in other regions. Guangdong and Sichuan are economically developed and geographically wide, with their expenditure on rural education and culture particularly noteworthy. In areas with less advanced education and economic development levels, such as Qinghai and Gansu, the overall financial expenditure on education and culture is relatively low.

TABLE 5 31PLAD Rural Civilization-Effective Financial Expenditure for Governance (Unit: 100 million).

Province	Rural civilization					Province	Effective governance				
	2005	2010	2015	2020	2025		2005	2010	2015	2020	2025
Beijing	23.04	65.54	102.02	134.11	187.26	Beijing	23.64	70.85	91.33	152.91	218.84
Tianjin	14.54	45.81	69.36	74.01	94.68	Tianjin	10.78	34.07	53.32	67.15	92.41
Hebei	93.83	204.53	597.80	923.64	1664.22	Hebei	36.35	109.59	150.35	244.61	354.63
Shanxi	55.63	121.02	316.18	372.79	593.32	Shanxi	25.39	67.39	78.17	125.97	169.17
Inner Mongolia	32.23	71.51	289.91	321.33	555.96	Inner Mongolia	22.99	77.55	92.35	114.84	138.68
Liaoning	54.53	116.68	199.85	242.81	341.42	Liaoning	32.09	106.34	104.71	129.88	140.20
Jilin	35.26	92.47	197.64	259.19	403.74	Jilin	14.97	58.95	72.43	94.14	117.75
Heilongjiang	42.75	85.63	251.52	280.28	451.67	Heilongjiang	22.55	67.73	70.86	93.03	107.08
Shanghai	30.23	55.75	71.11	85.25	105.04	Shanghai	27.46	79.52	84.05	144.21	190.89
Jiangsu	126.56	283.31	641.56	831.21	1311.92	Jiangsu	67.28	207.43	271.72	375.31	497.07
Zhejiang	134.36	224.64	514.19	740.66	1218.00	Zhejiang	54.88	143.20	193.67	328.40	481.63
Anhui	87.02	198.87	595.61	777.04	1326.63	Anhui	30.46	96.38	128.13	165.19	213.89
Fujian	74.20	141.71	341.84	463.55	757.33	Fujian	18.25	69.47	110.69	144.55	203.17
Jiangxi	48.03	120.90	490.41	659.38	1220.62	Jiangxi	19.03	68.87	129.09	175.20	264.94
Shandong	137.83	337.59	739.29	985.14	1554.85	Shandong	67.07	191.30	267.06	354.55	475.05
Henan	109.75	280.81	793.74	1203.57	2135.76	Henan	38.22	148.22	210.47	324.76	466.83
Hubei	70.48	148.26	362.69	490.67	804.14	Hubei	31.88	100.93	188.47	234.67	343.38
Hunan	87.22	175.01	562.29	789.89	1408.82	Hunan	36.33	116.37	199.64	260.49	376.32
Guangdong	154.38	227.38	654.50	1018.66	1932.84	Guangdong	74.65	211.09	306.73	593.07	935.90
Guangxi	64.68	175.88	469.11	648.90	1097.61	Guangxi	20.19	82.73	120.66	155.00	208.82
Hainan	12.40	42.85	110.74	165.32	284.88	Hainan	5.08	19.08	34.70	46.42	69.11
Chongqing	47.59	94.69	308.75	383.34	656.71	Chongqing	17.44	53.44	80.80	97.66	130.46
Sichuan	112.93	268.04	806.90	1012.76	1708.066	Sichuan	45.27	133.71	189.23	290.84	416.83
Guizhou	48.59	151.06	499.50	696.74	1248.15	Guizhou	21.64	68.39	139.15	153.34	221.61
Yunnan	76.39	194.45	571.33	822.26	1446.74	Yunnan	27.32	80.21	123.13	196.66	295.27
Tibet	7.39	16.43	113.53	128.54	245.39	Tibet	7.97	20.62	58.69	99.97	184.85
Shaanxi	46.90	163.12	393.52	418.67	630.93	Shaanxi	22.73	89.08	109.72	157.29	205.80
Gansu	40.99	117.57	304.45	409.30	679.91	Gansu	16.45	51.07	91.22	115.12	166.66
Qinghai	8.53	25.39	101.57	141.81	265.41	Qinghai	4.74	17.33	35.44	41.69	61.65
Ningxia	9.76	26.52	77.12	100.16	169.47	Ningxia	4.44	15.97	21.72	31.55	43.42
Xinjiang	43.25	130.84	335.61	578.00	1042.91	Xinjiang	19.84	59.36	110.43	145.71	217.50

Next, we present the effectiveness of the governance dimension's expenditure and its forecast results. It was difficult to obtain the measurement effect of this section. The land transfer income, as clearly mentioned in the policy, showcases that the direction of promotion does not cover this section, meaning that its measurement content was vaguely determined. The content herein includes the construction expenditure of administrative and public management and the expenses related to rural public management or administration, which have all been vaguely determined. Table 5 (right) shows the statistical results. The degree of effective fiscal expenditure is mainly restricted by that of the local economic development, while it is related to both the latter and fiscal revenue. For example, the overall regional economy in developed regions, such as Beijing and Shanghai, is progressing well, with the expenditure in the effective governance dimension being better than that in other dimensions. Additionally, the expenditure of the effective dimension of governance is also affected by the minority in local rural areas. Rural areas are wide in the area and large in quantity, meaning that the overall expenditure on affluent lifestyles is greater.

Further, we calculated the expenditure of the affluent living dimension and its forecast. The measurement of fiscal expenditure in this dimension is as follows. The overall affluence dimension is closely related to housing, the relevant statistics, and the housing-related equipment engineering costs. Table 6 shows these statistics.

TABLE 6 Financial expenditure of affluent living in 31PLAD (unit: 100 million).

Province	Rich life					Province	Rich life				
	2005	2010	2015	2020	2025		2005	2010	2015	2020	2025
Beijing	83.70	123.70	46.50	77.40	38.71	Hubei	185.50	371.20	416.80	202.10	207.29
Tianjin	81.70	112.70	12.50	8.30	1.17	Hunan	255.00	478.60	636.90	528.30	595.42
Hebei	524.30	1075.90	480.20	201.30	100.51	Guangdong	549.40	1198.70	381.70	346.00	106.18
Shanxi	101.90	272.10	303.30	89.20	108.10	Guangxi	146.80	390.00	481.20	446.00	495.13
Inner Mongolia	53.10	93.10	144.00	76.30	91.23	Hainan	17.10	31.20	89.60	82.00	124.54
Liaoning	234.70	441.00	185.80	79.10	37.13	Chongqing	89.20	128.90	117.40	59.00	52.33
Jilin	88.20	226.70	169.30	66.00	53.84	Sichuan	327.30	758.90	483.70	401.00	263.15
Heilongjiang	119.20	316.60	274.20	150.50	126.95	Guizhou	73.90	259.20	238.00	147.60	128.90
Shanghai	67.60	118.10	3.10	6.30	0.48	Yunnan	100.80	220.10	376.50	281.70	350.68
Jiangsu	1103.00	2726.00	287.40	129.00	23.23	Tibet	0.00	25.10	0.00	0.00	0.05
Zhejiang	1006.10	1845.50	607.10	478.00	151.45	Shaanxi	99.70	231.30	322.20	137.20	163.06
Anhui	270.10	672.50	552.40	304.50	2446.46	Gansu	48.50	140.80	100.60	83.10	60.62
Fujian	165.30	345.70	308.30	191.90	164.01	Qinghai	10.00	77.00	61.60	28.20	23.14
Jiangxi	153.20	386.00	362.10	339.00	317.74	Ningxia	42.90	56.00	66.20	40.20	41.44
Shandong	957.50	1928.60	702.20	612.44	219.26	Xinjiang	69.80	176.30	262.10	106.50	132.26
Henan	561.10	1223.50	616.50	408.00	207.56						

Some statistics in Tibet are unclear as the Tibetan data in this section not being particularly strong. As seen from Table 6, the financial expenditure of affluent life is also increasing sequentially. There are few rural areas in Beijing, Shanghai, and Tianjin, with the financial expenditure related to affluence not being high. From 2005 to 2010, the rural areas in Jiangsu and Zhejiang developed rapidly, with the housing investment related to affluence also increasing. Shandong and Henan have large populations and wide rural areas, with their financial expenditure related to affluent life being more than that of other regions. Roughly observed, the expenditure of affluence in other rural areas is similar at each stage.

3.2.2 Calculation and forecast of the fiscal expenditure ratio of the 31PLAD in each dimension

First, we present the calculation results of the fiscal expenditure ratio of each node in each dimension of the 31 PLAD. Using the specific fiscal expenditure data of each dimension mentioned above, the five-dimensional expenditure ratio of these four nodes was calculated, with the results shown in Tables 7, 8.

As shown in Tables 7, 8, the proportion of the industrial prosperity dimension expenditure in various PLAD is increasing, indicating that their investments related to farmland water conservancy and hydropower are increasing annually. Under the general policy of ensuring basic agriculture to protect cultivated land, the goal of high-quality farmland construction and the improvement of rural industrial development infrastructure are pursued. Conversely, the proportion of the affluent life dimension is extremely low in all PLAD. Either the demand for perfect rural housing is low, or the expenditure ratio is relatively low. Compared with the investment in urban real estate housing, it is not needed in rural areas. Most PLAD reached the largest investment in housing around 2010, with the subsequent investment dropping sharply. To a certain extent, this unproductive investment will not increase continuously over time but will change or fluctuate slightly with the need for depreciation or breakage. Investments in the rural ecological livability and civilization dimensions have increased to a certain extent, but the change in this proportion is not obvious. The living and natural environments in rural areas have greatly improved, with the state's financial support for these areas being strong. In particular, this has always been the focus of investment in the past and will continue in the future.

Next, we cover the forecast results of the fiscal expenditure ratio at the end of the 14th Five-Year Plan in 31PLAD. Using the GM (Yao and Shi, 2020) grey system prediction method, the data of the first five dimensions and four periods are predicted up to the next period, 2025, with the results shown in Table 9.

Table 9 shows that the change in fiscal expenditure ratio in this stage was not obvious compared with that of the previous period. Overall, the expenditure on industrial prosperity, ecological livability, and rural civilization is increasing, while the proportions of effective governance and affluent life dimensions are declining. When five dimensions are put into a system, the above results and changes exist. Considering the reasons underlying this prediction model, it reveals a certain

TABLE 7 Calculation results of each dimension proportion of 31 PLAD in 2005 and 2010.

2005	Prosperous industry	Ecological livability	Rural civilization	Effective governance	Rich life	2010	Prosperous industry	Ecological livability	Rural civilization	Effective governance	Rich life
Beijing	0.19	0.24	0.10	0.10	0.37	Beijing	0.30	0.21	0.12	0.13	0.23
Tianjin	0.09	0.15	0.10	0.08	0.58	Tianjin	0.20	0.22	0.14	0.10	0.34
Hebei	0.08	0.10	0.12	0.05	0.66	Hebei	0.17	0.05	0.11	0.06	0.60
Shanxi	0.16	0.21	0.19	0.09	0.35	Shanxi	0.26	0.13	0.16	0.09	0.36
Inner Mongolia	0.29	0.26	0.13	0.09	0.22	Inner Mongolia	0.42	0.23	0.11	0.11	0.14
Liaoning	0.16	0.11	0.12	0.07	0.53	Liaoning	0.27	0.09	0.11	0.10	0.42
Jilin	0.20	0.15	0.7	0.07	0.41	Jilin	0.35	0.10	0.13	0.09	0.33
Heilongjiang	0.21	0.15	0.15	0.08	0.41	Heilongjiang	0.37	0.13	0.09	0.07	0.34
Shanghai	0.15	0.30	0.13	0.12	0.30	Shanghai	0.30	0.21	0.11	0.16	0.23
Jiangsu	0.06	0.10	0.08	0.04	0.71	Jiangsu	0.12	0.08	0.07	0.05	0.68
Zhejiang	0.06	0.10	0.09	0.04	0.71	Zhejiang	0.11	0.09	0.08	0.05	0.67
Anhui	0.09	0.14	0.17	0.06	0.53	Anhui	0.21	0.11	0.14	0.07	0.47
Fujian	0.10	0.12	0.22	0.06	0.50	Fujian	0.19	0.14	0.17	0.08	0.41
Jiangxi	0.15	0.13	0.16	0.06	0.50	Jiangxi	0.25	0.12	0.13	0.08	0.42
Shandong	0.06	0.12	0.10	0.05	0.67	Shandong	0.14	0.10	0.10	0.06	0.59
Henan	0.09	0.05	0.14	0.05	0.69	Henan	0.18	0.07	0.13	0.07	0.56
Hubei	0.10	0.13	0.18	0.08	0.46	Hubei	0.28	0.16	0.14	0.09	0.34
Hunan	0.15	0.19	0.16	0.07	0.46	Hunan	0.26	0.12	0.14	0.09	0.39
Guangdong	0.06	0.09	0.16	0.08	0.56	Guangdong	0.15	0.10	0.10	0.10	0.55
Guangxi	0.08	0.09	0.21	0.07	0.48	Guangxi	0.26	0.09	0.18	0.08	0.39
Hainan	0.14	0.16	0.22	0.09	0.31	Hainan	0.44	0.09	0.21	0.10	0.16
Chongqing	0.13	0.19	0.21	0.08	0.39	Chongqing	0.28	0.23	0.17	0.09	0.23
Sichuan	0.11	0.16	0.16	0.07	0.47	Sichuan	0.21	0.17	0.14	0.07	0.40
Guizhou	0.16	0.16	0.21	0.09	0.32	Guizhou	0.30	0.11	0.19	0.08	0.32
Yunnan	0.23	0.15	0.23	0.08	0.31	Yunnan	0.35	0.12	0.21	0.09	0.24
Tibet	0.39	0.00	0.30	0.32	0.00	Tibet	0.51	0.14	0.09	0.12	0.14
Shaanxi	0.23	0.16	0.17	0.08	0.36	Shaanxi	0.30	0.15	0.18	0.10	0.26
Gansu	0.21	0.25	0.21	0.08	0.24	Gansu	0.32	0.18	0.19	0.08	0.23
Qinghai	0.31	0.22	0.18	0.10	0.21	Qinghai	0.32	0.13	0.12	0.08	0.35
Ningxia	0.33	0.09	0.10	0.05	0.44	Ningxia	0.40	0.18	0.11	0.07	0.24
Xinjiang	0.18	0.13	0.23	0.10	0.36	Xinjiang	0.34	0.10	0.20	0.09	0.27

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TABLE 8 Calculation results of each dimension proportion of 31PLAD in 2015 and 2020.

2015	Prosperous industry	Ecological livability	Rural civilization	Effective governance	Rich life	2020	Prosperous industry	Ecological livability	Rural civilization	Effective governance	Rich life
Beijing	0.45	0.29	0.11	0.10	0.05	Beijing	0.41	0.30	0.11	0.12	0.06
Tianjin	0.42	0.21	0.19	0.14	0.03	Tianjin	0.38	0.26	0.18	0.16	0.02
Hebei	0.33	0.10	0.28	0.07	0.22	Hebei	0.37	0.12	0.34	0.09	0.08
Shanxi	0.30	0.16	0.24	0.06	0.23	Shanxi	0.45	0.15	0.26	0.09	0.06
Inner Mongolia	0.43	0.23	0.19	0.06	0.09	Inner Mongolia	0.54	0.14	0.20	0.07	0.05
Liaoning	0.41	0.15	0.18	0.10	0.17	Liaoning	0.48	0.09	0.23	0.12	0.08
Jilin	0.42	0.14	0.20	0.07	0.17	Jilin	0.50	0.14	0.22	0.08	0.06
Heilongjiang	0.46	0.14	0.17	0.05	0.19	Heilongjiang	0.49	0.23	0.15	0.05	0.08
Shanghai	0.48	0.24	0.13	0.15	0.01	Shanghai	0.47	0.29	0.09	0.14	0.01
Jiangsu	0.36	0.21	0.23	0.10	0.10	Jiangsu	0.36	0.19	0.28	0.13	0.04
Zhejiang	0.29	0.19	0.20	0.08	0.24	Zhejiang	0.26	0.20	0.26	0.11	0.17
Anhui	0.27	0.13	0.28	0.06	0.26	Anhui	0.36	0.17	0.30	0.06	0.12
Fujian	0.27	0.27	0.21	0.07	0.19	Fujian	0.30	0.18	0.31	0.10	0.13
Jiangxi	0.32	0.13	0.28	0.07	0.21	Jiangxi	0.33	0.14	0.30	0.08	0.15
Shandong	0.27	0.26	0.21	0.07	0.19	Shandong	0.28	0.21	0.26	0.09	0.16
Henan	0.30	0.10	0.30	0.08	0.23	Henan	0.33	0.11	0.35	0.09	0.12
Hubei	0.32	0.17	0.19	0.10	0.22	Hubei	0.41	0.16	0.23	0.11	0.09
Hunan	0.27	0.16	0.23	0.08	0.26	Hunan	0.33	0.14	0.26	0.09	0.18
Guangdong	0.33	0.13	0.26	0.12	0.15	Guangdong	0.30	0.18	0.27	0.16	0.09
Guangxi	0.18	0.42	0.17	0.04	0.18	Guangxi	0.37	0.11	0.27	0.06	0.18
Hainan	0.36	0.12	0.24	0.08	0.20	Hainan	0.44	0.09	0.27	0.08	0.13
Chongqing	0.34	0.14	0.32	0.08	0.12	Chongqing	0.36	0.18	0.33	0.08	0.05
Sichuan	0.31	0.18	0.27	0.06	0.16	Sichuan	0.37	0.17	0.28	0.08	0.11
Guizhou	0.31	0.19	0.29	0.08	0.14	Guizhou	0.42	0.17	0.29	0.06	0.06
Yunnan	0.32	0.13	0.29	0.06	0.19	Yunnan	0.39	0.16	0.29	0.07	0.10
Tibet	0.50	0.08	0.28	0.15	0.00	Tibet	0.57	0.12	0.18	0.14	0.00
Shaanxi	0.33	0.14	0.25	0.07	0.20	Shaanxi	0.43	0.16	0.24	0.09	0.08
Gansu	0.43	0.14	0.27	0.08	0.09	Gansu	0.49	0.12	0.26	0.07	0.05
Qinghai	0.45	0.11	0.22	0.08	0.14	Qinghai	0.50	0.13	0.25	0.07	0.05
Ningxia	0.44	0.13	0.20	0.06	0.17	Ningxia	0.52	0.13	0.21	0.06	0.08
Xinjiang	0.41	0.10	0.23	0.08	0.18	Xinjiang	0.53	0.08	0.27	0.07	0.05

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TABLE 9 Forecast results of each dimension proportion of 31PLAD in 2025.

Region	Province/ Dimension	Prosperous industry	Ecological livability	Rural civilization	Effective governance	Rich life
I	Beijing	0.4319	0.3264	0.1017	0.1189	0.0210
	Tianjin	0.4167	0.2366	0.1744	0.1702	0.0021
	Shanghai	0.5089	0.296	0.0691	0.1256	0.0003
	Jiangsu	0.3776	0.183	0.3146	0.1192	0.0056
	Zhejiang	0.2997	0.2226	0.3144	0.1243	0.0391
	Guangdong	0.3187	0.1920	0.3120	0.1593	0.0181
II	Hebei	0.3750	0.1290	0.3895	0.0830	0.0235
	Fujian	0.3114	0.1847	0.3394	0.0911	0.0735
	Shandong	0.3118	0.2357	0.3129	0.0956	0.0441
	Hubei	0.4984	0.1279	0.2218	0.0947	0.0572
	Hunan	0.3443	0.1404	0.305	0.0815	0.1289
III	Heilongjiang	0.4954	0.2638	0.1586	0.0376	0.0446
	Anhui	0.3803	0.1696	0.3341	0.0539	0.0621
	Jiangxi	0.3434	0.1400	0.3497	0.0759	0.0910
	Henan	0.3463	0.115	0.4094	0.0895	0.0398
	Hainan	0.4371	0.0819	0.2864	0.0695	0.1252
	Chongqing	0.3659	0.1500	0.3788	0.0752	0.0302
	Ningxia	0.5460	0.1001	0.2358	0.0604	0.0577
IV	Shanxi	0.4774	0.1368	0.2629	0.0750	0.0479
	Inner Mongolia	0.5600	0.1232	0.2241	0.0559	0.0368
	Liaoning	0.5116	0.0889	0.2630	0.1080	0.0286
	Jilin	0.5146	0.1410	0.2417	0.0705	0.0322
	Guangxi	0.3876	0.1546	0.2789	0.0531	0.1258
	Sichuan	0.4064	0.1545	0.3141	0.0766	0.0484
	Guizhou	0.4398	0.1731	0.3022	0.0537	0.0312
	Yunnan	0.3904	0.1646	0.3076	0.0628	0.0746
	Tibet	0.5731	0.1009	0.1859	0.1400	0.0001
	Shaanxi	0.454	0.154	0.2474	0.0807	0.0639
	Gansu	0.538	0.1006	0.2709	0.0664	0.0242
	Qinghai	0.5126	0.1162	0.2813	0.0653	0.0245
	Xinjiang	0.5590	0.0740	0.2748	0.0573	0.0349

tendency to the data. When combined with the 14th Five-Year Plan and relevant policy opinions, the focus of rural revitalization in China still lies in the construction of high-standard farmland and its related water conservancy and hydropower facilities, the governance of its natural environment, and the improvement of its living environment, as well as an emphasis on rural education. These behavioral measures may mean that the orientation of fiscal expenditure to this system will continue. In addition, Table 9 showcases that the proportion of provinces (cities and districts) changes among different regions. The proportion of the whole industry prosperity is quite prominent, among which the proportion of industry prosperity in Region IV is slightly higher than that in other regions, while the proportion of affluent life is relatively small. In the dimension of rural civilization, the proportion change is the largest in Region II, the smallest in Region I, and is similar among Regions III and IV. The ecological livability dimension shows that the proportion value of Region I is large, while the proportion values of the other regions are similar.

3.2.3 Evolution results of the gini coefficient difference of fiscal expenditure in the 31PLAD in each dimension

Using the Dagum Gini coefficient and its subgroup decomposition method, the Gini coefficients of fiscal expenditure intensity in each dimension of rural revitalization in the 31PLAD were calculated, with the results shown in Table 10.

Table 10 shows the Gini numerical calculation results in 2005, 2010, 2015, and 2020 from five dimensions: prosperous

TABLE 10 Regional difference data results of 31PLAD based on Dagum.

Dimension	Year	G	G_w				G_{nb}						Contribution rate (%)		
		Overall	I	II	III	IV	I-II	I-III	I-IV	II-III	II-IV	III-IV	G_{nb}	G_t	G_w
Prosperous industry	2005	0.272	0.313	0.162	0.252	0.224	0.276	0.324	0.358	0.227	0.253	0.258	25.848	31.100	43.052
	2010	0.247	0.160	0.310	0.195	0.277	0.262	0.220	0.256	0.278	0.305	0.250	25.197	20.476	54.327
	2015	0.247	0.134	0.304	0.199	0.276	0.248	0.208	0.251	0.288	0.316	0.253	24.958	27.575	47.468
	2020	0.236	0.124	0.213	0.283	0.275	0.185	0.238	0.234	0.259	0.257	0.292	27.508	22.609	49.884
Ecological livability	2005	0.376	0.280	0.298	0.331	0.295	0.301	0.414	0.448	0.429	0.467	0.331	21.636	53.562	24.802
	2010	0.323	0.281	0.257	0.313	0.256	0.288	0.367	0.361	0.342	0.316	0.305	24.416	39.409	36.175
	2015	0.402	0.267	0.321	0.444	0.280	0.338	0.417	0.465	0.408	0.401	0.419	26.878	38.856	34.267
	2020	0.330	0.256	0.213	0.314	0.325	0.265	0.356	0.382	0.313	0.348	0.345	23.829	40.248	35.923
Effective governance	2005	0.364	0.133	0.390	0.363	0.293	0.34	0.346	0.345	0.465	0.467	0.342	21.771	40.073	38.156
	2010	0.313	0.303	0.176	0.236	0.345	0.276	0.376	0.413	0.290	0.342	0.302	22.051	45.348	32.601
	2015	0.304	0.158	0.322	0.199	0.343	0.274	0.303	0.357	0.359	0.408	0.290	20.840	46.841	32.319
	2020	0.333	0.351	0.144	0.207	0.370	0.301	0.414	0.461	0.307	0.370	0.313	20.091	50.036	29.872
Rural Civilization	2005	0.336	0.308	0.215	0.245	0.327	0.299	0.414	0.458	0.328	0.366	0.297	20.954	52.064	26.982
	2010	0.328	0.178	0.344	0.287	0.373	0.322	0.288	0.351	0.369	0.390	0.346	24.781	28.408	46.811
	2015	0.332	0.158	0.365	0.294	0.410	0.300	0.279	0.344	0.342	0.409	0.400	25.665	20.924	53.411
	2020	0.354	0.162	0.393	0.437	0.311	0.331	0.356	0.302	0.439	0.366	0.419	25.299	21.926	52.775
Rich Life	2005	0.565	0.485	0.369	0.490	0.422	0.480	0.633	0.718	0.526	0.630	0.510	18.066	59.963	21.971
	2010	0.560	0.526	0.369	0.514	0.371	0.514	0.650	0.717	0.513	0.571	0.509	18.620	55.320	26.060
	2015	0.396	0.158	0.388	0.343	0.544	0.345	0.381	0.453	0.393	0.488	0.480	23.308	38.582	38.110
	2020	0.465	0.269	0.390	0.546	0.456	0.418	0.496	0.498	0.489	0.449	0.529	23.916	34.768	41.316

Note: The intra-regional disparity is G_w, the inter-regional disparity is G_{nb}, and the hypervariable density is G_t.

industry, ecological livability, civilized rural customs, effective governance, and affluent life. Table 10 also visualizes the intra-regional, inter-regional, and super-density contribution rates of the various dimensions. The overall intra-regional and inter-regional differences in industrial prosperity are relatively stable and low, while those with affluent life are higher than the other dimensions. The differences among the other three dimensions are similar, but the numerical differences are not large.

4 Discussion

4.1 Interpretation of the mechanism of how land income supports rural revitalization

To industrialize and urbanize its cities faster, as well as to maximize China's advantage of being able to concentrate on multiple areas, the state is planning to tilt more resources to cities and towns. The national fiscal expenditure has primarily been directed to various fields in cities and towns to support the development of modernization. With the rapid development of urbanization and industrialization, China's overall fiscal revenue has been greatly improved. At this stage, the proportion of fiscal expenditure in rural areas is gradually increasing, with its overall situation improving, which can be compared with the level of investment in cities and towns over the past few years, although the results seem to be extremely low. This behavior has caused a great separation between rural and urban development, with high urbanization levels and low rural modernization (Ning, 2012; Zhang et al., 2018). Especially in rural areas of various underdeveloped areas, money and human elements flow out in great numbers (Wang, 2006). The loss of a rural labor force leads to a lack of resources for rural development. In some areas, only land has been expropriated or transferred, while money and human elements are not in place, and rural development lacks core elements. Figure 2 shows the mechanism of land transfer income supporting rural revitalization.

The imbalance between urban and rural development has produced numerous problems (Liu, 2018b). For rural areas, these include increasing wastelands and hollowing out, left-behind elderly, and children who lack care and support, among others. As far as cities are concerned, there are various other challenges, such as migrant workers living in cities without fixed homes, having to move around, crowded cities, high vacancy rates, and high housing prices. These problems require focus and proper solutions on the road toward prosperity. Rural revitalization is an important means to solve the problems of

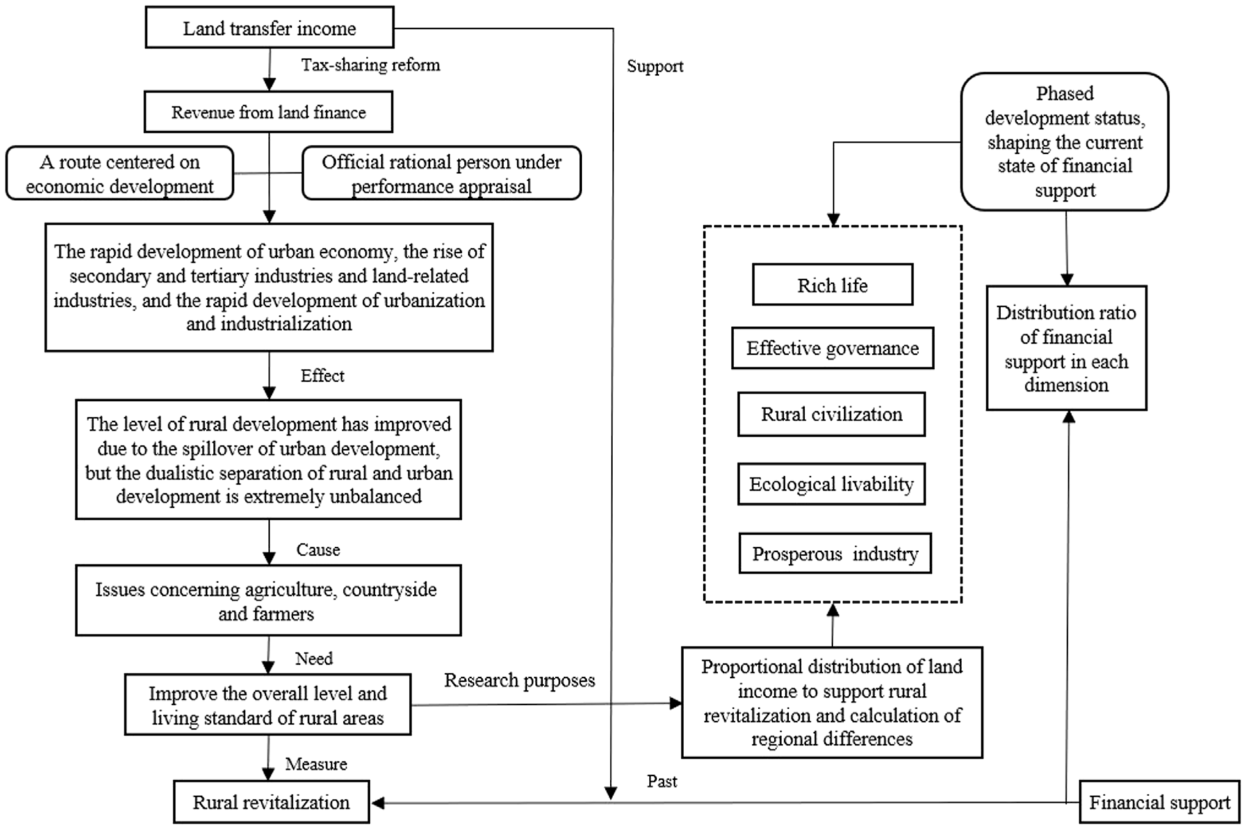

FIGURE 2
Operation mechanism of how land transfer income is used to support rural revitalization.

agriculture, rural areas, and farmers, as well as various exogenous problems derived from these (Wang and Su, 2017). In the process of urbanization, the role of land finance cannot be ignored. Land finance accounts for a high proportion of local finance and is the source of funds for urbanization in China. Further, land transfer income is a significant part of land finance. Generally speaking, land transfer is the income obtained by transferring land in various ways. In the past, it was rationalized by the local government as supporting urbanization. Now, to make up for the lack of resources for rural development, the existing policy orientation aims to use land transfer income for rural development. This includes a focus on financial input and where exactly to invest. In the past, it was unclear how to match the directions of financial support for agriculture in numerous fields in various PLAD. Further, the existing policies stipulate that the land transfer income should support rural revitalization with its key expenditure direction. Herein, according to the calculation of its key expenditure objects, the specific proportion of land transfer income supporting rural revitalization in various fields is observed. Based on this, the same proportion of land transfer income after 5 years was calculated, which is of constructive significance for different PLAD to formulate expenditure strategies.

4.2 Forecast of land transfer income supporting rural revitalization in the 31PLAD

Based on the proportion of each dimension predicted in Table 9, combined with the predicted data of land transfer income, the possible fiscal expenditure at the end of the 14th Five-Year Plan was calculated. The calculation results provide a reference for PLAD in formulating and implementing policy plans. The calculation results are shown in Table 11.

As shown in Table 11, the expenditure on land transfer income that supports rural revitalization in all dimensions is small as it is limited by the magnitude of land transfer income of each province, except for Beijing, Shanghai, Jiangsu, and Guangdong, which have better land transfer income and good expenditure in all dimensions, especially in terms of industrial prosperity and ecological livability. Moreover, few rural areas in Beijing and Shanghai are more developed than others, which

TABLE 11 Forecast of land transfer income support in 31 PLAD in 2025.

Region	Province/ Dimension	Prosperous industry	Ecological livability	Rural civilization	Effective governance	Rich life
I	Beijing	138.48	104.66	32.61	38.12	6.73
	Tianjin	64.68	36.73	27.07	26.42	0.33
	Shanghai	118.45	68.90	16.08	29.23	0.07
	Jiangsu	383.29	185.76	319.34	121.00	5.68
	Zhejiang	197.83	146.94	207.53	82.05	25.81
	Guangdong	312.38	188.19	305.81	156.14	17.74
II	Hebei	97.75	33.63	101.53	21.64	6.13
	Fujian	79.53	47.17	86.68	23.27	18.77
	Shandong	157.75	119.25	158.31	48.37	22.31
	Hubei	138.17	35.46	61.49	26.25	15.86
	Hunan	62.16	25.35	55.07	14.71	23.27
III	Heilongjiang	13.50	7.19	4.32	1.02	1.22
	Anhui	144.14	64.28	126.63	20.43	23.54
	Jiangxi	71.25	29.05	72.56	15.75	18.88
	Henan	116.53	38.70	137.77	30.12	13.39
	Hainan	16.52	3.09	10.82	2.63	4.73
	Chongqing	95.26	39.05	98.62	19.58	7.86
	Ningxia	4.58	0.84	1.98	0.51	0.48
IV	Shanxi	38.18	10.94	21.03	6.00	3.83
	Inner Mongolia	16.66	3.66	6.67	1.66	1.09
	Liaoning	30.16	5.24	15.50	6.37	1.69
	Jilin	18.54	5.08	8.71	2.54	1.16
	Guangxi	47.76	19.05	34.37	6.54	15.50
	Sichuan	120.72	45.89	93.30	22.75	14.38
	Guizhou	46.82	18.43	32.17	5.72	3.32
	Yunnan	27.14	11.44	21.38	4.37	5.19
	Tibet	6.35	1.12	2.06	1.55	0.00
	Shaanxi	38.65	13.11	21.06	6.87	5.44
	Gansu	21.57	4.03	10.86	2.66	0.97
	Qinghai	5.61	1.27	3.08	0.71	0.27
	Xinjiang	23.99	3.18	11.79	2.46	1.50

means their expenditure on rural education, governance, and affluence is less. Regions I and II are those with significant expenditure on rural civilization and ecological livability in China, with the expenditure magnitude being larger than that in other regions. Conversely, very few provinces in Region I have lower affluent living expenditures than those in Region IV, except for Guangxi, Sichuan, and Shaanxi. The expenditure magnitude of the governance effectiveness dimension in Regions III and IV is generally lower than that in Regions I and II.

4.3 Evolution of Gini Differences by region

According to the data in Table 9, the specific evolution of the Gini Differences is shown in Figures 3–6 as visual observation of its changes. Considering the difficulty of data retrieval, the data from 2005, 2010, 2015, and 2020 were selected for observation, with the missing years during each period, such as the data from 2005 to 2010, not being processed or counted, with them being positively correlated by default. From this, we can observe three consecutive planning periods: 2006–2010 is the 11th Five-Year Plan period, 2011–2015 is the 12th Five-Year Plan period, and 2016–2020 is the 13th Five-Year Plan period. This provides phased goals for developing agricultural and rural areas in different planning periods. The differences in overall, intra-regional, inter-regional, and super-density contributions in the different planning periods were also observed.

Figure 3 shows the overall Gini coefficient changes of the five dimensions. By placing their ordinates in the same interval, we

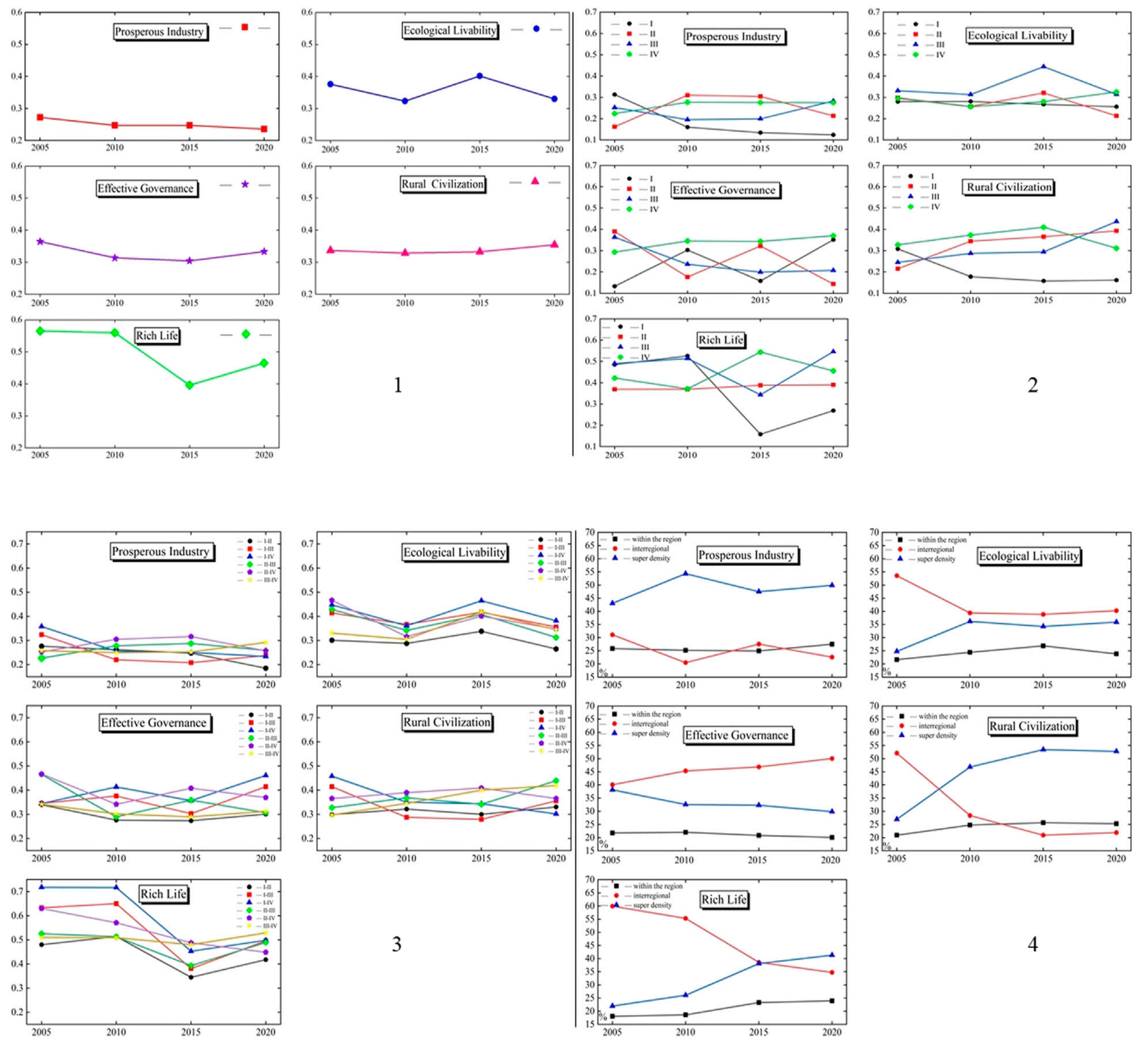

FIGURE 3
The evolution results of Gini coefficient of each type from 2005 to 2020.

not only see the changes in each dimension but can also make intuitive comparisons among each one.

The overall difference in industrial prosperity is lower than that of the other dimensions, with the dimension of affluence having the highest overall difference. The difference between effective governance and rural civilization is roughly similar. Herein, the prosperous industry, effective governance, and rural civilization dimensions have not changed significantly in these three planning periods, with the differences displayed fluctuating little. The overall difference in industrial prosperity was only 0.236 in 2020. This shows that the industry is booming and that there was little difference in the fiscal expenditure for developing agriculture and agriculture-related industries. In the three planning periods, the ecological livability dimension shows a fluctuating trend of initially falling, then rising, and then falling again. In the first two planning periods, the improvement effect of rural environmental remediation is obvious, with the rural environment improving within the capacity of PLAD. The difference between effective governance and rural civilization is about 0.3–0.4, with that in fiscal expenditure not being particularly large. However, the affluent life dimension was more limited by the economic development of each province, with a high Gini coefficient and large differences. This dimension reflects the large gap between the rich and the poor in the affluent life dimension in rural areas.

The intra-regional differences and their evolution are shown in Figure 3. The difference in the Gini coefficients between prosperous industry, effective governance, and rural civilization are similar, with it all occurring in the range of 0.1–0.4.

The Gini coefficient was the highest in 2005 and declined in the following years, reaching its lowest value of 0.124 in 2020. In the second region, it shows an inverted V-shaped trend, with the lowest point rising, reaching its highest in 2010, and then starting to decline again. However, the Gini coefficient in 2020 is still higher than that in 2005. In the third region, it presents a positive V shape, with the high point dropping to a low point and then rising again. Region IV demonstrates an overall upward trend, reaching the highest value of 0.277 in 2010, and slightly decreasing in the other 2 years, which were generally similar.

The difference in the ecological livable dimension in Region I is generally low and shows a downward trend, while the development of Region IV is generally upward. The trend of Region I in the last 2 years of 2010 is downward, while that of Region II is upward. The different trends of ecological livability in Regions II and III are the same, with both ups and downs.

Regions III and IV, with their effective governance, generally demonstrated a downward trend. The starting point of Region III is high, and the ending point is low, showing a downward trend as a whole. However, the intra-regional differences between Regions I and II declined in 2005 and 2010 and then showed different trends, with I first falling and then rising and II first rising and then falling. Wave curves with different trends in each stage are presented in Regions I and II.

There is a change in the regional differences of rural civilization, except for Region I, with those of Regions II, III, and IV rising in the first two stages and the differences between Regions II and III continuing to rise thereafter, while that of Region IV then begins to decline. From 2005 to 2015, China's economy developed rapidly, implying that people's demand for education increased. Compared with the PLAD, there is a gap in the rural magnitude and financial expenditure degree in the second and third regions.

The difference in affluent areas is somewhat higher than that in the other dimensions, with its range being large. Specifically, both Regions I and III show a state of repeated changes from top to bottom, with the changing state being the same in each stage, with them showing a trend of rising first, then falling, and then rising again. Region I had a large downward trend in the second stage, from 0.526 in 2010 to 0.158 in 2015, and the regional differences changed greatly.

Figure 3 shows the inter-regional gap and its evolution. The 31PLAD is divided into four regions, with six differences between them.

As shown in Figure 3, the trend changes of Regions II–IV and Regions II–III within the industrial prosperity dimension are similar. They rise in the first two stages and fall in the latter stage. The Gini coefficient of the difference between Regions I and II decreased. Between Regions I and IV, it first decreased, then slightly increased, and then decreased again. The Gini coefficient between Regions I-III initially decreased and then increased, while the difference between Regions III-IV first decreased slightly and then increased. The Gini coefficient of the regional differences in industrial prosperity is generally lower than 0.358.

Changes in the six regions in terms of the ecological livability dimension all showcase the same trend, as they first decline, then rise, and then fall. A possible reason for this is that the overall ecological livability dimension experienced the same trend as the other differences among the six regions. In this dimension, the regional differences of different revitalization intensity levels are similar to those among provinces.

Effective governance in Regions I–IV and II–IV showcase the same trend, falling initially, then rising, and then falling again. The trend between Regions I–III and I–IV is the opposite, first rising, then falling, and then rising again. However, the trend of Regions III–IV and I–II is the same as the overall trend, which decreases slowly in the first two stages and then rises slowly in the latter stage; however, the overall change is not large. Regions I–II and III–IV share a similar intensity of rural revitalization level, with the changes between these regions being similar to those between the whole.

From 2005 to 2020, the Gini coefficient between Regions I–IV of rural civilization decreased continuously, while that between Regions III–IV increased continuously. The intensity of rural revitalization varied greatly between Regions I and IV. The degree of rural revitalization in Regions III and IV was similar, with it rising continuously across all three stages, with the difference in fiscal expenditure between the two regions increasing. The trends of Regions I–II and II–III are the same in the first two stages but opposite in the latter stage. The difference between Regions I and III showcase a V-shaped trend, which first decreased, then slightly decreased again, and then increased in the next stage. The difference between Regions II and IV is inverted and V-shaped, rising first, then rising slightly again, and then falling.

In the affluent life dimension, the difference trend among the other four regions, except for Regions II–IV and III–IV, is almost the same as the overall difference trend. There may be a slight increase or a significant decrease in the first stage between the other IV regions. Further, the difference between other regions, such as Regions II–IV, decreased, and the decline was almost straight and inclined. The main difference between Regions III–IV is that their rise and decline are not obvious, with a slight increase in the first stage, a slight decrease in the second stage, and a slight increase in the third stage.

The changes in intra-regional, inter-regional, and super-density contribution rates among the five dimensions are shown in Figure 3.

As shown in Figure 3, the contribution within the region is the lowest of the five dimensions. The contribution rate of ultra-density is high in industrial prosperity and ranks second in the dimensions of ecological livability and effective governance. The contribution rates of the rural civilization and affluent life dimensions between regions and the over-density show large changes. The super-density contribution rate of rural civilization shows a sequentially rising trend, while the super-density contribution rate between regions decreased continuously in the first two stages and then rose slightly, with the highest super-density contribution rate reaching 52.775% and the highest inter-regional contribution rate reaching 52.064%. The super-density contribution rate of affluent life continues to rise, while the contribution rate between regions is declining at each stage, with the highest contribution rate of super-density reaching 41.316% and the highest contribution rate between regions reaching 59.963%. After observing the changes in these five dimensions, we can see that there is a negative correlation between the contribution rate of hyperdensity and that between regions.

5 Conclusion

This study attempted to investigate the fiscal expenditure on certain rural dimensions to examine its effectiveness and the degree of differences therein, as well as the possible future support ratio to make an effective forecast of future trends. According to the statistical data and the reasons for the index selection, there are some errors therein, indicating a margin for speculation. There may be a gap between the calculation of data expenditure and the actual expenditure. First, the gap source lies in the fact that the index coverage of statistical data cannot cover all relevant fiscal expenditures. After repeatedly considering the feasibility and computability of the indicators, the indicators with strong correlations are selected for calculation. Second, whether the indicators can represent the expenditure in this area is mainly analyzed using the existing data and interpreted subjectively, so there are differences from the specific real expenditure. It is the limitation of this study in estimating expenditure. However, the merit of this paper is to select a large number of minute indicators, collect and calculate them, and classify and sort the fiscal expenditure of various dimensions. All kinds of trend changes and overall proportion changes that may exist are obtained. The real expenditure value is not specific, but the change of proportion can be used for reference, which is also the core content of this study.

This paper explores the expenditure of each dimension from the results, provides references for provinces and cities to observe the development of each dimension and suggests policies on this basis. Each dimension pays more attention to supporting agriculture, that is, putting forward suggestions from the perspective of financial support for the development of each dimension. From the two levels of time and region, the former was used to investigate the changes in expenditure effectiveness in different periods in the same region, while the latter was used to investigate the differences in expenditure effectiveness in the same period in different regions. According to our results, we put forward the following policy recommendations.

First, in terms of all dimensions of rural revitalization, to enhance the linkage development among them—for example, when promoting industrial development—local industries should be examined simultaneously to develop tourism, expand investment, strengthen inter-regional mobility, and promote the development of basic culture, education, and entertainment. Villages should also focus on green development in developing industries and enhance the development of basic industries and the efficiency of governance on a pro-environmental basis.

Second, in the industrial prosperity dimension, we should try to scale agricultural operations, accelerate industrial diversification, and engage in local industries according to local conditions. Further, we should guide the land transfer income to gradually and reasonably flow into the construction and investment of basic agriculture. The state has always attached great importance to the development of basic agriculture, with the proportion of fiscal expenditure in various provinces being reflected herein. In addition to the large scale of fiscal expenditure, when arranging funds for supporting agriculture, we should also focus on the rational distribution of land transfer income to various industries. Based on the ecological livability dimension and rural living environment improvement, tourism development relies on the local ecological landscape, as well as the local history and culture. Increasing local characteristics and preserving their cultural forms is thus important herein. Rural infrastructure has developed well in recent years; however, environmental sanitation management is still imperfect and is less developed when compared with that of cities. Combined with the local governance level, building a high-level governance team is thus necessary.

Third, we should focus on basic education in less developed rural areas in the rural civilization dimension. The PLAD with relatively underdeveloped rural education in Regions II and III should improve their level of financial expenditure or land transfer income to support basic education, attach importance to educational infrastructure construction and basic education investment, introduce teachers with high-quality teaching level, and protect the rights and interests of teachers and students. In the effective dimension of governance, the distribution ratio among several regions is higher in the first region, while the expenditure degree of the effective dimension of governance in the second, third, and fourth regions is low. Another PLAD with weak rural revitalization intensity has a relatively low rural governance level and efficiency. Therefore, the rural grass-roots government organizations in the introspection (city, district) of this region should introduce high-level talent with advanced ideas suiting the local situation and gradually improve the level of grass-roots governance.

Finally, in terms of land revenue arrangement, combined with the data forecast to improve the use efficiency of land transfer revenue and clarify the path of grass-roots government and actual implementers, the following suggestions are provided. These include implementing phased planning mission objectives that comprehensively consider the financial strength of each region, the scale of land transfer income, and the needs of local production and development. Fund management should be strengthened and the overall fund structure should be planned. Further, provincial-level planning should be implemented and the difference ratio determined. Additionally, strengthening the accounting of capital revenue and expenditure, the degree of capital for all provinces, cities, and counties, as well as the degree of development of all dimensions, should be considered when making a unified plan. National key investment directions, such as farmland or basic water conservancy and hydropower construction funds, should primarily be retained in the policy coordination of provinces, cities, and counties (districts). Further, a clear supervision system and the establishment of land transfer income to support the rural development of the relevant institutions should be organized. Further, clear capital and personnel supervision need to be ensured. Next, fund supervision should be used to strengthen relevant audits to ensure the transparent and efficient use of funds. Additionally, personnel supervision should be used to strengthen internal and external supervision, as well as the opening of hotlines in relevant areas to ensure timely feedback of information and relevant amendments. Regions should also reasonably arrange their local organizational structure and be familiar with the measures and regulations for managing land transfer income to solve the problem of rural revitalization in cities, counties, and rural areas. The development of publicity methods to ensure the implementation of policies should also be ensured. All provinces, cities, and counties should observe the local rural characteristics and publicize them through multiple channels. Further, they should organize and arrange personnel to clarify the land transfer income and rural revitalization-related policies. Additionally, they should train personnel with high efficiency and strong execution ability to organize and implement relevant policies. Finally, the implementation of policies should be flexible overall.

Data availability statement

Publicly available datasets were analyzed in this study. This data can be found here: https://www.cnki.net/.

Author contributions

YW and YX wrote the main manuscript text. YW directed and revised the manuscript and contributed to all aspects of this work. YW and YX worked together to collect and process data. All author reviewed the manuscript.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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Estimating the non-linear effects of urban built environment at residence and workplace on carbon dioxide emissions from commuting

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Understanding the relationship between CO_2 emissions from commuting (CEC) and the built environment is crucial for sustainable transportation and land-use policymaking during the process of constructing a low carbon city. Previous studies usually assume that the relationship is linear, which may lead to inaccurate CEC prediction and ineffective policy. Using daily travel survey data of residents in the central city of Jinan, this study adopted a gradient boosting decision tree model to explore the threshold effect and the non-linear relationship between built environments and CEC. Our findings suggest that 40% of CEC is related to the workplace environment, which is higher than the residential environment and other socioeconomic variables. The five most important variables are road density within 1 km radius of the workplace (13.493%), distance to the center at workplace and residence (10.908%, 10.530%), population density at workplace (9.097%) and distance to bus stop from the residence (8.399%). Distance to city center plays the most important role and its non-linear relationship reflects the influence of the urban spatial structure of Jinan on CEC. Furthermore, the thresholds and non-linear relationships provide planning guidelines to support urban planning development policies for low carbon city.

KEYWORDS

built environment, gradient boosting decision model, CO_2 emissions from commuting, non-linear relationship, threshold effect

Introduction

As an important source of energy consumption, the transportation sector accounts for a substantial share of greenhouse gas (GHG) emissions (1, 2). Due to rapid urbanization and motorization, developing countries have higher transport-related energy consumption and GHG emissions (3). However, rapid urbanization and

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motorization brought along consequences such as heavy usage of vehicles, traffic congestion, road accidents, and air pollution in many major cities in China, which has a negative impact on the health of residents (4). Since commuting is an essential daily activity for urban residents, which accounts for approximately 50%∼60% of their total trips (5), it is necessary to develop methods to control CEC effectively.

The urban built environment is the spatial reflection of land-use policies, and the source of urban traffic demand. It also has a locked effect on travel behaviors (the commuting mode, commuting distance, and travel times), implying that the urban built environment could also affect CEC. Urban geography and urban planning scholars have attempted to create green transportation-oriented urban built environments and minimize automobile dependence to reduce CEC by optimizing urban spatial organization. Western countries which have adopted transportation and land-use policies including new urbanism, smart growth, and transit-oriented development (TOD) programs to alleviate the problem of urban sprawl have achieved positive results. However, some research found that these policies were weakened for large cities in China due to the urban spatial structural transformation and the complexity of institution reform (6). While existing literature attaches great importance to the effect of the built environment at residence, the effect of the built environment at workplace is often neglected. However, the built environment characteristics at workplace may be associated with the commute behaviors (7) and hence changing the daily CEC. Workers are less likely to choose their jobs based on the built environment characteristics at workplaces, representing the independent effects of the built environment instead of self-selection effects. However, the effects of the built environment characteristics at workplaces on CEC rarely have been explicitly examined. If the built environment at workplace has a significant effect on CEC, physical improvements in residential areas are insufficient to achieve the goal of carbon reduction. Moreover, some studies using the machine learning methods reveal that there is non-linear relationship between built environment and travel behavior (8–11). This would help decision makers understand the threshold of the built environment variables, and improve the outcomes of the urban planning process. Therefore, understanding CEC and its relationship to the built environment at residence and workplace is crucial and necessary for sustainable effective transportation and land-use policymaking.

Using the daily travel survey data of residents of the central city of Jinan in China, this study contributes to the existing literature from the following aspects: (1) Gradient boosting decision tree (GBDT) model is applied to estimate the non-linear effects of the built environment on CEC at both residential and workplace locations, this would help to examine the threshold of built environment variables, and better understand the CEC problem, (2) this study analyzes the importance of built environment on CEC, (3) our results provide the empirical evidence toward the development of large cities in developing countries.

The remainder of the paper is structured as follows. Section 2 provides a brief review of the impact of built environments on CEC. Section 3 introduces the research design, including regional characteristics, data sources, and research methods. Section 4 presents the results. Section 5 discusses research limitations and possible future research directions. Section 6 concludes the paper.

Literature

For over two decades, CEC has received significant attention. Urban built environments and socioeconomic factors have been considered to have significant impacts on CEC in previous studies. The urban built environment includes many factors, which referred to as 6D, i.e., density, diversity, design, destination accessibility, distance to bus stop, and demand management (9, 12). Above six factors are closely related to commuting behaviors. Based on aggregate (country/city) or disaggregate (individual/household) data, the direct and indirect impacts of different built environment variables on commuting behaviors and related CO_2 emissions are already well explored, especially for the built environment variables at the residence (13–16). Using different methodological approaches and geographies, many research showed that a community has great potential to reduce automobile use and CEC if its built environment characteristics include a high population density, good public transport accessibility, and a high land-use diversity, although the significance and magnitude of the effects of these built environment factors can vary substantially (12, 16).

Many empirical studies were conducted to examine the influence of the built environment on CEC in residential areas. Based on data from the 2006 Austin Household Travel Survey, Choi and Zhang (17) found that a 1% increase in density was found to reduce household vehicle emissions by 0.1%. However, this relationship is not consistent due to the different geographical contexts. Other studies have found that when the residential population density reaches a certain level of threshold, improving the density will not necessarily reduce CEC. Using the 2006 Puget Sound Household Travel Survey data, Hong (18) found that people living in denser neighborhoods tend to generate fewer CEC. However, this effect becomes insignificant as population density reaches a certain level. Most studies confirmed that the mixed degree of land use is negatively correlated with CEC, and improving the degree of land use mixing in urban suburbs is more helpful for reducing CEC than improving population density (19, 20). Distance to bus stop access is positively related with CEC (21). However, Chai et al. (19) found that households located far from the city center but with greater transit accessibility in Beijing increased their dependence on public transportation, thereby reducing the probability of commuting by private car. Similarly, improving street connectivity in residential areas will reduce CEC (22, 23).

However, as behavioral research deepens our understanding of people's daily behaviors, several studies started to focus on the effect of the built environment in non-residential locations. Researchers believe that people's commuting will be jointly influenced by the built environment of their residences and workplaces. The built environment at the workplace appears to have an important impact on travel behavior, but it is overlooked in the literature. Considering that only the geographical environment of residential areas may lead to misunderstanding of the results, overestimating the background impact of neighborhood areas and underestimating the impacts of other places (24). Huang et al. (25) represented the overall geographical environment in a more accurate way. Furthermore, examining the influence of built environment variables at workplace will provide a reference for the design and redevelopment of employment centers. Otherwise, urban planners may incorrectly estimate the effect of built environment attributes at both locations. Empirically, several studies have found that car ownership, commuting mode and commuting distance are all related with the built environment at both ends of commuting (7, 26–30). For instance, in terms of car ownership, Ding and Cao (30) found that the higher employment density and bus stop density at workplace could reduce the likelihood of owning vehicles in the New York metropolitan area, and the residential built environment had a greater impact on the ownership of cars. However, using data from residents in transit-supported suburban neighborhoods in Shanghai, Shen et al. (31) found that there is an insignificant connection between work location and car ownership. Nasri and Zhang (32) found that higher residential and employment densities at residences and workplaces decreased the probability of automobile use and increased the probability of non-motorized travel mode choices. However, Sun and Dan (33) used the Multi-nominal Logistic Regression model and conclude that increasing the population density in residential areas can significantly reduce the probability of private automobile use, while the built environment at workplace has a relatively weak influence on the choice of commuting mode in Shanghai. Dang et al. (28) used a cross-classified multilevel model to estimate the effect of land-use diversity at residences and workplaces on commuting distances and found that land-use diversity at the workplace is more important for reducing commuting distance than at residential areas. Thus, commuting behavior (such as commuting mode and commuting distance) could be affected by both locations. Therefore, we hypothesize that the built environment at both workplace and residential locations should influence CEC, which are closely related to commuting behavior. However, there is still insufficient research about effects of the built environment at both locations on CEC, and it is uncertain regarding the linearity of the relation. Linear models are used widely in the study of the relation between built environment variables and travel behaviors. However, these models cannot solve the multicollinearity between variables, and may cover up the local the non-linear correlation and the threshold effect, which will mislead the planning process (30, 34). Besides, according to previous studies, the built environment variables could have marginal effects on travel behaviors (35, 36). Considering the high density, high mixing degree and the complete public transport system in Chinese cities, the non-linear hypothesis between the built environment and travel behaviors should be adopted in the study of Chinese cities (37). In practice, it is also important for urban planners to explore the most effective impact range of the built environment for low-carbon travel. These research questions will help us understand the mechanism by which built environment variables affect CEC to formulate effective low-carbon urban planning and transportation policies. In addition, socioeconomic factors including income level, education level, and family size, have also been demonstrated to impact travel behaviors (38–41). To fill the gap in the current literature, we use the GBDT model to capture the marginal effects and importance of the built environment variables at residences and workplaces on CEC after controlling for the individual socioeconomic factors.

Data and methods

Data

Study area

The study area is the urban city of Jinan, which is the capital city of Shandong Province and the central city located within the downstream Yellow River area. As a typical major city in China, Jinan is going through rapid urbanization. For example, the number of household vehicles has increased significantly over the years, from 5.4 per 100 households in 2005 to 58.5 per 100 households in 2020. Similarly, there was an increase in the number of private cars from 0.254 million vehicles in 2005 to 2.962 million vehicles in 2020[1]. The rapid increase in vehicles have negative impacts on traffic and environmental conditions. During the past 5 years, Jinan ranked as the 5th most congested city and the 7th city with heavy air pollution in China[2,3]. Jinan's overall urban planning calls for low-carbon developments in the new era. Therefore, studying the relationship between the urban

1 Source: Bureau of Statistics of Jinan. (2002–2018) Jinan Statistical Year book. Beijing: China Statistic Press, China.

2 Source: Amap.com. China Major Cities Transportation Analysis Report 2018 Q3. 2018. Available online: https://trp.autonavi.com/traffic/ (accessed on March 15, 2019).

3 Source: Ministry of Environment Protection (MEP), 2018. Rank of national key monitoring cities air quality year. Environ. Educ. Z1, 16.

built environment and CEC could provide a solid foundation for the development of a low-carbon city.

According to the overall urban plan for Jinan (2021–2030)[4], this study is conducted primarily in the central area of Jinan, which is located east of the Yufu River, west of the east ring line of the expressway, south of the Yellow River and north of the mountain area. This area encompasses five administrative regions, namely, the Huaiyin District, the Licheng District, the Lixia District, the Shizhong District, and the Tianqiao District. The entire study area is 337 km^2 and has a population of 2.82 million people which accounts for 77.3% of the urban population in Jinan.

Data and variables

The data is obtained from a travel survey from January to July in 2021 for residents over 18 years old. The survey design takes into consideration of error control mechanism and introduces randomness to ensure equal participation opportunities for residents located in each subdistrict. Besides, the number of participants was determined based on the proportion of the population within each district. For 1,200 surveys distributed, the residence address, work address and socioeconomic attributes are sampled at the same time, while participants with no employment information (e.g., students, retirees, and freelancers, are removed from the sample. After applying all filters, our sample contains 920 observations from 64 residential subdistricts and 57 workplace subdistricts.

To better understand the distribution of geographical locations for the respondents, the location of the residential areas and workplaces are obtained through spatial analysis methods from ArcGIS 10.2 platform. Based on the distribution of the residential and workplace respondents presented in Figure 1, it is obvious that most of the respondents are located within the second ring. The distribution of residences is relatively scattered, and the employment sites are more concentrated in the central business district (CBD). Since the local government moved to the eastern suburb in 2009, the city is in transition from the monocentric to polycentric.

The survey is composed of three parts, i.e., individual travel behaviors, socioeconomic factors and several urban built environment factors. Based on the data, descriptive statistical analyses were performed on the travel behavior characteristics, the residential and workplace-built environments, and the socioeconomic attributes of respondents (Table 1).

Travel behavior characteristics include the daily commute mode and commuting distance of the resident. There are eight commute modes included in this study, which are walking, bicycle, electric bicycle, motorcycle, bus, unit shuttle, private car, and taxi. Approximately 41.17% of the residents choose private cars to travel, and 29.48% of the residents choose walking, bicycles, electric cars or other green travel methods. The remaining residents rely on bus traveling. In our analysis, the commuting mode is a dummy variable, and 1 (0) represents car traveling (other transportation methods). The commute distance is obtained from the Baidu map through identifying the respondent's residence and work location. The results indicate that approximately 48.15% of the residents have a commuting distance of more than 6 km and that the average one-way commute distance is 7.155 km.

The socioeconomic variables of individuals and families considered in this study include age, monthly income, level of education, family size and the number of private cars within the household. Combination of these variables reflects the impacts of family demands, life cycle and travel ability on family travel (19). Our result suggested that 47.93% of the respondents are under the age of 40, and 36.53% have an average monthly income of more than 5000 RMB. Additionally, the average family size of the respondents is 3.263, and 77.96% own car.

With respect to the built environment factors, prior studies suggest that the following five variables should be considered (9, 12, 16, 33) distance from the city center, road density, distance to bus stop, population density, and land-use diversity.

The distance from the city center of Jinan is measured by the average straight distance to the main urban center and sub center, in ArcGIS 10.2 software. The average distance from residential areas is 7.593 km, while the average distance from workplaces is 6.807 km. The population density is calculated by dividing the populations by the subdistrict area and is based on survey data from the sixth census of Jinan. The average residential population density is 12136.57 person/km^2, and the average population density at the workplace is 12303.65 persons/km^2. The road density reflects the urban design, which is the sum road length within 1 km radius at residence or workplace, and the average value is 5.029 km/km^2 and 5.691 km/km^2, respectively. The distance to bus stop reflects access to bus and is captured by the distance from the location (residence or workplace) to the bus stop. The average distance to bus stop from residential areas and workplaces is 221.094 m and 188.459 m, respectively. The land-use diversity reflects the degree of mixing of different land-use types and is calculated following previous studies (28, 42). The value is between 0 and 1. The larger the value is, the higher the degree of land-use diversity and the greater the balance in the distribution of the land functions. In this paper, the subdistrict is used as the unit of measurement. Based on the land use map of Jinan in 2020, four types of land use which are closely related to residences and work are selected: residential land, public service facilities land, industrial land, and municipal utility land. The average diversity of land use at the residential and workplace levels is 0.713 and

4 Source: Jinan Municipal Planning Bureau. Jinan Urban Development Strategic Plan (2018-2050) [2019–04–02]. Available online: http://nrp.jinan.gov.cn/art/2019/4/2/art_43830_3510946.html (accessed on April 2, 2019).

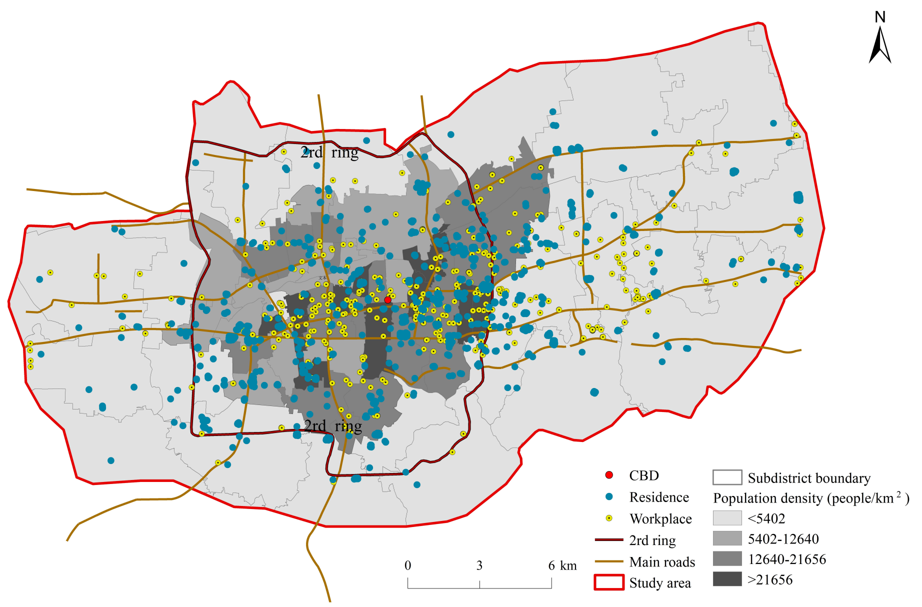

FIGURE 1
Locations of the residential areas and workplaces of respondents in central Jinan.

0.741, respectively. Descriptions of the variables in this study are shown in Table 1.

Methodology

Measurement of CEC

To calculate CEC accurately, this study measured CO_2 emissions based on trip distance methods proposed by current travel research (19, 43–45). Based on transportation modes and the commuting distances obtained through surveys, the commuting CO_2 emissions could be directly calculated using the following formula:

$$CE_i = \sum_t \sum_j D_{itj} \times F_j \quad (1)$$

Where CE_i is the daily commuting CO_2 emission of respondent i. D_{itj} is commuting distance of respondent i using the commuting mode j for the commute t. And F_j represents the CO_2 emission factor of the commuting mode j. According to the studies on China's transportation CO_2 emissions (45, 46), the relevant parameters are presented in Table 2, where CO_2 emissions are direct emissions.

Based on Equation (1), the commuting carbon emissions of each respondent in central city of Jinan could be obtained for a single day. For all respondents, the average value of the commuting CO_2 emissions is 1641.579 g, and for the respondents commuting by car and by bus, the average value is 3687.849 g and 529.618 g, respectively. Figure 2 shows the Lorenz curve of CO_2 emissions from private cars, buses, and all respondents in the central city of Jinan. The distribution of the commuting CO_2 emissions from all respondents is not equal and reflects the 70/20 principle, in which 70% of the CO_2 emissions are generated by approximately 20% of the residents. For respondents commuting by cars and buses, the distributions approximately fit a 60/30 distribution, indicating that 60% of the CO_2 emissions are generated by 30% of the residents.

The GBDT model

The GBDT model is applied in this study to explore the association between built environment characteristics and CEC. Through building decision trees, GBDT model is popular in dealing with many classification and regression problems. The literature has shown that the GBDT model is a powerful tool to deal with small sample size (9). Compared with the traditional regression models, the GBDT approach cannot produce the statistical inference and the significance level of variables, but it can deal with multicollinearity among variables more effectively, determining the importance of variables, and allowing for accurate predictions (47). The GBDT model can be expressed as follows:

$$F_M(x) = \sum_{m=1}^{M} T(x, \theta_m) \quad (2)$$

TABLE 1 Descriptive statistics for variables.

Variable	Description	Mean	Min	Max	Std. Dev.
Individual travel behavior variables					
Commuting mode	0 = Commuting by the other modes (58.83%).	0.412	0	1	0.492
	1 = commuting by car (41.17%)				
Commuting distance (km)	Daily commuting traveled distance (one way)	7.155	0.533	37.237	5.906
Individual socioeconomic variables					
Gender	0 = Female (52.28%); 1 = Male (47.72%)	0.478	0	1	0.500
Age (years)	Age	38.270	18	68	8.045
Monthly income (RMB/month)	1 = Below 2000 RMB (19.24%)	2.943	1	6	1.191
	2 = 2000 to 2999 RMB (9.35%)				
	3 = 3000 to 4999 RMB (34.89%)				
	4 = 5000 to 6999 RMB (31.96%)				
	5 = 7000 to 9999 RMB (3.48%)				
	6 = 10000 RMB and above (1.09%)				
Family size (people)	Number of household members	3.263	1	7	0.983
Car ownership	0 = No car (22.04%).	0.92	0	3	0.608
	1 = Owing one car (63.7%)				
	2 = Owing 2 cars (13.59%)				
	3 = Owing 3 or more cars (0.43%)				
Built environment variables at residential place					
Distance to city center (km)	Straight line distance from CBD and sub center	7.593	4.913	29.480	3.096
Road density (km/km^2)	Road length within a 1 km radius of residence	5.029	0.363	11.676	2.295
Distance to bus stop (m)	The nearest distance to bus stops from the residence	221.094	24.329	922.03	151.981
Population density(people /km^2)	Population/subdistrict area	12136.57	297	32870.5	10078.75
Land-use diversity	Degree of mixing of different land uses in residence*	0.713	0.434	0.888	0.102
Built environment variables at workplace					
Distance to city center (km)	Straight-line distance from CBD and sub center	6.807	4.913	18.937	2.449
Road density (km/km^2)	Road length within a 1 km radius of workplace	5691	0.337	12.174	2.362
Distance to bus stop (m)	The nearest distance to the bus stops from the workplace	188.459	19.333	1210.28	119.540
Population density (people /km^2)	Population/subdistrict area	12303.65	598	32870.5	10728.46
Land-use diversity	Degree of mixing of different land uses in workplace	0.741	0.434	0.888	0.088

920 persons, 64 residential subdistricts, 57 workplace subdistricts. The values in brackets in the description column denote the proportion of each categorical variable.

$*Hland_i = \frac{-\sum_{K=1}^{n} p_{K,i}\ln(p_{K,i})}{\ln(K,i)}$.

TABLE 2 Carbon emission factor by transportation modes.

Transportation mode	Transportation tool	CO_2 intensity (g/person km)
Car	Private car, taxi,	233
Public transit	Bus,	26
	Unit shuttle	20.3
Personal assistive mobility device	Electric bicycle, light motorcycle	10
Other	Walking, bicycle	0

Where $T(x, \theta_m)$ is the decision tree; M is the number of trees, θ_m is the parameters of the decision tree.

In the GBDT model, the loss function of the decision tree is the squared error function, which is denoted by $L(\bullet)$. And the minimum loss function is used to determine the parameters of the next decision tree, where $T_{m-1}(x_i)$ is the current decision tree.

$$\hat{\theta}_m = argmin \sum_{i=1}^{N} L[y_i; T_{m-1}(x_i) + T(x; \theta_m)] \quad (3)$$

To obtain robust model results, the GBDT model is estimated by R software in this study. Specifically, the sample is divided into five subsets, at each iteration, the model is fitted using four different subsets (80% of the data) and validated by the remaining subset (20%

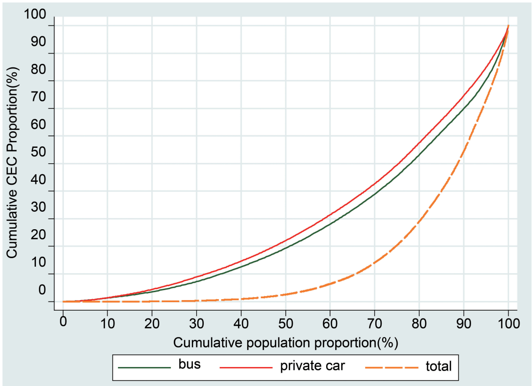

FIGURE 2
Lorenz curve of the distribution of daily CEC from cars, buses and all respondents in Jinan.

TABLE 3 The relative importance of variables.

Variables	Importance (%)	Rank
Individual socioeconomic variables	(30.502)	
Car ownership	21.299	1
Income	5.285	7
Age	1.825	14
Gender	0.257	15
Family size	1.836	13
Built environment at residence	(29.577)	
Distance to center	10.530	4
Road density	4.253	8
Population density	2.587	11
Distance to bus stop	8.399	6
Land use diversity	3.808	10
Built environment at workplace	(39.915)	
Distance to center	10.908	3
Road density	13.493	2
Population density	9.097	5
Distance to bus stop	4.244	9
Land use diversity	2.173	12

of the data). Overall, a maximum of trees and the shrinkage parameter is set to 1000 and 0.05, respectively. And we chose five-way interaction, and the best results could be obtained after 2,500 boosting iterations. The R squared is 0.221. The relative importance of independent variables and partial dependence plots are derived for further analysis.

Results

The relative influence of independent variables

Table 3 presents the relative influence of built environment characteristics and individual socioeconomic variables. The relative influence of a predictor measures its relative empirical improvement in reducing prediction errors. The total relative influence of all predictors adds up to 100%. The built environment is more important in predicting CEC than individual socioeconomic variables. This finding is consistent with other studies that applied the GBDT model to examine built environment effects on driving behavior (8). Specifically, the ten built environment characteristics at residence and workplace collectively contribute to almost 70% of the predictive power, whereas the five individual socioeconomic variables account for about 30%. Besides, the built environment characteristics at workplace contribute to almost 40%, more significant than those at residence, which account for around 30%.

The most important predicting variable is car ownership (21.299%). Owning a car will directly increase the probability of car commuting, resulting in high carbon emissions. Therefore, the impact is relatively large. The second is the road density in the workplace (13.493%). The road density in the workplace reflects the density and connectivity of road facilities and is an important factor affecting CEC. The third is the distance from the workplace to the city center (10.908%), and the fourth is the distance from the place of residence to the city center (10.530%). The distance between living and working places to the city center jointly determines the commuting distance. These two factors reflect the location characteristics, respectively. The importance of location on commuting behavior has been confirmed in many studies (27), with a total of 21.4% contribution. The fifth is the population density of the workplace (9.097%). The concentration of the population in the workplace is an important factor affecting the commuting behavior of residents. The sixth is the distance from the bus stop in the residence (8.399%). The distance from the bus station reflects the service capability of the public transportation facilities in the residence, and depicts the convenience of residents' commuting by bus, which is of high importance. The importance of other variables is similar, and the value is $< 5\%$. In contrast to most studies which showed that the variable of land use diversity has a greater effect on CEC, our results did not discover important relation between land use diversity and CEC. This result could be related to the calculation method at the street scale. At the street scale, the main urban area has a high degree of land use and development, and the average land use diversity at residence and workplace is 0.713 and 0.741, respectively. The homogeneity is strong, resulting in the weak explanatory power when compared with other variables.

The effects of built environment at the residence and workplace

In the linear model, the coefficient of the independent variable remains unchanged globally, while the independent variable in GBDT does not maintain a stable slope. This may have a non-linear effect on the dependent variable, and there is a threshold effect in the region where the slope changes suddenly. In this way, it can help decision makers find the thresholds of variables and realize the efficient development of urban planning. In this study, we used the GBDT and produced partial dependence plots to illustrate the relationships between built environment variables and CEC (Figures 3–7). A partial dependence plot demonstrates the marginal effect of an independent variable on the predicted response while controlling for all other variables in the model. The vertical axis is CEC, the horizontal axis represents the respective variable. The fitted curve is smoothed to better show the changes. The overall trend of all independent variables is consistent with our expectations.

Figures 3A,B illustrates the impact of distance to center, with the relative importance presented along with the label for the horizontal axis. Distance to city center has positive threshold effects on CEC. When the distance is < 12 km, its slope is relatively steep. Once it exceeds 12 km, its slope becomes smooth. When people live close to the city center, the accessibility to facilities is high and people have more travel mode choices instead of driving, and the CEC would be lower. However, for people live far from the city center, they tend to commute by car due to the lower accessibility and inconvenient transit service. Therefore, CEC would be higher. However, once the distance is beyond 12 km, the CEC remains relatively unchanged.

By contrast, distance from workplace to center also takes on non-linear effects on CEC, which decreases before increases. The results show that individuals who work closer to the center within 5 km tend to emit more CEC, since they often reside far away from the center due to the tradeoff between the commuting cost and housing price (32). And according to the survey, the negative correlation are also found between the workplace location and residence location. Since most cities like Jinan in China are still monocentric, there are gradient characteristics such as population density, employment density and housing prices (5). In our sample, 21.3% of those who work within 5 km from the urban center have to commute 10 km or more distance. Thus, people tend to work in close proximity to the center, while residences are far from the center. As the distance increasing, the job-home separation could be improved, and many people will lower the CEC. However, once the distance exceeds 5 km, the CEC shows an increasing trend. The longer distance from the workplace to the city center, the higher dependence on the car when commuting, resulting in an increasing CEC. Similar to the variable of distance to the center at residence, once the distance exceeds 13 km, CEC remains unchanged. The results show that the location of residence and workplace jointly affect CEC, and it is important to form the polycentric spatial structure in central city of Jinan in the future.

Figure 4A illustrates the relation between CEC and distance to bus stop at residence. Overall, the higher accessible transit service has a negative relation with CEC. When the nearest distance to the public transit is <500 meters of a residence, the increase of the distance to bus stop leads to a higher CEC. This pattern is consistent with Gallivan et al. (48). Beyond this range, the change of CEC is trivial as the distance increases. Figure 3B shows the impact of the distance to bus stop at workplaces, and is similar to that at residence which means that better access to bus stop at workplace could lower CEC. This result is consistent with previous research (45). However, once the distance exceeds 500 meters, the change of CEC is insignificant. Therefore, the distance to bus stop at residences and workplaces plays an important role in CEC. The access to public transit at the residences has a significant impact on CEC. This is due to the uneven spatial distribution of bus facilities. Dense bus routes are highly concentrated in the employment center instead of the residences (9).

Figures 5A,B shows the influences of population density. It shows the threshold effect of population density at residence on CEC. Overall, the effect of population density at residence reaches a high level at about 22,000 people/km^2 before slowly decreases. This could be explained by the concentration of human activities because of high density (36). For most cities in China, locations with low population density often coincide with an inconvenient public transportation and less employment opportunities, which means that residences in these areas are more likely to commute by car. As the population density increasing, the government will improve the supply of public facilities and infrastructures, indicating that there would be a higher usage of the public transport system and less CEC. However, with the further increase of population density, public infrastructure will eventually fail to meet public needs, and car commuting would increase. Once the population density reaches above 22,000 people/km^2, the issue of traffic congestion would emerge. Preference for the public transport increases, which results in less CEC. In general, there exists a U-shaped relationship between the population density at residence and the CEC. Figure 5B suggests that the increase in population density at the workplace also lowers the CEC. The reason is that urban centers are important areas of employment, and there are normally a complete public transportation system and high population density in these areas. When the population density of workplace increases, traffic jams and high parking charges will occur. Besides, commuting by car is more energy and time consuming. As a

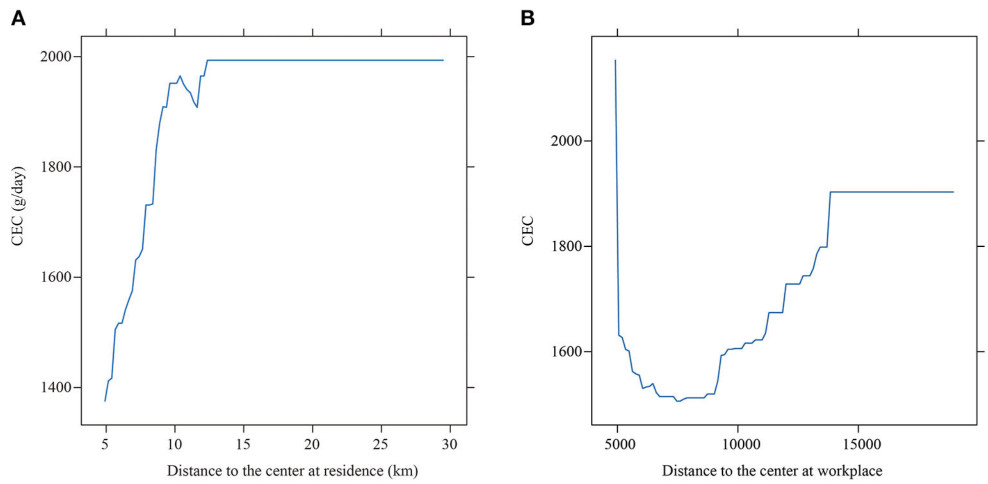

FIGURE 3
The partial effect of distance to the center on CEC. **(A)** At residence (10.530%). **(B)** At workplace (10.908%).

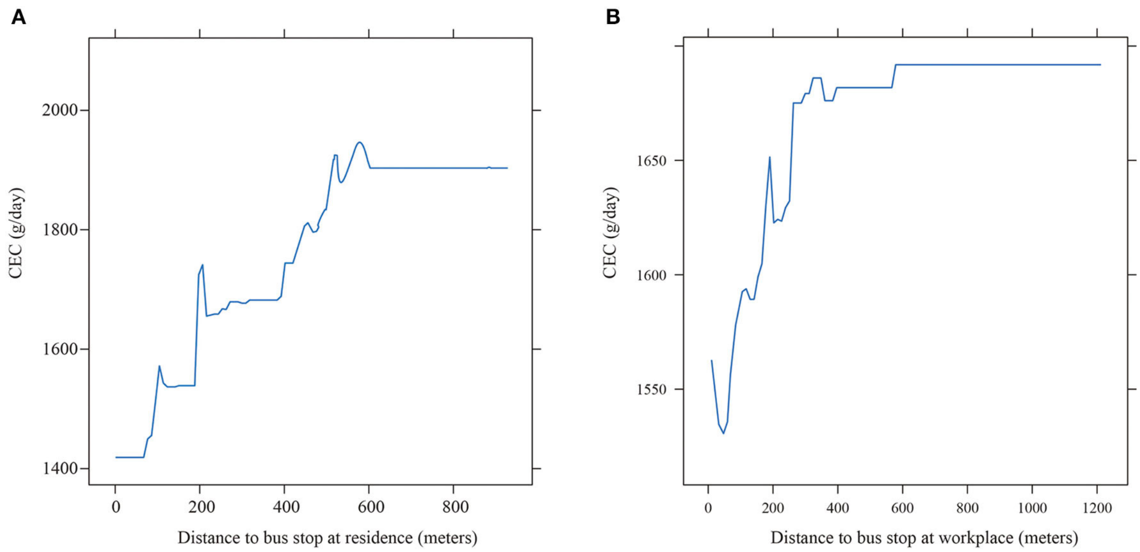

FIGURE 4
The partial effect of distance to the bus stop on CEC. **(A)** At residence (8.399%). **(B)** At workplace (4.244%).

result, an increase in the population density at the workplace will reduce the likelihood of car commuting, as well as the corresponding CEC.

As a diversity indicator, land use entropy index at residence is negatively correlated with CEC in Figure 6A. This negative relationship is consistent with the previous literature (49, 50). However, the land-use diversity at the workplace also has a non-linear effect on CEC, and 0. 55, 0.7 and 0.75 are the important turning points. When land use diversity is relatively homogeneous (entropy $<$ 0.55), it has a trivial influence on CEC. However, when there are several types of land-uses (0.55≤entropy≤0.7), CEC decreases. Moreover, land use diversity has increasing effect once all types of land use are relatively evenly distributed (entropy $>$ 0.7). On the other hand, if the land use diversity is higher than 0.75, it will lower the CEC. Overall, land use diversity is effective on CEC when it

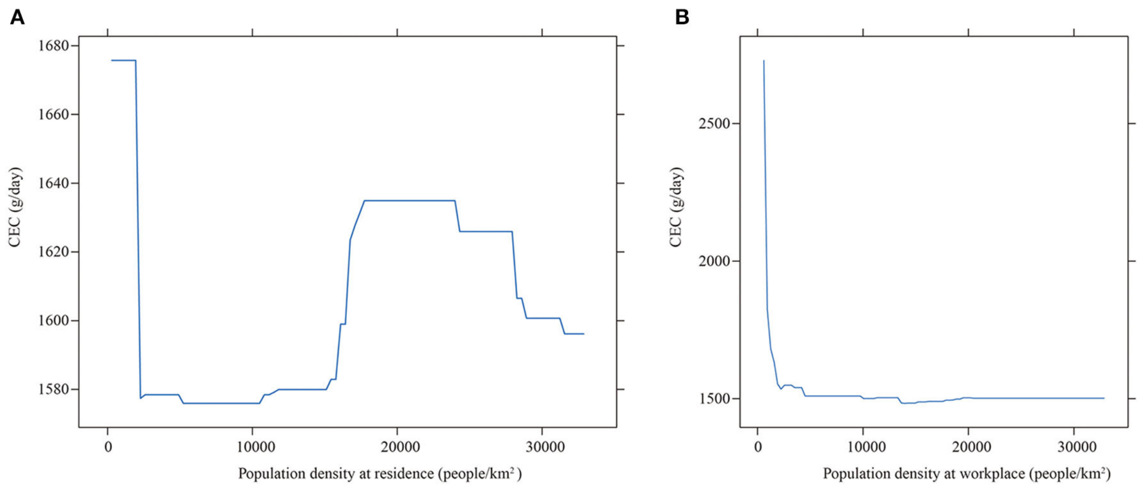

FIGURE 5
The partial effect of population density on CEC. **(A)** At residence (2.587%). **(B)** At workplace (9.097%).

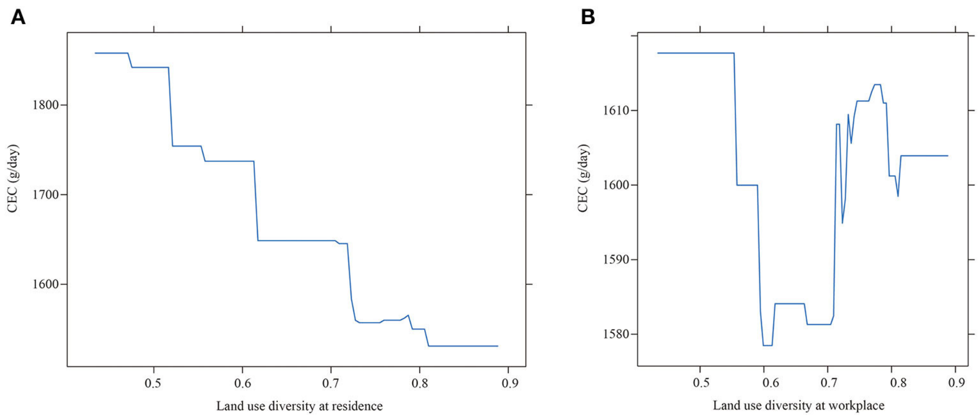

FIGURE 6
The partial effect of land use diversity on CEC. **(A)** At residence (3.808%). **(B)** At workplace (2.173%).

reaches a certain level, but it has a diminishing return once it reaches a different threshold. The reason is that to give full play to the agglomeration benefits of land, the land use types are often dominated by industrial land and commercial land, and residential land is often distributed in peripheral areas with few job opportunities. This results in a higher degree of home-work separation and more CEC.

Road density could reflect the street connectivity. The literature suggests that it is negatively related to driving distance and positively related to transit use (16). Thus, road density could lead to the decrease of CEC. As shown in Figure 7, the road density at residence within 1 km buffer of residence shows a negative correlation with CEC, similar to that of workplace. It hugely lowers CEC when the road density at residence is higher than 2 km/km^2, but the decreasing effect is trivial once the road density is higher than 8 km/km^2.

The comparison with log-linear regression

A traditional log-linear regression model is constructed to compare with the GBDT model, and natural logarithmic transformation is performed on variables with positive or

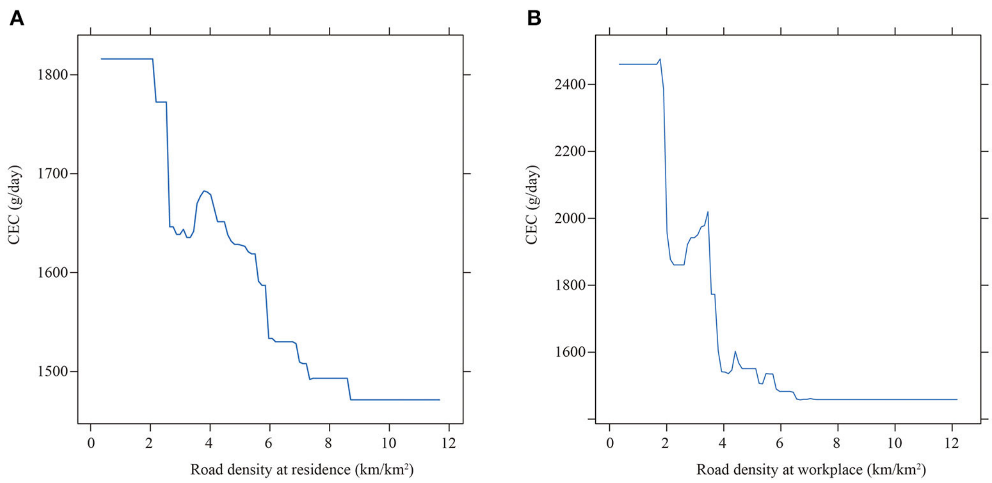

FIGURE 7
The partial effect of road density on CEC. **(A)** At residence (4.253%). **(B)** At workplace (13.493%).

negative skew distribution, which can effectively improve the fitness of the linear model. To achieve desired results, the natural logarithm standardization was performed on all continuous variables. Analyzing the results of OLS model estimation in Table 4, it can be found that the *p*-value of the F test is < 0.001, indicating that the results are reliable. The standardized coefficients of the variables show the relative agreement between the traditional model and the GBDT model on the overall expected effect, but the significance and the relative importance of the variables of the GBDT model are quite different. Specifically, we include the built environment variables of residence and workplace in the regression model, respectively, and results show that the significant variable either at residence or at workplace could be found. However, after including all variables in the regression model, the variable at workplace (distance to center from workplace) becomes insignificant. These results confirm that the linear regression could cover up the local impact of variables. Besides, the R^2 of the log-linear regression is 0.137, which is lower than that of GBDT (0.223), indicating that the GBDT method is more suitable for explaining the impact of built environment variables on CEC. The difference is due to the biased estimation caused by the pre-existing linearity assumption, reflecting the advantages of non-linear models.

Discussion and limitations

Accuracy of the GBDT model

The GBDT model is adopted in this study to examine the non-linear relationship between built environment characteristics and CEC at residence and workplace. In contrast to the parametric specification of non-linear relationships, this model considers the non-linear relationships between built environment variables and CEC. It also assesses the relative importance of different built environment characteristics in reducing CEC and the collective contribution of built environment variables relative to individual socioeconomic characteristics. Since the patterns of non-linear relationships vary among built environment variables, this makes parametric specification of non-linear relationships inefficient and inaccurate. Apart from that, it is suggested that applying the threshold of built environment variables during the urban planning process would help achieve the goal of a low carbon city (51).

The effects of built environment

Consistent with prior research, our results confirmed that the built environment has stronger impacts on CEC compared with the individual socioeconomic variables. Compared with built environment variables at residence, those at workplace have affect CEC significantly, indicating that the built environment characteristics of work center can be used to meet the low carbon development goal in the future. For example, according to the current urban spatial structure of Jinan, employment land is concentrated in the urban center and residential land is spread outward. This structure offers individuals employed in the central urban area a wider range of locations to choose their residences.

The five built environment variables together, i.e., the road density at workplace, the distance to the center at workplace,

TABLE 4 The results of log-linear regression.

Variables	(1)	(2)	(3)
Individual socioeconomic variables			
Age	−0.024**	−0.026**	−0.024*
	(0.012)	(0.012)	(0.012)
Gender	0.250	0.251	0.238
	(0.191)	(0.194)	(0.193)
Income	0.242***	0.217**	0.240***
	(0.087)	(0.089)	(0.088)
Car ownership	1.447***	1.443***	1.447***
	(0.165)	(0.165)	(0.165)
Family size	0.230**	0.197**	0.227**
	(0.094)	(0.095)	(0.095)
Built environment at residence			
Distance to center	1.172***		1.110***
	(0.360)		(0.402)
Road density	0.065		0.035
	(0.252)		(0.258)
Population density	−0.013		0.005
	(0.091)		(0.094)
Distance to bus stop	0.290**		0.288**
	(0.127)		(0.128)
Land use diversity	−0.113		−0.114
	(1.677)		(1.720)
Built environment at workplace			
Distance to center		0.742**	0.087
		(0.373)	(0.416)
Road density		0.118	0.035
		(0.247)	(0.250)
Population density		−0.088	−0.062
		(0.075)	(0.077)
Distance to bus stop		0.005	0.015
		(0.139)	(0.138)
Land use diversity		−0.288	−0.335
		(1.836)	(1.859)
Constant	−7.464	−1.773	−7.076
	(4.869)	(4.877)	(6.070)
Observations	920	920	920
R^2	0.137	0.118	0.137
F	14.29***	12.05***	9.59***

***, ** and * indicate that the p-value is significant at the 1, 5 and 10%, respectively.
Figures in brackets denote standard errors.

the distance to the center at residence, the population density at workplace and the distance to bus top, contribute to more than 5% of CEC. Among all variables, the distance to the center at residence and workplace, representing the regional location, played the most important role in reducing CEC. The regional location largely determines land use characteristics and transportation infrastructure surrounding the region (20). On the other hand, land use diversity tends to be less influential. This is different from research findings in Western countries, which attached more importance to the effect of high land use diversity and high population density in reducing CEC (9). While in China, majority of big cities are characterized by dense population, high land use diversity and complete public transport networks. Therefore, the regional location will have a stronger impact on CEC than other variables in China.

Specifically, the road density at workplace has the strongest impact on CEC. It lowers CEC significantly when the road density is higher than 2 km/km^2, once the road density is higher than 8 km/km^2 the decreasing trend becomes trivial. This indicates that road density is not negatively related to CEC under all circumstances.

The distance to the center at residence and workplace indicates the local location, which jointly contribute to 20% of the total CEC. In general, due to the dislocation of workplace and residence, the distance from the city center is positively related to the level of CEC. However, according to the threshold effect, when the distance to center reaches 12 km, the CEC remains high, indicating that the government could formulate the industry layout within such distance.

The increase in population density at workplace also has a negative impact on CEC. This implies that urban planners could increase residential land supply in the employment center accordingly to alleviate home-work separation, meanwhile raise awareness of compact development. This could increase the mixed functionality of urban land and create more employment opportunities nearby, which could effectively reduce the reliance on commuting by cars, lowering the CEC accordingly.

The distance to the bus stop at residence which represents the public transit accessibility also plays a vital role in determining CEC. Many studies have also confirmed that the higher the accessibility of public transport, the more likely residents are to choose non-motorized commuting. Individuals who live in longer distance from the bus stop will emit more CEC. As the distance from residence to the bus stop increases, the demand for taking the bus decreases and many people will prefer to commute by car. Consistent with previous studies (21, 25), the more commute they take, the higher CO_2 emissions there will be (44). Therefore, it is necessary to solve the last mile problem during commuting to effectively limit the demand for car commuting, and reduce CO_2 emissions. These results can help planning practitioners effectively prioritize objects for urban built environment intervention.

The findings in the study have direct policy implications for Chinese cities like Jinan, which are in the process of rapid motorization.

First, this study shows that if planners focus on future population and employment growth in central urban areas (or up to 12 km from centers), the amount of increase in CEC associated with population and employment growth will be minimized. Multicenter development is actively advocated to provide more job opportunities, especially in outer areas of the central city, to shorten the commuting distance as well as reduce the related CO_2 emissions. Second, in terms of land use planning, urban planners should pay more attention to the built environment variables at workplace. This would help to improve the road network quality at employment centers. Additionally, due to the high level of land use diversity in employment centers, continuously increasing the land use diversity will not lead to a reduction in CEC. However, it should appropriately increase the supply of residential land in the employment center to alleviate the home-work separation. Third, it is important to improve the transportation access at both residence and workplace to decrease CEC, and solve the problem of last mile during commuting, enhancing the attractiveness of public transportation. This is especially the case for those who prefer to commute by car, and reduce potential CEC. In addition, multimodal transportation systems and more plausible land-use patterns should be established to support sustainable urban development, such as acceleration of the construction of multiple urban public transport modes (e.g., subway and BRT), and managing the personal commuting activities through big data and information technology.

Limitations

This study has the following limitations. First, the computation of CEC was based on existing emission factors, and we did not consider vehicle or transit occupancy, which could affect the true CEC from commuting. Second, the population density and land-use diversity are measured at subdistrict level. However, the effect of the built environment variables is measured at different spatial scale (such as traffic zone, community, and 1 km or 500 m radius of a residence). In addition, policymakers are more concerned about which dimensions of the built environment can lower CEC. Therefore, the comparative study of the effects of variables at different scales requires further study in the future; Third, in terms of the power of the CO_2 emission from commuting model, it could be improved by incorporating additional built environment variables, such as road network design, employment density, and parking availability, into the models for a more in-depth analysis. Lastly, since the data are cross-sectional, the influence found in this study is more of an association than causality, similar to most studies in the literature. In general, this study helps to understand the impact of built environment variables at both residences and workplaces on the CEC to large cities of China.

Conclusions

Based on the assumption of non-linear relationship between built environment and travel behavior, this study applies the GBDT model in analyzing the impact of the built environment at both residences and workplaces on CEC using the daily travel survey data of residents in the central city of Jinan. After controlling the socioeconomic factors, we examine the non-linear threshold effect of each variable on CEC, which enriches the existing theoretical and empirical research. Our findings suggest that:

(1) Built environment variables collectively are more important in predicting CEC than individual socioeconomic variables, which is consistent with most studies using parametric models. The following five variables have the highest predicting power among built environment characteristics: road density at workplace (13.493%), distance to the center at workplace and residence (10.908 and 10.530%, respectively), population density at workplace (9.097%), and distance to bus stop from the residence (8.399%). The distance to the center at residence and workplace, representing the local location, jointly contribute to 20% of CEC. In terms of the socioeconomic variables, car ownership has the highest predictive power (21.299%). On the other hand, land use diversity tends to be less influential either at residence or at workplace.

(2) The built environment at workplace contributes to 40% of the total CEC, which is higher than the build environment at residence. It is necessary to perform a planned intervention of the built environment elements at both residence and workplace. Majority of built environment variables at residence had similar impacts on CEC as those of workplace except population density and land use diversity, the impact of which on CEC varies significantly between the residence and workplace. Contrary to the impact of land-use diversity at residence, there are threshold effects for the land-use diversity at workplace affecting CEC. For the population density, the threshold effect only exists for residence.

(3) The non-linear and threshold effects of the urban built environment and CEC are determined in the Jinan city, and the threshold value of built environment variables could be obtained using the GBDT methods, which could guide the urban layout in future during the low carbon city construction.

Data availability statement

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

Author contributions

Conceptualization: JY. Methodology and formal analysis: QL and PZ. Data curation: QL, PZ, and YZ.

Writing—original draft preparation and writing view and editing: QL and ZZ. Visualization and software: PZ. Project administration, validation, and funding acquisition: QL. All authors have read and agreed to the published version of the manuscript.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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Effects of sanitation and hygiene perceptions on international travelers' health, travel plans and trip experiences in India

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Background: International travelers often experience travelers' diarrhea. However, there is paucity of data on whether self-reported gastrointestinal symptoms influence travelers' perceptions of adequacy of sanitation and hygiene services encountered during travel, and to what degree their travel plans, and overall trip experience are impacted.

Methods: A cross-sectional face-to-face survey was conducted amongst international travelers in India. Data collected included socio-demographics, travel characteristics, self-reported occurrence and frequency/severity of gastrointestinal symptoms, perceptions of sanitation and hygiene encountered, and adverse effects of symptoms on travel plans and trip experiences. Chi-square tests and logistic regression were performed to describe differences and associations between categorical variables.

Results: Of the 300 international travelers surveyed, 46.3% experienced diarrhea. At least two thirds of travelers perceived the quality of sanitation (67.0%) and hygiene (70.0%) encountered to be inadequate. Perceptions of inadequate sanitation (adjusted OR = 3.0; 95% CI 1.7–5.5) and poor hygiene (adjusted OR = 7.7; 95% CI 4.1–15.5) were higher among travelers who experienced diarrhea. Additionally, both higher likelihood of travel plans being affected (adjusted OR = 10.7; 95% CI 5.1–23.6) and adverse impacts on overall trip experience (adjusted OR = 2.8; 95% CI 1.4–5.8) were reported among those who experienced diarrhea.

Conclusions: More than two thirds of travelers surveyed in India experienced inadequate sanitation and hygiene services, with perceptions influenced by occurrence and frequency of diarrhea. Self-reported diarrhea was also associated with adverse effects on travel plans and overall trip experience. While these results may seem intuitive, they have important implications and suggest that improving sanitation and hygiene standards in India could potentially enhance tourism.

KEYWORDS

diarrhea, hygiene, sanitation, travel health, travel experience

Background

Inadequate sanitation and hygiene pose a major health challenge in many low- and middle-income countries, including India. In a 2018 Indian Government report, on average the proportions of households with access to an improved water supply or improved sanitation facilities (latrines) were 96%; ~85% (of both rural and urban populations accessing latrine) respectively. Similarly, the proportions of households practicing hand washing with water and soap/detergent after defecation and before meals were 74 and 35.8%, respectively (1). Access to an improved water supply and latrines does not necessarily equate with optimal sanitation management practices, which ideally should include safe disposal of septic waste to avoid environmental contamination. Furthermore, the majority of public toilets in India lack proper infrastructure, cleanliness, adequate water supply and hand washing facilities, therefore failing to meet optimal hygiene standards (2, 3).

Travelers who visit countries with poor hygiene and sanitation are at increased risk of exposure to diseases transmitted through the feco-oral route (4). Consumption of fecally contaminated water or food, and exposure to fecally contaminated environments, are associated with a range of diseases affecting travelers (5), in particular travelers' diarrhea (TD). TD is the most frequent illness reported amongst international travelers to developing nations (6), reported in up to half (7).

Travelers visiting India are at higher risk of acquiring travel-associated gastrointestinal illnesses than travelers to other regions (8–11). A study reporting a case of diarrhea in a traveler returning from India emphasized on the duration of symptoms as a significant factor for identifying the cause of diarrhea among travelers (12). The evidence on traveler's diarrhea suggests its association with the presence or predominance of bacteria such as Carbapenemase-producing Enterobacterales in tropical regions like India, which happens to be a reservoir for multi-drug resistant bacteria (13–15).

India, a popular tourist destination with about 10.6 million international tourists visiting in 2018 (16), is predicted to become the third-largest tourism economy worldwide by 2028 (17). However, the fact that perceived health risk is strongly associated with the tourists' decision and travel behavior, is well-established. Tourism industry is significantly impacted by such consumer behavior that includes change in destination, postponement of trips etc. (18). Negative experiences may impact future travel plans and tourists avoid destinations with more perceived health risks (19). Poor sanitation and hygiene are recognized as factors that negatively impact tourism services (20–22). Previous studies have demonstrated a strong correlation between improving hygiene standards at a travel destination and declining rates of diseases transmitted *via* the fecal-oral route among travelers (5). A study by Kozak et al. reported that tourist's travel experience is inversely proportional to the perceived risk (6). Therefore, overall improvement in sanitation and hygiene standards in India could potentially decrease the rate of fecal-orally transmitted diseases amongst visiting travelers and their perceptions of future travel would not be negatively influenced.

Despite the reportedly high rates of fecal-orally transmitted diseases in travelers (5–7), it is currently unknown whether gastrointestinal illness and perceptions of sanitation and hygiene conditions at a destination have an impact on trip experiences and future travel plans amongst tourists.

The purpose of this study was to: (i) describe associations between occurrence (including frequency and severity) of self-reported gastrointestinal illness and perceptions of inadequate sanitation/hygiene among tourists in India, and (ii) determine whether negative health experiences (e.g., diarrhea) and/or negative perceptions of sanitation or hygiene influence travel plans or travel experiences.

Methods

Study design

This was a cross-sectional study conducted amongst international travelers visiting the Northern Indian city of Rishikesh, located 250 km northeast of the capital city of India, New Delhi. An international traveler was defined as any tourist with a nationality other than Indian who had been in India for at least 7 days. A non-probability convenience sampling approach was used to recruit 300 travelers for the study.

The sample size was calculated on the likely prevalence of self-reported gastrointestinal illnesses (i.e., travelers' diarrhea). Since this was a pilot, exploratory study with a novel outcome, we made the following assumptions for assessing an association between prevalence of diarrhea in past 7 days and perception of sanitation experience among international travelers to India: (i) 34% of international travelers to India experience diarrhea, (ii) 2/3rd (67%) the travelers who experience diarrhea and half (50%) of the travelers who do not experience diarrhea report their perception of sanitation experience in India to be negative (inadequate), (iii) this results in the calculated odds ratio (effect size) of 2.03, and (iv) 5% precision (two-tailed), and 80% power. These assumptions therefore resulted in the total sample size of 300.

De-identified data were collected between September 2019 and February 2020 through face-to-face surveys using a paper-based questionnaire with closed-ended items. The survey tool design (Appendix in Supplementary material) was based on data collection tools available in travel medicine and public health literature (3, 10, 11). Local travel, tour, and restaurant/hotel operators were contacted and asked for permission to approach their guests for the study. Where permission was granted, trained research assistants approached guests of these operators, as well as tourists visiting local tourist attractions. An explanatory statement was provided to all those approached and written informed consent was obtained from those who agreed to participate in the study.

Ethics approval

The study protocol was reviewed and approved by the human research ethical committees of Governmental Doon Medical College in India (IEC-049, GDMC) and Monash University in Australia (MUHREC 20359).

Participants and data collection

Eligible participants were international travelers aged 18 years or older who had already been in India for at least 7 days. Data collected included information on socio-demographics, travel characteristics (e.g., purpose and duration of the visit), food and drink habits, hand hygiene practices, and medication use. Additionally, data on self-reported health outcomes (including occurrence and frequency of gastrointestinal symptoms such as diarrhea, nausea/vomiting, loss of appetite and abdominal pain) and their relationship to travel plans/experiences, medical advice or vaccinations prior to the trip, and access to and perceptions of sanitation and hygiene services were also collected.

Variables of interest included perception of sanitation and/or hygiene as inadequate, occurrence of self-reported diarrhea in the past 7 days (23, 24), self-reported severity of diarrhea (mild, moderate, or severe) (25); frequency of diarrhea (always, often, sometimes, rarely), occurrence of other gastrointestinal symptoms (nausea/vomiting, loss of appetite, abdominal pain, including cramping/stomach ache, bloody stool) (9–11), alteration in current and future travel plans and adverse impact on trip experience.

Data analysis

De-identified data from paper-based surveys were entered and stored in a customized REDCap^{TM} database (HELIX, Monash University) by research assistances in India. Raw data were extracted for analysis.

Frequencies and proportions were computed for descriptive results. Chi-square tests were performed to evaluate statistical differences among categorical data. Logistic regression was performed to assess associations between (i) occurrence and/or severity of self-reported gastrointestinal illnesses and perceptions of sanitation and hygiene experiences among travelers, and (ii) negative health experiences (e.g., diarrhea) and/or negative perceptions of water, sanitation and hygiene facilities and travelers' future travel planning.

Frequency of diarrhea and other gastrointestinal illness symptoms were grouped into less frequent (sometimes and rarely) and more frequent (always and often) categories. Similarly, duration of stay in India was also grouped into "<2 weeks" and "equal or more than 2 weeks." Association of the duration of time spent in India with the occurrence and frequency of diarrhea and other gastro-intestinal symptoms was estimated using the chi-square test. Bivariate logistic regression was used to estimate odds ratios with 95% CIs after adjusting for demographic factors. For all statistical tests, $p < 0.05$ were considered statistically significant. All statistical analyses were carried out using STATA (version 14, StataCorp, College Station, TX, USA) and SPSS version 23.

Results

Demographic and travel characteristics

As illustrated in Table 1, majority of the travelers were females being 61% ($N = 300$). Most of the travelers were of 40 years or less. The traveler's were from across the globe with 69% from China, the USA, the UK, Australia, Italy, Canada, France, Russia, and Germany. Majority of the tourists were on vacation and about 17% visited India for education or volunteer work. Approximately half of the travelers' planned their trip for more than 4 weeks with more than 40% who preferred to stay in a hotel. Antibiotics were the most common medicine carried by about 60% of the travelers and 70% preferred bottled water. About half of the travelers didn't seek any medical advice prior to their trip as illustrated in Figure 1. The incidence of diarrhea were reported by 46% of the travelers (Figure 2).

TABLE 1 Travelers' demographic and travel characteristics.

S. no.	Variables ($n = 300$)	Frequency (%)
1	**Sex**	
	Females	182 (60.7%)
	Males	117 (39.0%)
	No answer	1 (0.3%)
2	**Age (years)**	
	18–30	151 (50.3%)
	31–40	115 (38.4%)
	>40	34 (11.3%)
3	**Country of origin**	
	China	42 (14.0%)
	USA	35 (11.7%)
	UK	27 (9.4%)
	Australia	23 (7.7%)
	Italy	22 (7.3%)
	Canada	17 (5.7%)
	France	16 (5.3%)
	Russia	15 (5.0%)
	Germany	10 (3.3%)
	Other countries	93 (30.6%)
4	**Ethnicity**	
	White	212 (70.7%)
	Asian (Far-East)	33 (11.0%)
	Asian (Indian subcontinent)	16 (5.3%)
	Hispanic/Latino	14 (4.7%)
	Black	10 (3.3%)
	Bi/Multi-racial	10 (3.3%)
	Middle Eastern	5 (1.7%)
5	**Highest level of education**	
	University degree	188 (62.7%)
	Secondary school	100 (33.3%)
	Primary school	12 (4.0%)
6	**Travel reasons**	
	Tourism/vacation	179 (59.7%)
	Educational/research	40 (13.3%)
	Volunteer/missionary	14 (4.7%)
	Visiting friends/relatives	12 (4.0%)
	Business	8 (2.7%)
	Other	47 (15.7%).
7	**Planned travel duration**	
	>4 weeks	148 (49.3%)
	3–4 weeks	92 (30.7%)
	1–2 weeks	51 (17.0%)
	<1 week	9 (3.0%)
8	**Traveling partners***	
	With friend(s)/family	162 (54.4%)
	None	136 (45.6%)
9	**Time already spent in India***	
	<2 weeks	112 (37.5)%
	2–4 weeks	111 (37.1)%
	>4 weeks	76 (25.4)%
10	**Stay venues**	
	Hotel	125 (41.7%)
	Guesthouse	57 (19.0%)
	Home stay/friend's home	26 (8.7%)
	Apartment	14 (4.7%)
	Other (non-specified)	78 (26.0%)
11	**Underlying health conditions**	
	No	275 (91.7%)
	Yes	25 (8.3%)
12	**Hepatitis A vaccination**	
	Never received	155 (51.7%)
	Single dose received (>12 months ago)	29 (9.7%)
	Two doses received (completed course)	58 (19.3%)
	Received within 12 months	58 (19.3%)
13	**Typhoid vaccination within last 3 years***	
	No	200 (66.9%)
	Yes	99 (33.1%)
14	**Travelers who carried medicines/drugs**	
	Probiotics	79 (26.3%)
	Anti-biotics	180 (60%)
	Anti-emetics	77 (25.7%)
	Anti-motility	44 (14.7%)
15	**Travelers' intake of drinking water**†	
	Bottled water	210 (70%)
	Boiled water	90 (30%)
	Tap water	19 (6.3%)
	UV treated water	46 (15.3%)
	Chlorinated water	21 (7%)

*Data missing in 1 (Time already Spent in India and Typhoid vaccination status) or 2 (Traveling partners) patients.
† Multiple choice question.

Perception of sanitation and hygiene experiences

Perceptions of inadequate sanitation and inadequate hygiene were reported by about 67 and 70% of travelers respectively. These perceptions did not differ across sexes ($p > 0.05$). One in four travelers (24.1%) reported difficulties in finding a public toilet; just over half reported they were able to find a public toilet when needed. Almost half the travelers (43.8%) reported that most public toilets did not have a hand washing basin with soap

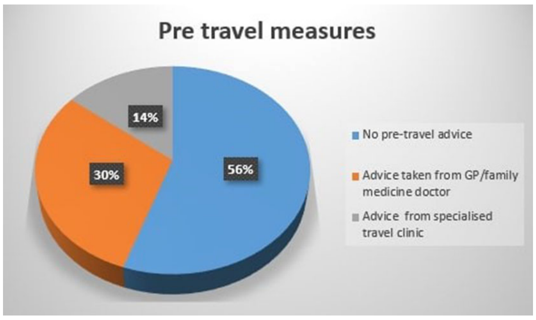

FIGURE 1
Pre-travel medical advice taken by travelers.

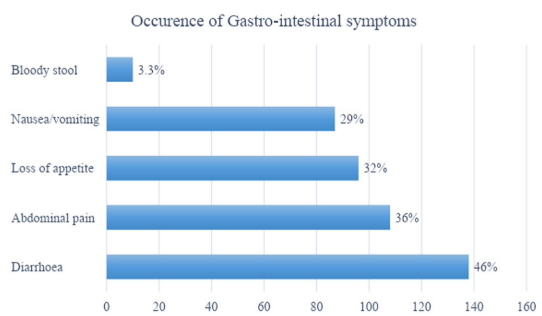

FIGURE 2
Occurrence of gastro-intestinal symptoms among travelers.

or hand sanitizer. Approximately equal proportions of travelers reported that their experiences of toilet and hand-washing facilities were better than (28%) or worse than (28.7%) expected. The perception of inadequate sanitation and hygiene was found to be different according to the use of water (e.g., bottled water, boiled water and tap water). The perception of sanitation was significantly different among the travelers using bottled water and boiled water ($Chi^2 = 4.95$, $p = 0.03$; $Chi^2 = 9.17$, $p = 0.002$, respectively). Similarly, the perception of inadequate hygiene was found to be significantly different among the travelers using tap water ($Chi^2 = 4.05$, 5.24 for bottled and boiled water respectively). Supplementary Tables A,B summarize travelers' perception of sanitation and hygiene experiences, and frequency of gastro-intestinal symptoms.

Travel-related gastro-intestinal symptoms, frequency/severity, and consequences

Health outcome data for travelers is reported in Table 1. Forty six percent of travelers experienced diarrhea in the past 7 days; most (88%) had mild (tolerable) symptoms. Other gastro-intestinal symptoms experienced included abdominal pain (36%), loss of appetite (32%) and nausea/vomiting (29%). Of the travelers who experienced gastro-intestinal symptoms during their trip, nearly one-third (32.9%) reported that their symptoms adversely affected their overall trip experience. Over one-third of travelers reported that their gastro-intestinal symptoms affected their travel plans, of whom 51% stopped traveling, 26% needed to change travel plans, 15% needed a medical consultation, and 8% needed hospitalization.

Associations between gastro-intestinal symptoms, perception of inadequate sanitation or inadequate hygiene and impact on travel plans

Travelers who reported symptoms of diarrhea in the past 7 days were significantly more likely to report perceptions of inadequate sanitation (adjusted OR = 3.0; 95% CI 1.7–5.5, $p = 0.0001$) or inadequate hygiene (adjusted OR = 7.7; 95% CI 4.1–15.5, $p < 0.0001$) compared to those without diarrhea (Table 2). These associations were even more pronounced among travelers who reported frequent diarrheal symptoms (inadequate sanitation: adjusted OR = 5.5; 95% CI 1.3–3.1, $p = 0.03$; inadequate hygiene: adjusted OR = 38.4; 95% CI 3.0–2,090.4, $p = 0.03$). Additionally, travelers who had frequent loss of appetite or abdominal pain were also significantly more likely to have a perception of inadequate sanitation or hygiene experiences compared with those who had less frequent symptoms.

Among those with self-reported diarrhea in the past week, travel plans were more likely to have been impacted (adjusted OR = 10.6; 95% CI 5.1–23.7, $p < 0.001$) and the overall trip experience adversely affected (adjusted OR = 2.8; 95% CI 1.4–5.8 $p = 0.004$). Adverse impacts on both travel plans and on overall trip experience were also more likely to be reported by those who reported perceptions of inadequate sanitation (adjusted OR = 2.3; 95% CI 1.2–4.6, $p = 0.01$; and adjusted OR = 2.5; 95% CI 1.1–5.8, $p = 0.02$, respectively) or inadequate hygiene (adjusted OR = 3.1; 95% CI 1.5–6.6, $p = 0.002$; and OR = 3.6; 95% CI 1.6–9.2, $p = 0.003$, respectively).

Associations between gastro-intestinal symptoms, and receipt of medical advice prior to the trip, purpose of travel, duration of travel and type of accommodation

Travelers who experienced diarrhea in the past 7 days were more likely to have spent more time in India and they were

TABLE 2 Associations between occurrence, frequency of gastro-intestinal symptoms, and perception of inadequate hygiene and inadequate sanitation experience.

Gastro-intestinal symptoms[†]		Perceived inadequate hygiene						Perceived inadequate sanitation					
		No	Yes	Crude OR (95% CI)	*p* value	Adjusted OR* (95% CI)	*p* value	No	Yes	Crude OR (95% CI)	*p* value	Adjusted OR* (95%CI)	*p* value
Occurrence of	No	72	88	Ref				70	90	Ref			
diarrhea	Yes	17	121	5.8 (3.3–10.8)	0	7.7 (4.1–15.5)	< 0.0001	29	109	2.9 (1.8–4.9)	0.00	3.04 (1.7–5.5)	0.0001
Frequency of	Less frequent	16	86	Ref				25	77	Ref			
diarrhea	More frequent	1	34	6.3 (1.2–116.4)	0.08	38.4 (3.0–2,090.4)	0.02	3	32	3.5 (1.1–15.3)	0.05	5.46 (1.3–3.1)	0.03
Loss of appetite	Less frequent	88	186	Ref				98	176	Ref			
	More frequent	1	25	11.8 (2.4–213.0)	0.01	12.2 (2.4–223.4)	0.01	1	25	13.9 (2.9–250.5)	0.01	12.84 (2.51–235.7)	0.01
Abdominal	Less frequent	86	178	Ref				96	168	Ref			
pain	More frequent	3	33	5.3 (1.8–22.5)	0.00	5.80 (1.9–25.8)	0.00	3	33	6.3 (2.2–26.6)	0.00	5.84 (1.9–25.8)	0.006

*Adjusted for age, sex, education, ethnicity, and underlying health conditions.
[†]Self-reported.

TABLE 3 Associations between gastro-intestinal symptoms and receipt of medical advice prior to the trip, purpose of travel, duration of travel and type of accommodation.

Gastro-intestinal symptoms ($n = 300$)[†]	Receipt of medical advice prior to trip			Purpose of travel			Duration of travel/stay			Type of accommodation		
	Odd's ratio (95% CI)	Chi-square value	*p* value*	Odd's ratio (95% CI)	Chi-square value	*p* value*	Odd's ratio (95% CI)	Chi-square value	*p* value*	Odd's ratio (95% CI)	Chi-square value	*p* value*
Occurrence of diarrhea												
No	Ref	14.53	0.00	Ref	3.88	0.04	Ref	7.56	0.00	Ref	7.72	0.00
Yes	0.4 (0.25–0.64)			1.59 (1.00–2.53)			1.93 (1.2–3.1)			1.93 (1.21–3.10)		
Nausea and vomiting												
Less frequent	Ref	3.58	0.00	Ref	0.19	0.66	Ref	1.47	0.23	Ref	1.02	0.31
More frequent	0.41 (0.15–1.08)			0.81 (0.32–2.03)			1.74 (0.7–4.3)			1.59 (0.64–3.95)		
Loss of appetite												
Less frequent	Ref	5.81	0.01	Ref	0.00	0.96	Ref	1.44	0.22	Ref	0.44	0.50
More frequent	0.36 (0.16–0.85)			1.01 (0.45–2.27)			0.94 (0.4–1.9)			0.75 (0.32–1.73)		
Abdominal pain												
Less frequent	Ref	12.56	0.00	Ref	0.80	0.30	Ref	0.26	0.87	Ref	1.06	0.30
More frequent	0.26 (0.12–0.57)			1.37 (0.68–2.77)			1.63 (0.7–3.6)			1.44 (0.71–2.9)		

[†]Detailed distribution is given in Supplementary Tables C (I–IV).
*Significance level <0.05.

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also significantly more likely to have sought medical advice prior to trip. In Table 3, the association between gastro-intestinal symptoms and above-mentioned variables are represented.

Impacts on future travel

Nearly all of the travelers ($n = 296$) reported that they would consider altering their future travel plans due to their sanitation and hygiene experiences by selecting better accommodation (45.9%, $n = 136$), avoiding rural areas (17.9%, $n = 53$), or making other itinerary changes (36.1%, $n = 107$). Further, 41.3% ($n = 124$) of travelers reported that their sanitation and hygiene experiences would influence where they choose to travel in the future. When considering their experiences of water, sanitation, and hygiene facilities in India, 32% of travelers either said they would not recommend (10.1%, $n = 30$) or were unsure about recommending (22%, $n = 65$) a visit to India.

Discussion

This study assessed the associations between travelers' perceptions of sanitation and hygiene conditions during their time in India, the occurrence of diarrhea and gastrointestinal symptoms, and the impact of symptoms on travel plans and overall trip experiences.

Our results suggest that sanitation and hygiene conditions are inadequate for travelers in India, with nearly a quarter of the travelers reporting difficulty finding a public toilet when needed, more than one third reporting that most of the public toilets they used did not have a working flush, and almost 45% reporting a lack of hand washing basins with soap or hand sanitizer. This may be not surprising given the known inadequacies of sanitation and hygiene in India (1, 26) and its impact on diarrheal deaths among the endemic population, especially among children <5 years of age (25). Despite this, 28% of travelers mentioned that their experiences of toilet and hand washing facilities were better than they had expected. About 56% travelers carried an antibiotic and approximately 25% travelers carried anti-emetics and probiotics, with 15% carrying medicines for anti-motility. Among all travelers, 70% preferred bottled water for drinking.

In general, adequate sanitation and hygiene are important for a pleasurable travel experience and their absence may impact travelers' perceptions of a destination and may reduce tourist arrivals (16, 27, 28). The current study suggested that among those with self-reported diarrhea in the past week, travel plans were more likely to have been disrupted and the overall trip experience adversely affected as compared to those without diarrhea. In addition to the need for adequate sanitation and hygiene, the factors concerning overall travel-related health also include pre-travel measures. Approximately half of the travelers did not take any medical advice prior to the trip and the same proportion of travelers were neither vaccinated for Hepatitis A nor for typhoid. The most common drugs carried by the travelers were antibiotics. These findings of the current study align with the results of the study conducted by Bhajoni et al., suggesting a lack of promptness for pre-travel health measures for long-distance travels (29). It is reported in the literature that the decision of pre-travel vaccination is of utmost importance and depends on the assessment of risk an individual might be exposed (e.g., duration of stay, age of traveler, risk of activities they are planning during their trip etc.) (30). Hence, the study in alignment with the evidence reported in literature (31) suggests that there is a need to take pre-travel health measures sincerely and travelers should be aware enough in advance about the associated risks with international travels and improve the preventative health seeking behavior. The evidence in literature suggests that the safety of food has an influence on the destination choice of the travelers (32). This study highlighted significant association between GI symptoms and type of accommodation. However, adverse impacts on both travel plans and on overall trip experience were reported by those who had perceptions of poor sanitation and poor hygiene experiences.

Prior to the COVID-19 pandemic, the travel and tourism industry was one of the top export services for revenue generation, accounting for more than 10% of the World's Gross Domestic Product (33). This industry is vulnerable to people's perceptions, and if sanitation facilities are suboptimal or travelers are dissatisfied with their travel experience, they are less likely to visit again or recommend the destination to others. Therefore, improving sanitation and hygiene not only has obvious importance for the health of the local population but may also have an impact on the local tourism industry. This, in turn, helps in boosting the local and national economy mainly by generating earnings from foreign exchange and revenue (34). For India, it has been estimated that a reduction in the risk of travel-related infectious diseases including malaria, dengue and others would increase tourist arrivals by more than 8%. The implications for tourism could be considerable should the risks of hygiene and sanitation-related travel diseases (e.g., diarrhea and other gastrointestinal symptoms) are taken into account. This is particularly obvious in the era of post-COVID tourism where travelers' are expected to practice improved hygiene and sanitation (e.g., hand-washing) services.

Travelers who stay in home or other stay facilities with poor infrastructure, and those who engage in eco-tourism activities have been reported previously to be particularly susceptible to exposure to sub-optimal sanitation and hygiene conditions and practices (27, 28). In our study, nearly 61% of travelers stayed in hotels/ guesthouse, and these travelers had higher odds of perceiving hygiene to be inadequate.

Occurrence of diarrhea in travelers has a range of potential associated morbidities beyond the acute episode, including disruption of the gastrointestinal micro biome and an increased risk of colonization with multi-drug resistant organisms (35). This is particularly relevant for travelers to India given the high burden of multi-drug resistant infections among Indian populations (36). Evidence reports that ~50% of travelers from Asia carry an extended-spectrum beta-lactamase producing Enterobacteriaceae, and can result in a potential source for spread in their home countries (28). Occasionally, irritable bowel syndrome symptoms may occur among returnee travelers following the onset of traveler's diarrhea (37). A recent study conducted among Finish international travelers showed that travelers' diarrhea was a major risk factor for urinary tract infection, particularly among women (38).

We found that reported experiences of inadequate sanitation and hygiene conditions were higher among tourists who experienced diarrhea, particularly those with frequent symptoms. Gastrointestinal symptoms were also associated with travel plan disruptions, adverse impacts on the overall trip experience and potential impacts on future travel plans, such as consideration of better accommodation or changing itineraries. These results clearly indicate potential negative effects of inadequate sanitation and hygiene services on current and future international travelers.

This study has some limitations. The data were only collected from Rishikesh, the Yoga capital of the world, a popular international travel destination for spiritual and adventure tourism (39, 40). Additionally, it is possible that travelers who had experienced diarrhea or other gastrointestinal symptoms during the trip and consequently had stronger negative perceptions of inadequate sanitation and hygiene conditions may have been more likely to participate. Though food hygiene could also be associated with sanitation and hygiene perceptions, our study did not collect data on food hygiene related services or practices of the travelers. Also, the sample size, while adequate to find statistically significant results, was too small to enable generalizability of findings, and future research could explore this in other settings.

In conclusion, although it may seem intuitive that gastrointestinal illness during travel impacts on perceptions regarding the adequacy of sanitation and hygiene services, disruption to travel plans and overall trip satisfaction, to the best of our knowledge, this has not been explicitly studied previously. The poor perceptions of sanitation and hygiene practices together with their negative impact on overall trip experiences make the travel and tourism sector in India vulnerable. Therefore, it could be suggested that the Indian tourism sector should consider improving sanitation and hygiene issues in the country, which improves the health of both the local population as well as international travelers in the country. Also, in order to improve travel-related health, travelers should be sincere about their pre-travel measures and preventative health management. The precautionary measures on individual level to minimize gastrointestinal symptoms (e.g., diarrhea) should be encouraged. However, the need for maintaining sanitation and hygiene is definitely a state issue and importance of implementing such policies cannot be queried.

Data availability statement

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

Ethics statement

The studies involving human participants were reviewed and approved by the Human Research Ethical Committees of Governmental Doon Medical College in India (IEC-049, GDMC) and Monash University in Australia (MUHREC 20359). The patients/participants provided their written informed consent to participate in this study.

Author contributions

RC: investigation, formal analysis, writing—original draft, and writing—review and editing. SS: investigation, data curation, formal analysis, and writing—review and editing. BN: methodology, data curation, writing—review and editing, resources and editing, funding acquisition, and supervision. CC: conceptualization, methodology, investigation, data curation, writing—review and editing. RK: investigation, data curation, writing—review and editing, and resources. KDJ: conceptualization, data curation, and project administration. RS: formal analysis and writing—review and editing. RB: conceptualization, methodology, and writing–review and editing. JC and KJ: investigation, data curation, and writing—review and editing. CB: conceptualization, methodology, investigation, data curation, writing—original draft, writing—review and editing, resources and supervision. All authors contributed to the article and approved the submitted version.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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Supplementary material

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/fpubh.2022.1042880/full#supplementary-material

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Influenza incidence and air pollution: Findings from a four-year surveillance study of prefecture-level cities in China

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Background: Influenza is a serious public health problem, and its prevalence and spread show significant spatiotemporal characteristics. Previous studies have found that air pollutants are linked to an increased risk of influenza. However, the mechanism of influence and the degree of their association have not been determined. This study aimed to determine the influence of the air environment on the spatiotemporal distribution of influenza.

Methods: The kernel density estimation and Getis-Ord *Gi** statistic were used to analyze the spatial distribution of the influenza incidence and air pollutants in China. A simple analysis of the correlation between influenza and air pollutants was performed using Spearman's correlation coefficients. A linear regression analysis was performed to examine changes in the influenza incidence in response to air pollutants. The sensitivity of the influenza incidence to changes in air pollutants was evaluated by performing a gray correlation analysis. Lastly, the entropy weight method was used to calculate the weight coefficient of each method and thus the comprehensive sensitivity of influenza incidence to six pollution elements.

Results: The results of the sensitivity analysis using Spearman's correlation coefficients showed the following ranking of the contributions of the air pollutants to the influenza incidence in descending order: SO_2 >NO_2 >CO> $PM_{2.5}$ >O_3 >PM_{10}. The sensitivity results obtained from the linear regression analysis revealed the following ranking: CO>NO_2 >SO_2 >O_3 >$PM_{2.5}$ >PM_{10}. Lastly, the sensitivity results obtained from the gray correlation analysis showed the following ranking: NO_2 >CO>PM_{10} >$PM_{2.5}$ >SO_2 >O_3. According to the sensitivity score, the study area can be divided into hypersensitive, medium-sensitive, and low-sensitive areas.

Conclusion: The influenza incidence showed a strong spatial correlation and associated sensitivity to changes in concentrations of air pollutants. Hypersensitive areas were mainly located in the southeastern part of northeastern China, the coastal areas of the Yellow River Basin, the Beijing-Tianjin-Hebei region and surrounding areas, and the Yangtze River Delta. The influenza incidence was most sensitive to CO, NO_2, and SO_2, with the occurrence of influenza being most likely in areas with elevated concentrations of these three pollutants. Therefore, the formulation of targeted influenza prevention and control strategies tailored for hypersensitive, medium-sensitive, low-sensitive, and insensitive areas are urgently needed.

KEYWORDS

influenza incidence, air pollutants, sensitivity, sensitive division, China

Introduction

Influenza poses a serious threat to human health because of its high contagiousness and incidence. Several global pandemics have directly caused casualties and indirectly caused economic losses, which creating major problems for many countries in the last hundred years (1). Influenza is an infectious disease that has not been fully brought under control (2). China's urbanization and ecological civilization construction processes remain to be synchronized, which has indirectly resulted in the integration and complication of influenza-influencing factors and the generation of numerous potential health-related crises within the population (3, 4). Historical experience has shown that widespread epidemics of infectious diseases, such as influenza, are often exacerbated by the polluted air environment (5). Air pollutants are plausible biological factors explaining the occurrence of influenza cases. Short- and long-term exposure to air pollutants increase the risk of morbidity and mortality from a wide range of systemic diseases, including cardiovascular, respiratory, and other diseases, thereby contributing to the emergence and spread of influenza (6, 7). In 2012, the International Council for Science launched the Future Earth Initiative. This initiative emphasizes the need to strengthen research on the direct and complex relationship between changes in environmental pollution and human health. The Chinese government has also proposed the Healthy China Initiative, which meets national priorities and the emphasis on sustainable development. The government has clearly identified measures required to implement comprehensive urban air quality management to meet standards and promote significant improvements in ambient air quality in cities nationwide and effectively resolve outstanding environmental problems that affect the health of the population (8). The following questions arise. What have been the characteristics of the spatiotemporal distribution of influenza and air pollutants in recent years? How can the relationship between the incidence of influenza and air pollutants be studied? How can the pattern of sensitivity of influenza to air pollutants be scientifically measured? These issues are major problems and challenges for the prevention and control of influenza and air pollutants in key areas and regions of their occurrence.

The notion that airborne pollution particles provide "condensation nuclei" to which influenza virus droplets attach has been prevalent within environmental health research for several decades. Toxicological studies have suggested that air pollutants are biologically plausible factors leading to the occurrence of influenza-like cases. The main mechanisms driving these cases include inflammatory responses, oxidative stress, and genetic damage (9–11). Exposure to air pollutants, which produce free radicals, can lead to mucosal irritation of the airways and mechanical damage, affecting mucus clearance by cilia and reducing an individual's resistance to viral infections, such as influenza (12). Epidemiological evidence also suggests that short or long-term exposure to air pollutants significantly increases the risk of influenza morbidity and mortality (13–18). Different pollutants have different health effects on the population (19, 20). $PM_{2.5}$ contains toxic substances, such as nickel, vanadium, acidic oxides, and pathogenic bacteria. When inhaled into the airways, these toxic substances adsorb to the alveoli, where they interact with the surfactant secreted by the lung cells, causing damage to the alveolar walls. This process causes inflammation and increases the vulnerability of the population to viruses (21). PM_{10} contains heavy metals, polycyclic aromatic hydrocarbons, and other toxic and harmful substances, which can lead to lesions in human organs following their entry into the alveoli (22). SO_2 stimulates peripheral nerve receptors in the smooth muscles of the upper and bronchial airways, weakening the ability of the respiratory tract to block pathogens and inducing susceptibility to infection by the influenza virus (23). Nitrogen oxides can generate irritants, such as HNO_2 and HNO_3, when they enter the alveoli through inhalation. This process increases the permeability of lung capillaries and causes respiratory diseases, such as bronchitis, pneumonia, and emphysema, and heightens the risk of influenza infection (24). Inhalation of a certain concentration of CO into the body decreases oxygen absorption into the blood. Moreover, the altered dissociative properties of oxyhemoglobin further reduce oxygen delivery to the tissues, and resistance to the influenza virus is reduced (25). Inhalation of certain concentrations of O_3 promotes lipid peroxidation in the epithelial cells of the respiratory tract, which increases the production of arachidonic acid. Such substances induce inflammatory lesions in the upper respiratory tract, weakening its defenses (26). Pathogenic reactions of these air pollutants in humans increase the potential for the production and transmission of influenza viruses within the population.

The impacts of six key air pollutants on the incidence of influenza have rarely been studied in the field of environmental health. Applying a generalized summation model, Feng et al. (27) demonstrated that ambient $PM_{2.5}$ concentrations were significantly associated with the risk of influenza-like illness in Beijing during the flu season and that the effect of $PM_{2.5}$ differed across age groups, in this city. Adults comprised the most significantly affected population, probably because of their longer exposure to outdoor pollution. Ali et al. (28) reported a statistically significant negative association between O_3 and influenza transmission in Hong Kong, China. They suggested that this finding could be related to the virucidal activity of O_3 and its effect on host defense and even immunity to influenza viruses. Liu et al. (16)found a positive association between $PM_{2.5}$ and the incidence of clinical influenza in Hefei Province in China and a negative association between PM_{10} and the incidence of clinical influenza. No relationship has been reported between NO_2 concentrations and the influenza incidence. Su et al. (29) found that $PM_{2.5}$, PM_{10}, CO, and SO_2 concentrations were associated with influenza-like cases in Jinan, China. Moreover, there was a lagged effect of air pollutants on the incidence of influenza. Recent studies on the correlation between the influenza incidence and air pollutants have mostly applied statistical models, such as correlation analysis (30), regression analysis (30), machine learning (31), and non-linear models (32). To the best of our knowledge, few studies have developed and applied sensitivity analysis to examine the relationship between disease and environment. Sensitivity analysis is an important research method for measuring changes and interactions among geographic elements (33). This research approach constitutes a frontier and hotspot within geographic environmental modeling research (34). It can be effectively used to identify the main environmental pollutants linked to the influenza incidence and to identify the magnitude of the contribution of each risk factor to the influenza incidence (35–38).

Relatively few studies have quantitatively analyzed the association between influenza and the full range of air pollutants. Most of these studies have been conducted at the level of prefecture-level cities within individual provinces. However, the spatiotemporal distribution of influenza determined through a nationwide study encompassing municipal, macro, meso, and micro scales and a long-time series has not yet been conducted. Relatively few studies have applied sensitivity analysis in the field of health geography. Accordingly, we collected data on the incidence of influenza and air pollutants in Chinese prefecture-level cities during the period 2014–2017 and explored the spatial clustering characteristics of influenza and air pollutants in these cities. Moreover, we studied the interrelationship between infection with human influenza and air environment factors using Spearman's correlation coefficients, a linear regression model, and gray correlation analysis in an attempt to address this research gap. The results obtained were used to delineate national influenza control zones.

This study had three aims. The first was to determine the influence of the air environment on the spatiotemporal distribution of influenza and to enrich the theory informing the relationship between the environment and infectious diseases in health geography. The second was to build a "comprehensive model of susceptibility" to generate hierarchical and progressive innovation in susceptibility research methods and to provide a new research paradigm for exploring the relationship between infectious diseases and environmental pollution. The final aim was to provide theoretical support and policy inputs for national and local Centers for Disease Control and Prevention to implement infectious disease prevention and control, formulate regionalized prevention and control strategies, establish long-term prevention and control mechanisms and set environmental health standards, and effectively contribute to and advance the Healthy China Initiative.

Materials and methods

Theoretical framework

We introduced a sensitivity research framework for investigating the relationship between the influenza incidence and air pollutants. As shown in Figure 1, we applied a method for characterizing the degree of response of one factor to a change in another factor. Our framework, which encompassed sensitive subjects, factors, judgments, and results, was aimed at discovering scientific laws of organic correlation between two or more factors. A sensitive subject was defined as a system or individual whose response is affected by a change in one or more factors. In the context of environmental health, sensitive subjects include the status of human health, disease morbidity, and mortality. In this study, sensitive subjects mainly referred to the influenza incidence. Sensitive elements were defined as factors that lead to the changes that influence sensitive subjects and involve the natural environment as well as socioeconomic and individual factors. In our study, these elements were the six air pollutants elements: $PM_{2.5}$, PM_{10}, SO_2, NO_2, CO, and O_3. Changes in sensitive elements affect sensitive subjects, which consequently respond to these elements.

To assess sensitivity, we performed a Spearman's correlation analysis, linear regression analysis, and gray correlation analysis, which could determine the specific impacts of sensitive elements on subjects. Spearman's correlation coefficients were applied to determine a simple correlation between the influenza incidence and air pollutants, while regression analysis was performed to observe their fitting effect according to their level of correlation, and gray correlation analysis was performed to assess the degree of association. In light of an overview of the results of each model, we ranked elemental sensitivity and spatial sensitivity to morbidity for each of the pollutants. Accordingly, we delineated prefecture-level cities into high,

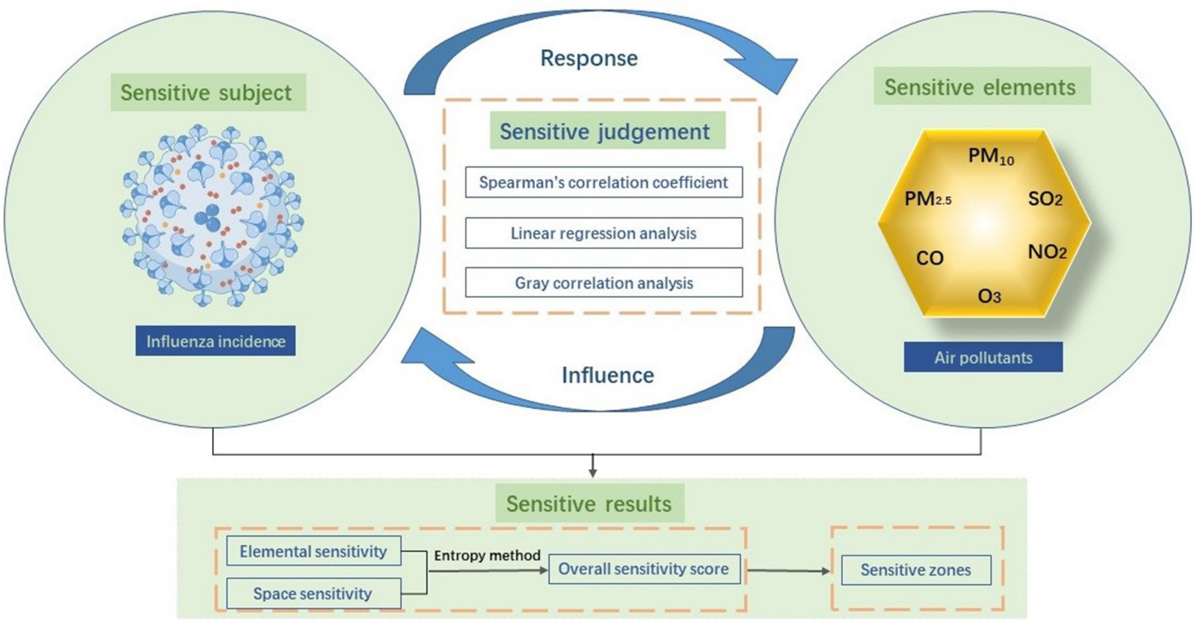

FIGURE 1
Theoretical framework.

medium, low, and insensitive zones according to their sensitivity scores. This research paradigm can be extended to cover more disease types and research areas and provides a theoretical and methodological foundation for tracing environmental pollution and health protection technologies relating to diseases of high prevalence at a regional level.

Data and processing

Prefecture-level cities constituted the basic unit and scale for this study. We used data compiled from 31 provinces, municipalities, and autonomous regions in China (excluding Hong Kong, Macau, and Taiwan) (Figure 2). The research was conducted from 2014 to 2017, and the compiled data comprised the influenza incidence, air quality, and maps (Table 1). We also obtained monthly data on the influenza incidence in prefecture-level cities. To examine the regional and temporal aspects of the influenza incidence, all of the reported data were utilized as samples. During the study period, the number of cities for which annual data on the influenza incidence were available increased from 359 in 2014 to 366 in 2017. The data were sourced from the Data Center of China Public Health Science, under the China Center for Disease Control and Prevention (https://www.chinacdc.cn/). Given the small number of deaths recorded, we used data on the number of influenza cases calculated as follows: incidence = the number of cases $\times$100 000/ total population. Statistical data for some regions were missing for several years within the study period. Consequently, the data on influenza were not spatially continuous. The missing data were treated as blank and not interpolated. The layers of data used in administrative maps of prefecture-level cities were obtained from the Geographic Information Bureau of the State Bureau of Surveying and Mapping (http://bzdt.ch.mnr.gov.cn/). Pollutant indices for air quality were obtained from real-time air quality monitoring data published by the China National Environmental Monitoring Center (http://www.cnemc.cn/) and included data on fine particulate matter ($PM_{2.5}$), inhalable particulate matter (PM_{10}), sulfur dioxide (SO_2), nitrogen dioxide (NO_2), ozone (O_3), and carbon monoxide (CO). A total of 190 cities were monitored daily for air quality in 2014, and 366 were monitored in 2015–2017. Accordingly, the monthly mean value for each city was calculated based on the daily data. Differences in the number of samples between years affected statistical efficiency but did not compromise our statistical inferences because the total coverage was sufficiently large. We have ensured the consistency of the spatial and temporal resolution of the two data through processing. Spatially, because the influenza incidence and air pollution base data were at the prefecture-level city scale and the number of reported prefectures varied among years, we selected the intersection of the two datasets from 2014–2017 as the original dataset for sensitivity analysis, and missing data were treated as blank. Temporally, we calculated monthly means for each city based on daily data of air pollution, to match monthly values of influenza incidence.

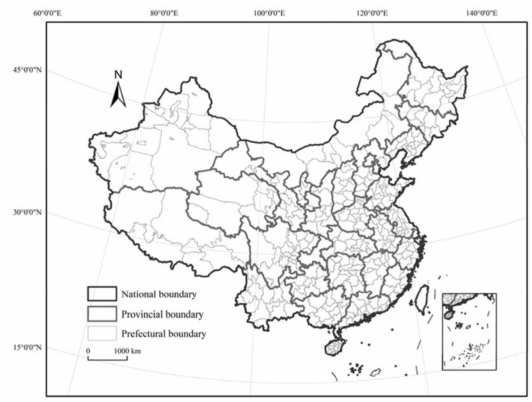

FIGURE 2
The study area.

TABLE 1 Data source and processing.

Data	Source	Processing
Influenza incidence	The Data Center of China Public Health Science (https://www.chinacdc.cn/)	Incidence = the number of cases × 100 000 people without interpolation
Air quality	The China National Environmental Monitoring Center (http://www.cnemc.cn/)	Calculate monthly mean value by daily data
Maps	The Geographic Information Bureau of the State Bureau of Surveying and Mapping (http://bzdt.ch.mnr.gov.cn/)	Processed and produced by the standard map with the review number GS (2019)1825, with no modification

Methods

Spatial analysis

Kernel density estimation is a non-parametric method of estimating the probability density function of a random variable (39). The method is particularly useful for analyzing and displaying the distribution of influenza incidence.

The local Getis-Ord *Gi** hotspot detection is a typical statistical method of local spatial autocorrelation that can be used to identify spatial variation (40). It can accurately reflect the distribution of hotspots for air pollutants in a given area.

Statistical analysis

Correlations between air pollutant concentrations and influenza incidence during the study period were estimated using Spearman's correlation coefficients due to the abnormal distributions of all these variables (41).

Regression analysis is a statistical analysis method used to determine the quantitative relationship of interdependence between two or more variables. A linear regression model of the influenza incidence and air pollutants was developed to enable the degree of the sensitivity to the influenza incidence to changes in air pollutants to be quantitatively analyzed.

Gray correlation analysis is performed to measure the closeness of association by comparing the geometric similarity of curves composed of multiple series (42). This method of statistical analysis has no rigid requirements on the sample size and on the presence (or not) of a pattern connecting samples. It was deemed a useful method for conducting a more in-depth evaluation of the sensitivity of the influenza incidence to changes in air pollutants as the sensitive elements. The first step entailed processing the index data indicator data without considering their dimensions. Next, the correlation coefficient was calculated, with the discriminant coefficient, $\rho \in [0, 1]$, used to weaken the effect of distortion induced by excessive maximum values. The value of ρ is usually taken as 0.5. The third step entailed calculating the correlation; a higher correlation corresponded to a stronger association between air pollutants and the influenza incidence. According to previous studies (43), the correlations can be classified into four levels. When $0 < r_{ij} \leq 0.35$, the correlation is weak; when $0.35 < r_{ij} \leq 0.65$, the correlation is moderate; when $0.65 < r_{ij} \leq 0.85$, the correlation is strong; when $0.85 < r_{ij} \leq 1.00$, the correlation is extremely strong.

The concept of entropy originates from thermodynamics and is a measure of the uncertainty of the state of a system. The entropy weight method is a mathematical method used to judge the degree of dispersion of a certain index, enabling the index to be assigned and calculated more objectively. A larger value indicates that more information provided by the index corresponds to its stronger influence on the comprehensive evaluation, and to a higher associated weight. We used the entropy weighting method to compare and synthesize the sensitivity results obtained using different methods. The detailed procedures of entropy method are described as follows (44):

(1) Standardize the original value of indicators:

$$X'_{ij} = \frac{X_{ij} - \min(X_j)}{\max\left(X_j\right) - \min(X_j)} \quad (1)$$

where X'_{ij} is the standardized value of the ith evaluating object on the jth indicator, X_{ij} is the original value, and the original value of this study mainly refers to the absolute value of the median of the correlation coefficient, the absolute value of the mean of the regression coefficient and the absolute value of the gray correlation coefficient; $\max\left(X_j\right)$ and $\min\left(X_j\right)$ are the maximum and the minimum, respectively.

(2) The proportion of the ith evaluating object on the jth indicator is calculated:

TABLE 2 The weights for each method.

Method	Weight
Spearman's correlation method	0.14
Regression analysis	0.77
Gray Correlation analysis	0.09

$$Y_{ij} = \frac{X'_{ij}}{\sum_{i=1}^{m} X'_{ij}} \tag{2}$$

where m is the number of evaluating objects, which refers to six air pollutants in this study.

(3) The entropy of each evaluating indicator can be defined as:

$$e_j = -k \sum_{i=1}^{m} \left(Y_{ij} \times \ln Y_{ij}\right) \tag{3}$$

Where $k = \frac{1}{\ln m}$. The evaluating object i on the indicator j is excluded if $Y_{ij} = 0$.

(4) The redundancy of the entropy is computed as follows:

$$d_j = 1 - e_j \tag{4}$$

(5) The weight of entropy of each evaluating indicator could be expressed as:

$$w_j = \frac{d_j}{\sum_{j=1}^{n} d_j} \tag{5}$$

where n is the number of methods in this study.

Weights for all methods are listed in Table 2.

The comprehensive sensitivity score was calculated using the weights obtained with the entropy weighting method, which were then multiplied by the standardized data of each indicator to obtain its sensitivity score. Next, the sensitivity scores of each indicator for each prefecture-level city were summed. The calculation formula was as follows:

$$S_i = \sum_{n=1}^{6} \left(C_n \times 0.14 + R_n^{*} 0.77 + G_n^{*} 0.09\right) \tag{6}$$

where S_i denotes the sensitivity composite score for prefecture-level cities; i is the prefecture-level city; C_n denotes normalized data for correlation coefficients between morbidity and six air pollutants in the Spearman's correlation analysis; R_n denotes normalized data for the correlation coefficient between morbidity and six air pollutants in the linear regression model; *and* G_n denotes normalized data for the correlation coefficient between morbidity and six air pollutants in the gray correlation analysis.

Results

Analysis of the pattern of the influenza incidence and air pollutants

We analyzed the kernel density of influenza incidence in the study area, and hotspot agglomeration area could be judged from the peak distribution of kernel density values. Relevant studies have shown that the larger the search radius, the smoother the surface of the generated results, and the selection of the search radius value also changes with the scale of the study (45). In this study, we examined the distribution of agglomerations based on the scale of countries, and thus a high search radius should be chosen. By trying different search radius, the results showed that the spatial difference in density of elements was most obvious at a search radius of 200 km, which portrayed large and medium agglomerations while also outlining relatively small agglomerations. Figure 3 shows the kernel density of the spatial distribution of the influenza incidence in China from 2014 to 2017. The incidence of influenza was high and concentrated in Beijing and the provinces of Hubei, Anhui, Zhejiang, and Guangdong. Zhuhai, Zhongshan, Huizhou, Guangzhou, and Handan were typical high-incidence cities, which may be related to rapid economic development and the increase in the number of factories in recent years.

Figure 4 shows the local spatial autocorrelation characteristics of air pollutants. During the period 2014–2017, air pollutants in China showed obvious clustering characteristics and a clear delineation of cold and hot spots. Their distribution characteristics were similar to those of China's population as indicated by the characteristic "Hu line," indicating the density of distribution of the country's population, which accords with the findings of previous studies (46, 47). Air pollutants tend to cluster in the region east of the Hu line, especially in the Beijing-Tianjin-Hebei region. High-concentration agglomerations were evident in Henan, Hunan, and Shandong Provinces, and at the junction of Shandong and Jiangsu Provinces, which formed hubs from which the air pollutants diffused widely into surrounding areas. The distribution of air pollutants also showed some correlation with topographic features. Specifically, the air pollutants showed significant clustering characteristics in the Tarim and Sichuan Basins and the Kuan-chung, Fenhe, North China, and Yangtze (middle and lower) Plains. These characteristics are associated with the convergence of air pollutant particles, and consequently their limited diffusion, when they are deposited in low-lying terrains (48–52). Some provincial capitals, such as Zhengzhou, Shijiazhuang, Xi'an, Wuhan, Jinan, and Chengdu, are heavily polluted. There has been a trend of expansion to surrounding grades, with these cities at the center. This trend may be related to the per capita

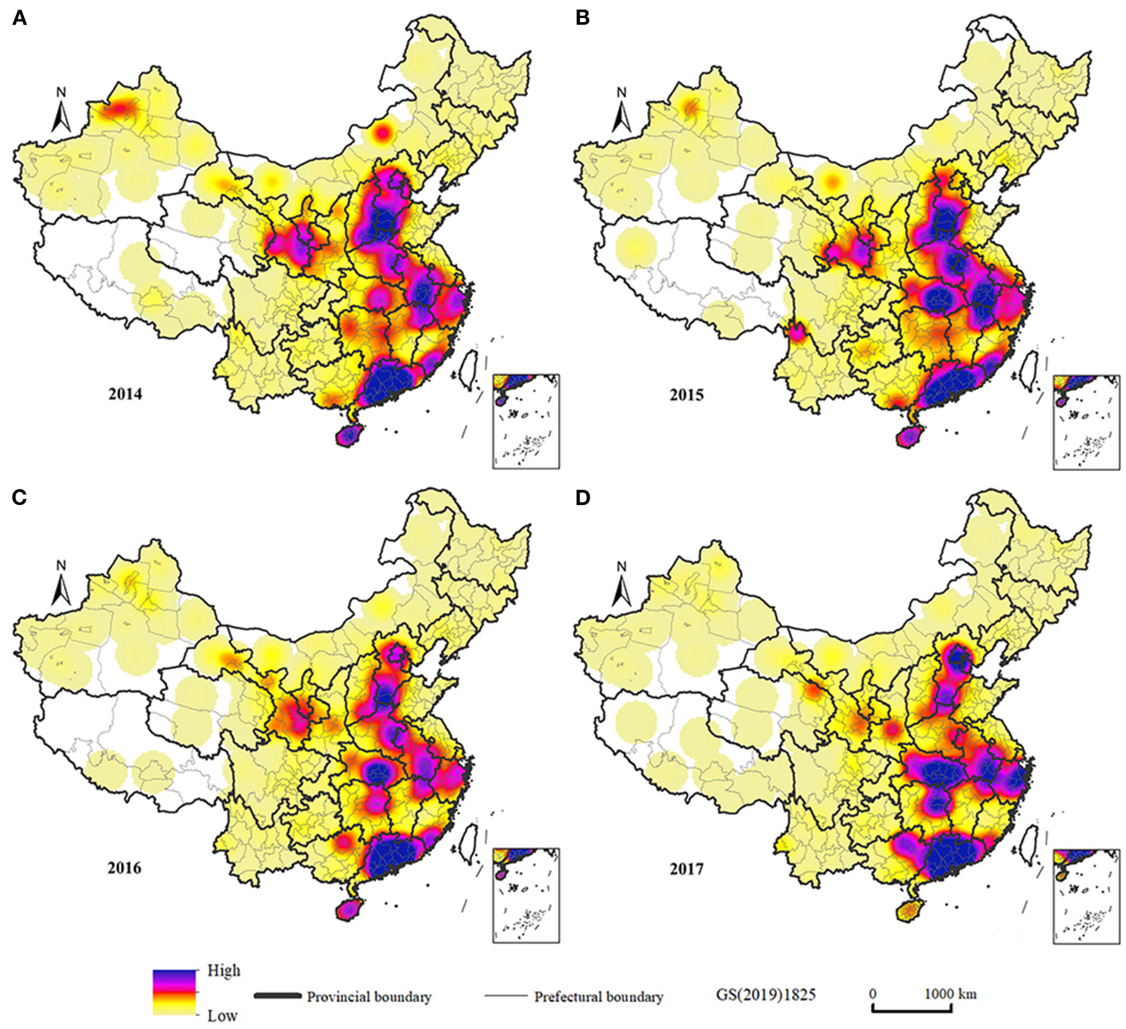

FIGURE 3
Kernel density estimation of influenza incidence in China. **(A)** Influenza incidence in 2014. **(B)** Influenza incidence in 2015. **(C)** Influenza incidence in 2016. **(D)** Influenza incidence in 2017.

car ownership in the provincial capitals and the development of secondary industries (53).

A sensitivity analysis based on spearman's correlation coefficients

Table 3 shows the correlation coefficients between the influenza incidence and air pollutants in various prefecture-level cities in China, with a *p*-value below 0.05. The correlation coefficients between the respective concentrations of $PM_{2.5}$, PM_{10}, SO_2, NO_2, CO, and O_3, and the influenza incidence were all above 0.5. The first five factors had positive values, with the maximum and minimum values within a range of 0.5–1.0 and median values mostly concentrated around a value of 0.75, indicating a strong correlation. However, the correlation coefficients between the O_3 concentrations and influenza incidence had negative values, with a median value concentrated around −0.750, indicating a negative correlation. Our comparison of the degrees of correlation between the five other air pollutants, which were positively correlated with the influenza incidence, revealed that their absolute values showed differences that were not significant. The correlation between the influenza incidence and the SO_2 concentration was the highest among all of the pollutants, with the highest median value (0.795). The average median values of NO_2 and CO concentrations were, respectively, 0.790 and 0.774. Those of $PM_{2.5}$ and PM_{10} were lower, at 0.764 and 0.747, respectively. The average median correlation coefficient between the O_3 concentration and the influenza

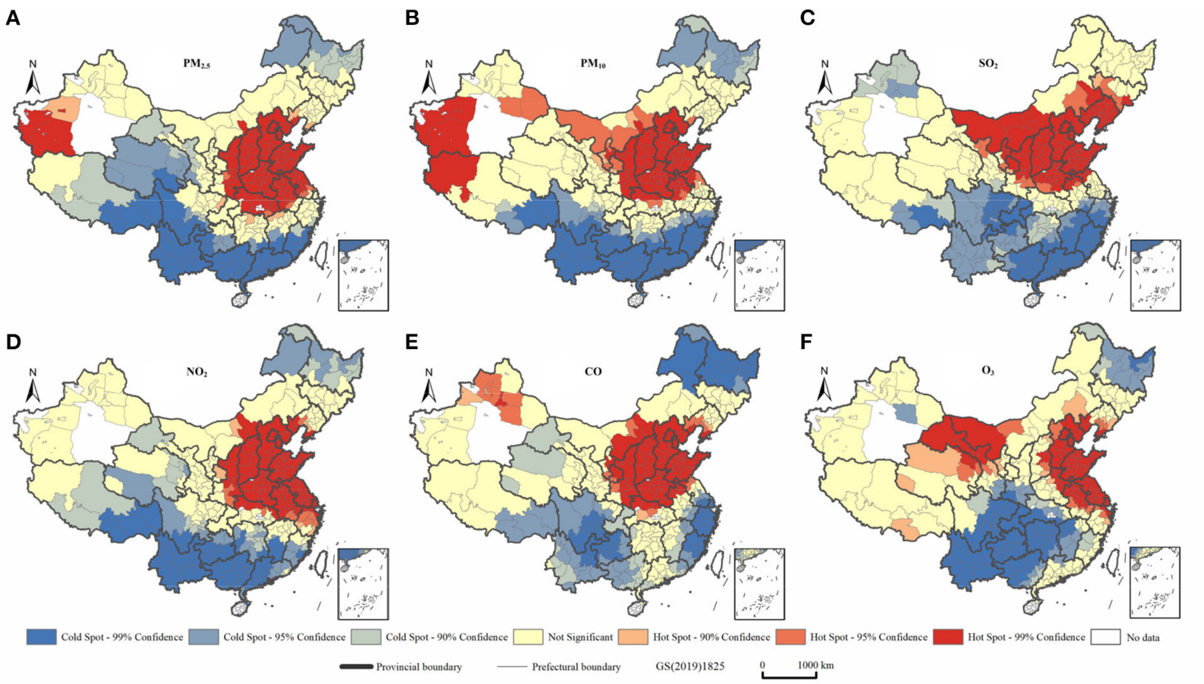

FIGURE 4
Analysis of six types of air pollutants in China during the period 2014-2017 using the local Getis-Ord Gi* statistic. **(A)** $PM_{2.5}$. **(B)** PM_{10}. **(C)** SO_2. **(D)** NO_2. **(E)** CO. **(F)** O_3.

TABLE 3 Median correlation coefficients between the influenza incidence and air pollutants in China's prefecture-level cities during the period 2014–2017.

	$PM_{2.5}$	PM_{10}	SO_2	NO_2	CO	O_3
2014	0.769	0.728	0.811	0.810	0.804	−0.851
2015	0.748	0.741	0.769	0.770	0.777	−0.734
2016	0.753	0.765	0.803	0.772	0.752	−0.710
2017	0.785	0.754	0.797	0.809	0.763	−0.754
Mean value	0.764	0.747	0.795	0.790	0.774	−0.762

incidence was −0.763, indicating a significant negative correlation.

A sensitivity analysis based on a linear regression model

According to the results of the correlation analysis, the prefecture-level cities that showed a strong correlation between the influenza incidence and air pollutants were selected for further analysis to control for the influence of meteorological, topographical, and human factors on the model. Using monthly data on the incidence of influenza and air pollutants in each prefecture-level city from 2014 to 2017, and after screening as the original data, we built a linear regression model to calculate the regression coefficients at the national scale. Figure 5 shows a significant relationship between the influenza incidence and the concentration of air pollutants in the majority of regions. The regression coefficients of $PM_{2.5}$, PM_{10}, SO_2, NO_2, and CO with the influenza incidence were mostly positive, and the regression coefficients of O_3 with the influenza incidence were mostly negative. Our results indicated that the influenza incidence was most sensitive to changes in CO concentrations; for example, for every 1 $\mu g/m^3$ increase in the CO concentration in Ningbo, the influenza incidence increased by 32.54. For every 1 $\mu g/m^3$ increase in the CO concentration in Zhangzhou, the influenza incidence increased by 33.18. The ranking of the contribution of each element to the influenza incidence, in descending order, was as follows: CO>NO_2 >SO_2 >O_3 >$PM_{2.5}$ >PM_{10}. Areas demonstrating significant sensitivity were mostly located in the Beijing-Tianjin-Hebei region; the Fenwei Plain, Jiangsu, Anhui, Shandong, Henan and the Yangtze River Delta. Referring to the regression results for the influenza incidence and the six air pollutants during the period 2014–2017, we selected provinces in which the influenza incidence was more sensitive to changes in air pollutants for a scattering fitting. Figure 6 shows a high R^2 and a good linear fit. Specifically, the influenza incidences in Guangdong, Fujian, Guangxi, and Shanghai were

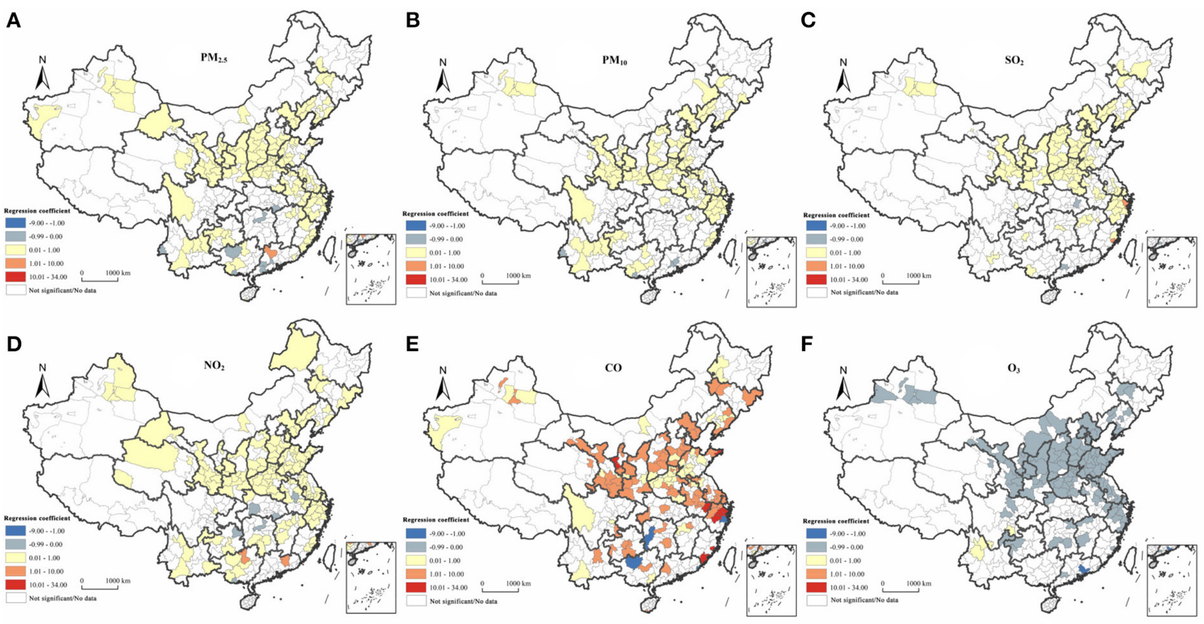

FIGURE 5
The spatial distribution of regression coefficients between the influenza incidence and six types of air pollutants in China during the period 2014-2017. **(A)** $PM_{2.5}$. **(B)** PM_{10}. **(C)** SO_2. **(D)** NO_2. **(E)** CO. **(F)** O_3.

strongly correlated with air pollutants, and the degree of the fit was higher.

A sensitivity analysis based on gray correlation analysis

We performed gray correlation analysis to calculate the integrated gray correlations between air pollutants and the influenza incidence in prefecture-level cities from 2014 to 2017. Our calculations indicated that the integrated correlations of the influenza incidence with $PM_{2.5}$, PM_{10}, SO_2, NO_2, CO, and O_3 concentrations in China were 0.792, 0.793, 0.789, 0.798, 0.796 and 0.753, respectively, and the overall ranking was NO_2 >CO>PM_{10} >$PM_{2.5}$ >SO_2 >O_3. It can be seen that the absolute difference between the influenza incidence and the six air pollutants in China was small, with all of the elements showing a strong correlation with the influenza incidence. The highest correlation occurred between NO_2 concentrations and the influenza incidence, revealing that they were most strongly related, whereas O_3 concentrations had a relatively small effect on the influenza incidence.

We averaged the values for the prefecture-level city correlations during the period 2014–2017 and calculated the sensitivity of the influenza incidence to air pollutants in prefecture-level cities. Figure 7 shows that there was a significant geographical correlation between the influenza incidence and air pollutants in China. The degree of correlation relating to the distribution characteristics of each element was relatively consistent, with a large proportion of cities evidencing moderate or stronger correlations. Cities with very strong correlation levels were mainly located in the Beijing-Tianjin-Hebei region, the Yangtze River Delta, and the eastern part of the southwestern region. The strong correlation between NO_2 concentrations and the influenza incidence occurred in the largest number of cities (320), and conversely, the smallest number of cities (288) evidenced strong correlations between levels of O_3 and the influenza incidence. This finding is consistent with the results of the sensitivity ranking of sub-elements using gray correlation analysis.

Results synthesis and sensitive division

The entropy weighting method was performed to determine the weights of three methods (integrated Spearman's correlation coefficients, linear regression analysis, and gray correlation analysis, and Table 2). We applied formula (6) to measure the combined sensitivity and spatial divergence results (Table 4). The sensitivity scores for CO, NO_2 and SO_2 were the highest, and the influenza incidence was most sensitive to changes in the concentrations of these three pollutants, with influenza most likely to occur when their concentrations increased.

Using the natural breaks classification method, we delineated the scores for the prefecture-level cities into three levels (0, 0.60], [0.61, 1.23], and [1.24, 1.67], which respectively

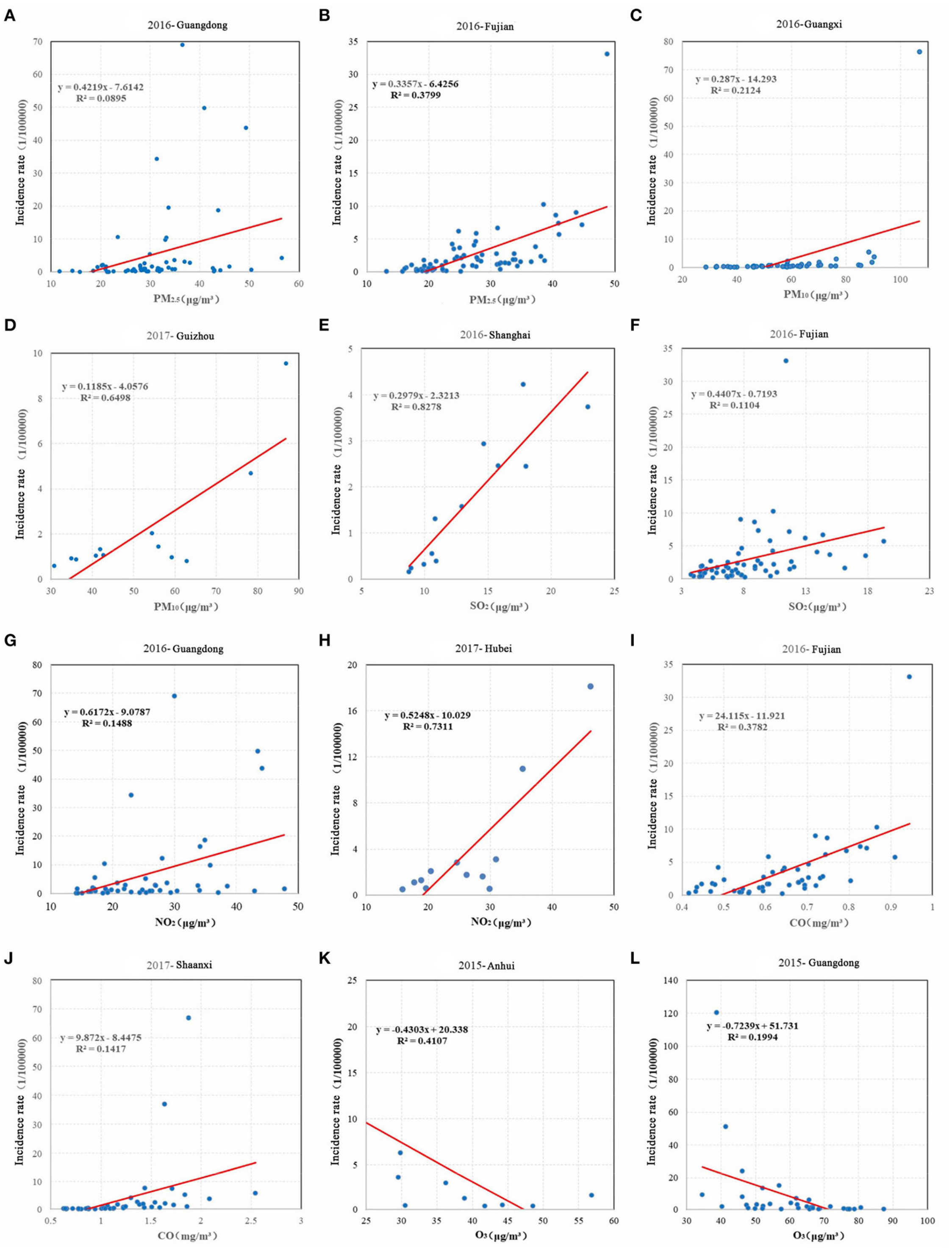

FIGURE 6

Scatter fitting of the influenza incidence and air pollution in typical sensitive provinces during 2014-2017. **(A)** Regression fitting of $PM_{2.5}$ and incidence rates in Guangdong Province in 2016. **(B)** Regression fitting of $PM_{2.5}$ and incidence rates in Fujian Province in 2016. **(C)** Regression fitting of PM_{10} and incidence rates in Guangxi Province in 2016. **(D)** Regression fitting of PM_{10} and incidence rates in Guizhou Province in 2017. **(E)** Regression fitting of SO_2 and incidence rates in Shanghai Province in 2016. **(F)** Regression fitting of SO_2 and incidence rates in Fujian Province in 2016. **(G)** Regression fitting of NO_2 and incidence rates in Guangdong Province in 2016. **(H)** Regression fitting of NO_2 and incidence rates in Hebei Province in 2017. **(I)** Regression fitting of CO and incidence rates in Fujian Province in 2016. **(J)** Regression fitting of CO and incidence rates in Shaanxi Province in 2017. **(K)** Regression fitting of O3 and incidence rates in Anhui Province in 2015. **(L)** Regression fitting of O_3 and incidence rates in Guangdong Province in 2015.

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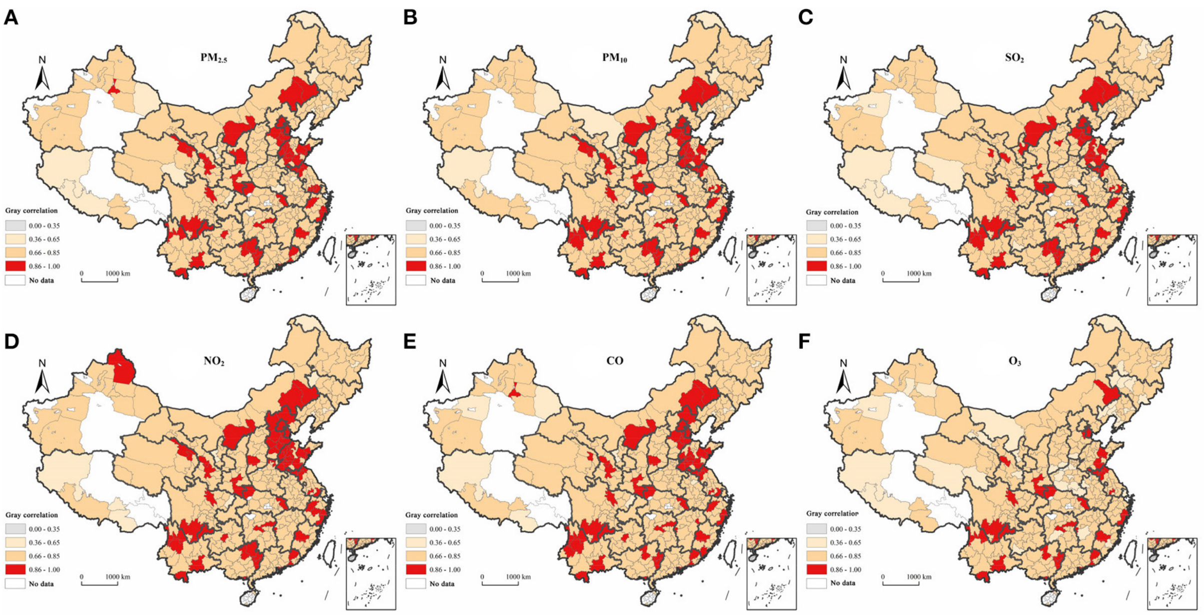

FIGURE 7
The spatial distribution of the degree of gray association between the influenza incidence and six types of air pollutants in China during the period 2014-2017. **(A)** $PM_{2.5}$. **(B)** PM_{10}. **(C)** SO_2. **(D)** NO_2. **(E)** CO. **(F)** O_3.

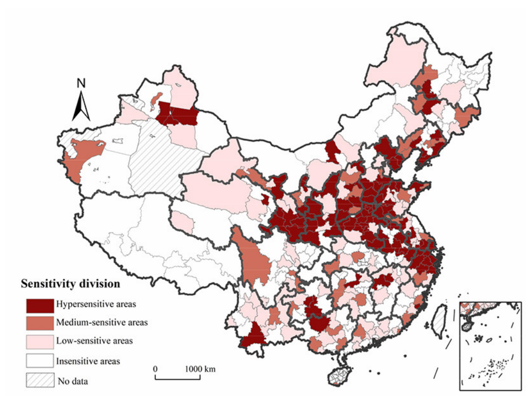

FIGURE 8
Sensitivity-based zones relating to the influenza incidence and air pollution in China.

TABLE 4 The overall score for each index obtained using the entropy weighting method.

Elements	Correlation coefficient	Regression coefficient	Gray correlation coefficient	Overall score
$PM_{2.5}$	0.35	0.00	0.87	0.13
PM_{10}	0.00	0.00	0.89	0.08
SO_2	1.00	0.01	0.80	0.22
NO_2	0.90	0.03	1.00	0.24
CO	0.56	1.00	0.96	0.93
O_3	0.33	0.01	0.00	0.05

corresponded to hypersensitive, medium-sensitive, and low-sensitive areas. Figure 8 shows that the influenza incidence was sensitive to changes in the concentrations of air pollutants in most regions of China. Hypersensitive areas were mainly located in the southeastern part of northeastern China, the coastal areas of the Yellow River Basin, the Beijing-Tianjin-Hebei region and surrounding areas, and the Yangtze River Delta, revealing a "Y" shaped distribution. Influenza is most likely to occur when air pollutant levels rise in these areas. The impacts of changes in the concentration of air pollutants on the influenza incidence in medium-sensitive areas, such as eastern coastal areas, Guangxi and Guizhou Provinces, were not strong. Lastly, in low-sensitive and non-sensitive areas, the impacts of changes in the concentration of air pollutants on the influenza incidence were weaker and more dispersed.

Discussion

Discussion of the data

Several weaknesses should be acknowledged in our data. First, the data on influenza used in this study were sampled data, and entailed a certain rate of under-reporting, which influenced the results to some extent (54). Second, we observed differences in statistical capacities across regions and during different years as well as missing data for some periods or regions because of adjustments made in administrative divisions. These problems may have led to deviations between the results obtained and the empirical conditions. Third, the results of the sensitivity analysis of the influenza incidence in relation to air pollutants were correlated with the quantity and quality of the data. Large cities not only have large populations and infected persons, but they also have strong and accurate statistical and reporting capacities. Consequently, the results of the analyses of cities for which more basic data were available tended to be more accurate. But the accuracy of the study results can support the national study due to the sufficient amount of data.

Discussion of the results

Our findings point to a spatial interpretation of influenza, and are closely aligned with those of previous epidemiological and pathological studies (22, 25, 26, 55–62). Most of the other research results indicated that there was a certain correlation between exposure to air pollutants and disease. When pollutants are absorbed into the blood and tissues, they will have a greater impact on the defense function of the respiratory tract in humans, inducing an inflammatory response in the airways, which could also cause a decrease in the levels of interferon and hemagglutinin inhibitors. These are possible biological mechanisms that increase the risk of influenza-like cases associated with air pollutants (63).

In this study, we observed that the influenza incidence was most sensitive to SO_2, CO and NO_2. The underlying mechanism could be that SO_2 stimulates peripheral nerve receptors in the smooth muscles of the upper and bronchial upper airways, weakening their blockage by the respiratory tract and thus predisposing them to influenza virus infection (23). Inhalation of a certain concentration of CO will reduce the capacity of the blood to absorb oxygen, while changes in the dissociative properties of oxyhemoglobin further reduce the delivery of oxygen to tissues. Consequently, the body's ability to exchange pollutants with oxygen becomes weaker, making it more susceptible to infection by the influenza virus (25). When nitrogen oxides enter the alveoli, they can form irritants, such as HNO_2 and HNO_3, which can cause a variety of respiratory diseases, thus increasing the risk of contracting influenza (24). In addition, $PM_{2.5}$ and PM_{10}, which are small-sized atmospheric particulate matter, facilitate the attachment of viral droplets to condensation nuclei, thus facilitating the long-range transmission of influenza viruses (64).

The results of this study show that influenza is negatively correlated with the concentration of O_3 and may have a specific correlation with the bactericidal characteristics of O_3. However, epidemiological studies indicate that a negative correlation cannot verify the effect of the interaction between the two entities under consideration because they were generated at different times. The concentration of O_3 tends to be higher in summer, and lower in fall and winter, when a higher incidence of influenza has been observed. Furthermore, long-term ozone inhalation has been associated with increased morbidity and mortality caused by respiratory diseases (65). Moreover, some environmental pollutants may have a lagging effect on human health (66). Therefore, the scientific community should engage in in-depth research to explore the complexity of pathogenic mechanisms.

In addition, we found a large variability in the weights of the three methods using the entropy weighting method, with the regression analysis method weighing 0.77. This may be attributed to the smaller original data for the regression analysis method and the larger standard deviation of the data distribution during the standardization process, resulting in more informative data. According to the definition of the entropy weighting method, the greater the data fluctuation and information, the greater the weight assigned (44). This may slightly affect the accuracy of research results.

Planning responses and policy suggestions

A novel contribution of this study is its provision of evidence from China that can inform environmental health theories on the relationship between the air environment and human health. Its findings also have important policy implications for guiding the planning and development of healthy cities in China and promoting the construction of a healthy China. Government agencies should consider the following suggestions.

First, we recommend the addition of special planning for influenza and other infectious diseases to the current planning system. Components of this special planning should include establishing a transport system for influenza patients, setting up influenza isolation and treatment facilities, and developing an influenza research system and an early warning system for influenza.

Second, more attention should focus on the Pearl River Delta, the eastern part of China, the Beijing-Tianjin-Hebei region, and other areas with higher incidences of influenza as well as specific cities, such as Beijing, Handan, Zhuhai, Zhongshan, and Huizhou. Efforts should also focus on areas and times of high influenza prevalence.

Third, the distribution of medical institutions should be optimized to facilitate equitable distribution of high-quality medical resources in key high-incidence areas. Additional influenza-specific medical and vaccination points should be set up during the first and fourth quarters of the year when influenza is highly prevalent and people are susceptible to infection.

Fourth, innovations in air-quality eco-compensation programs are needed. A list of enterprises that emit polluting gases, such as SO_2, CO, and NO_2, should be developed. More attention should also be paid to the sources of emissions that increase concentrations of $PM_{2.5}$ and PM_{10} (67, 68). The rate of air quality should be established as a binding indicator for atmospheric assessments, and assessments of the weights of SO_2, CO and NO_2 concentrations should be conducted more frequently. Furthermore, coefficients of ecological compensation should be optimized, and compensation amounts for curbing the three sensitive pollutant emissions should be increased.

Fifth, in light of the results of our delineation of zones according to the sensitivity of the influenza incidence to changes in the concentrations of air pollutants, we recommend refining prevention and pollution control measures through the formulation of targeted influenza prevention and control strategies tailored for hypersensitive, medium-sensitive, low-sensitive, and insensitive areas. Special guidelines and pollution control should be strategically implemented in hypersensitive areas This strategy encompasses the establishment of county-level special planning for influenza prevention and control and strict control of chemical raw material manufacturing, non-ferrous metal smelting industries, petroleum processing industries, chemical reagent manufacturing, and other industries associated with high CO, SO_2 and NO_2 emissions. The location of highly pathogenic industrial spaces close to densely populated areas should be avoided, and low-pollution urban industrial development models should be selected. Efforts should focus on reducing the presence of polluting enterprises with high emissions and high pathogenicity and increasing the introduction and planning of new environmentally friendly industries. A strategy of promoting reasonable layouts and appropriate prevention and control should be pursued in medium-sensitive areas. Specifically, the layout of polluting buildings should be planned reasonably, so that they are located downwind of the city and away from the urban area to reduce the contribution of air pollutants to the influenza incidence. The focus should simultaneously be on the layout of medical buildings, according to the influenza incidence. Prevention-oriented, root-cause prevention and control strategies should be implemented in low-sensitive areas. Accordingly, residents should be actively vaccinated against influenza before the peak influenza season to prevent the emergence and spread of influenza at the source, and possible influenza susceptibility factors in the natural and built environment should be explored.

Lastly, a national influenza risk index should be developed, and the influenza surveillance and early warning system in China should be improved. The six air pollutants should be incorporated as key factors and signals of danger into the influenza classification and warning model, and warning thresholds should be set. Changes in influenza incidence rates, key incidence periods, and key incidence areas under scenarios such as increased pollution and improved pollution should be projected, and early warning programs should be introduced.

Research limitations

This study had some limitations. First, the effects of the natural and socio-economic factors, such as temperature, precipitation, and population movement, on influenza incidence sensitivity factors were not considered, and the specific causes and effects need to be further explored in the context of other natural and social factors. Second, the lagged effect of influenza on changes in air pollutants was not considered because we used monthly data, whereas the lagged effect of influenza on air pollutants is generally measured in days.

Conclusion

Influenza outbreaks are a major public health issue worldwide, posing a huge threat to human life and health. We used a top-down approach to analyze the spatiotemporal characteristics of the influenza incidence and air pollutants in China and identified and quantified the relationships between the influenza incidence and parameters of air pollutants within different methodological models. Three main conclusions were derived from this study.

First, high incidences of influenza were concentrated in Beijing as well as in Hubei, Anhui, Zhejiang, and Guangdong Provinces. Air pollutants tended to be concentrated in the area east of the Hu line.

Second, the influenza incidence showed a strong spatial correlation and associated sensitivity to changes in concentrations of air pollutants. Sensitivity was highest in the Yangtze River Delta, the Beijing-Tianjin area, and other areas. The influenza incidence was most sensitive to CO, NO_2, and SO_2 levels, with the occurrence of influenza being most likely in areas with elevated concentrations of these three pollutants.

Third, we delineated three sensitivity zones at the national level: hypersensitive, medium-sensitive, and low-sensitive areas according to the combined sensitivity scores obtained for each prefecture-level city. Hypersensitive areas were roughly distributed in a "Y" shaped curve, mainly in the southeastern part of the northeastern China, in coastal areas of the Yellow River Basin, in the Beijing-Tianjin-Hebei region, and in the Yangtze River Delta.

A set of prospects is presented below. First, the scope and sites of research could be appropriately narrowed down in future studies to focus on the association between the micro-scale influenza incidence and air pollutants. Second, more control variables should be incorporated into future studies to explore whether there are any crossover effects of air pollutants with meteorological factors, or with population movements, on the influenza incidence. Third, the impact of the lag effect requires investigation using lagged non-linear models and machine learning. Lastly, it is necessary to construct a comprehensive spatial and temporal risk assessment system and a comprehensive diagnostic model for influenza to assess the environmental risk levels of influenza occurrence nationwide and to develop risk zoning for influenza and other more infectious diseases.

Data availability statement

The datasets presented in this study can be found in online repositories. The names of the repository/repositories and accession number(s) can be found in the article/supplementary material.

Ethics statement

The studies involving human participants were reviewed and approved by the Ethics Committee of the Chinese Center for Disease Control and Prevention. Written informed consent to participate in this study was provided by the participants' legal guardian/next of kin.

Author contributions

YS led the overall study, contributed to the data collection, and interpretation. YZ designed research, analyzed data, and drafted the manuscript. YZ, SW, ZF, and YS contributed to the writing of the manuscript. All authors read and approved the final manuscript.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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Walkability assessment of metro catchment area: A machine learning method based on the fusion of subject-objective perspectives

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China's metro system is developing rapidly. Walking is the most frequently adopted mode to connect to the metro, the attributes of the pedestrian-built environment around the stations directly influence people's willingness to use the metro. However, few studies have paid attention to the comprehensive assessments of the built environment in the metro catchment area. Thus, this paper attempts to construct a walkability evaluation model that combines subjective and objective perspectives. We collected field data of the built environment factors affecting on walkability in the 800 m buffer zone of eight case metro stations in Dalian city, China. We also collected on-site interviews from 867 passengers to evaluate the walkability. A machine learning-based approach was developed to calculate the weights of walkability variables, followed by constructing a *Score-Effectiveness* framework to identify the built environment factors in the metro catchment area that need to be improved. The study found that the shading facilities, obstacle barriers, and resting seats around pedestrian walkways are the most efficient and imbalanced variables recognized by the crowd. The convenience of overpasses and underpasses are additional efficient imbalance-type variables for leisure and commuting populations, respectively. This indicates that the current level of construction of the above five built environment factors is relatively low, but the construction has a significant impact on the degree of friendliness in supporting pedestrian walkability. In this paper, improvement measures are proposed in a targeted manner in order to achieve the effect of effectively improving the current level of metro catchment area's walkability. The results of the study can provide references to provide strategies for precise pedestrian planning in the metro catchment area, leading to a pedestrian environment with high walking quality.

KEYWORDS
metro catchment area, walkability, built environment, machine learning, efficient imbalance-type factors, optimization strategies

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Introduction

The metro is featured with safety and punctuality, leading to an advantage of avoiding congestion caused by uncertainty compared to other modes of ground transportation. Thus, an increasing number of travelers choose the metro as their primary mode of transportation. The popularity of the metro has led to a rapid increase in pedestrian flow within the catchment area, which in turn has triggered changes in land values and has had a positive impact on housing prices around the stations (1). Even the impact of the COVID-19 epidemic does not jeopardize the price trend of real estate, indicating that the metro has a strong appeal to people (2). At the same time, the metro itself and its combination with other modes of transportation can significantly reduce urban carbon emissions, improve air quality, reduce noise caused by traffic, and promote the physical activity of travelers (3–6). In the context of calling for carbon neutrality in various countries around the world, metro transportation is a strong pillar of sustainable transportation systems. In light of this, effectively guiding travelers' shift from individual motorized transport to transit transportation is the major challenge for sustainable urban transport development in the future faced by planners and policymakers (7–9). By the end of 2021, 48 cities in mainland China have opened metros, with an operational mileage of 7209.7 km, ranking first in the world and showing an increase of 14.8% compared to 2019. The increasing number indicates that China is currently in a period of rapid development of metro transit, and the metro is becoming more and more prominent in China's urban transportation system.

As the most frequently used mode of transportation, walking usually possesses a higher level of satisfaction compared to public transportation and automobiles (10). Improving the pedestrian environment around metro stations will encourage people in the vicinity of the station to walk to the station instead of using other transport modes (11), but travelers are also limited by the time spent and the distance traveled within a certain range (12, 13). Yet, when the purpose of the trip is clear, travelers may also undertake more walking distance and walking time (14). In this sense, the improvement of the walking environment in the metro catchment can fit with the primary goal of Transit Oriented Development (TOD), which aims to create pedestrian-friendly and livable communities that are closely linked to public transit stations (15). Related results highlight that the pedestrian friendliness of the built environment around a site affects people's choice of travel mode, and improving walkability will significantly increase the likelihood that travelers will choose to walk to the site (16). Nevertheless, how the subjective and objective built environment factors of the current situation affect the walkability of the metro catchment areas these factors have not been fully explored (17).

Furthermore, by taking eight metro stations in Dalian, China as a case study, this study attempts to establish a comprehensive framework for the evaluation of the walking environment of the metro catchment area. The framework combines the subjective environmental perception of pedestrians and the objective environmental accessibility of the metro catchment area. In the framework, a machine learning-based approach is developed to systematically identify the weight of key factors that affect the walkability of metro catchment areas. It is expected that the development framework can provide policymakers and planners with references to form strategy directions for improving the walkability environment of metro catchment areas.

The remainder of this paper is organized as follows. Section Literature review presents the review work on the concept of walkability, followed by an overview of influencing factors of walkability, methods of walkability evaluation, and walkability in the metro catchment areas; Section Data introduces the study area, data collection, and description; Section Methodology describes the idea of evaluating the walkability of metro catchment areas, including the introduction of a new method of machine learning; Section Results explains the statistical and modeling results, followed by Section Discussion which holds the discussion and offers policy and practice implications; Section Conclusion concludes the paper and summarizes research limitations.

Literature review

Walkability and influencing factors

Walkability refers to the ability of humans to walk (18). In previous studies, several scholars and experts have proposed different definitions of *walkability* from various research perspectives. In the field of urban planning, *walkability* means the degree to the features of the built environment that are friendly to residents' living, commuting, shopping, and leisure (19). In other words, it means how pedestrian-friendly the urban space is (20), and thus, walkability is frequently used to assess the friendliness of walking in an area (21) and then to promote the active behavior of walking (22). Walkability is also considered to be one of the basic criteria of urban planning to counteract urban sprawl by creating good walkable areas for different activities and services (23). In the field of public health, friendly walkable areas can serve as a mental incentive for people to actively take up walking, which can effectively prevent cardiovascular diseases and enhance physical and mental health (24). In addition, scholars in geography have used detailed traffic data to understand the relationship between the built environment and walking behavior (25). By reviewing previous related studies, walkability in this study is defined as the degree to which the built environment allows walking (26) and encourages people to walk in a friendly manner (20, 22). Usually, areas with high walkability can encourage people to increase their subconscious maximum walking distance (27). Thus, improving pedestrian infrastructure in the metro catchment area can strengthen the willingness of travelers to connect to the metro by walking and effectively increase ridership (28).

The built environment factors that influence walkability are multifaceted and can be broadly divided into mesoscale neighborhood factors and microscale pedestrian factors. The former are mainly presented at the neighborhood or community level, such as street connectivity, residential density, and the mix of land uses associated with daily use facilities (29–33). The latter places more emphasis on walkability, focusing on the real pedestrian experience, such as street furniture, walkway width and quality, and other micro factors that affect pedestrian perception and experience (34, 35).

Although most studies have used mesoscale walkability as a research lens, few scholars hold to argue that built environment factors, such as neighborhood size, street network density, and community-level facility diversity, do not reflect how pedestrian-friendly facilities are (36). Also, factors that present positive effects at the mesoscale may even become negative at the microscale, such as road intersection density. For instance, a higher road intersection density represents better connectivity (31, 37). On the contrary, at the microscopic level, the increase in the density of roadway intersections may cause safety concerns due to frequent street crossings (35). As a result, increasing attention has been paid to walkability studies at the microscopic scale, which can truly depict the conditions of the pedestrian-built environment (36). Recent studies on the built environment affecting walkability have focused on walking paths, sidewalks, and lighting at the microscopic scale (32, 35). Walkable areas should also be enhanced with urban imagery such as historic buildings and public artwork, all of which can improve the quality of the pedestrian environment (38). As such, the walkability of an area is largely influenced by the built environment, such as pedestrian trail facilities and pedestrian services (39).

Walkability evaluation

Evaluating how pedestrian friendly an area is can be divided into two perspectives: a subjective or an objective evaluation. People living in the same built environment may exhibit different willingness to travel due to their individual judgments on the walkability of potential routes (40, 41). As such, the spatial experience of the walking process (42) affects the characteristics of their trips (43).

Subjective methods to evaluate walkability are usually based on questionnaires to obtain pedestrians' subjective perceptions of the built environment, such as the Neighborhood Environment Walkability Scale (NEWS), Semantic Differential (SD), Public Life in Public Space (PLPS), Neighborhood Quality of Life Study (NQLS) and Pedestrian Environment Review System (PERS) (44–46). Among them, the NEWS is a widely adopted method for subjective evaluation on walkability (47). The assessment variables involve with several dimensions such as comfort, safety, and convenience (43). The assessment of the quality of the street environment captures people's perceptions of the pedestrian environment (48), including pedestrians' opinions on the aesthetics of the surrounding built environment, pedestrian traffic safety, social crime safety, or neighborhood satisfaction (49).

Studies evaluating walkability by objective methods typically construct multiple environmental variables (50), which are then integrated and calculated to obtain a score value to measure walkability (51). Various types of examples, walkability index, which helps to quantitatively measure walkability, have been proposed by many scholars (52, 53). Particularly, Walk Score is the most popular and commonly used quantitative tool for objectively calculating walkability degree. The tool was introduced in 2007 by a US company to promote walkable communities and has become popular among real estate agents to promote walkable urban areas. The Walk Score considers the vicinity of different facilities *via* walking by taking into account the attenuation effects due to walking distance, intersection density, and block length (54). However, some scholars point out that the definition, classification, and importance of facilities as well as the raster-based distance decay pattern may differ among different urban regions. This also leads to the problem of non-comparability of walk scores in different regions, especially in high-density Asian regions that differ significantly from North America (28). For example, Hino et al. developed the Japanese Walkability Index (JWI) to measure walkability in cities based on the high-density urban structure of Yokohama. Since the JWI preferentially considers amenities, road networks, and land prices rather than density variables, it is superior for high-density Asian cities (55). Moreover, the European urban context is distinctive from that of US, which featured with low population density, low land use mix, and connectivity. To obtain a walkability index more in line with the European urban context, European scholars adjusted the choice of environmental variables and the size of weights in the walkability index. For example, Grasser et al. (25) used population density, household density, land use mix entropy index, and three-way cross density to construct a walkability index that fits the European regional context.

Moreover, it has been shown that Walk Score presents a positive correlation with both objective built environment factors (29) and the subjective perceived built environment factors (56–60). This suggests that the Walk Score should consider the effect of individual's perception, rather than only deriving from objective evaluation. Actually, the pedestrian experience during walking also plays a corresponding role in promoting or inhibiting walking, such as the degree of sidewalk continuity, safety during walking (61), and sidewalk quality (35).

Walkability of the metro catchment area

The concept of walkability is used by Dutch scholars to explain the link between the built environment and walking as an important component of TOD (37). Current policies also tend to promote a shift to non-motorized and public transportation (62, 63). However, improving the efficiency of public transportation alone is not enough to improve the ridership of public transportation. Enhancing the availability of public transportation (i.e., metro transit) *via* walking is also essential for promoting the public transport usage. Obviously, inadequate walkability around transit stations may reduce the patronage of the metro (28, 64). For instance, scholars in Italy have shown that public transportation in the country is currently inefficient and unreliable because the built environment in the vicinity of a station is not friendly enough for people to walk, including factors such as insecurity for pedestrian safety, low-quality sidewalks, and impassability due to the presence of obstacles on the sidewalk (35). In addition, the level of walkability in the metro catchment area is significantly and positively correlated with the probability of choosing to walk to and from the station. The study on metro passenger transfer modes by Wu et al. (65) showed that the quality of the pedestrian environment in the metro catchment area was positively related to the probability of passengers choosing walking as a transfer mode. In a medium-sized urban context in Colombia, Arellana et al. (66) also argue that the walkability and friendliness of the built environment, such as sidewalk condition and attractiveness, play an important role in pedestrian travel mode decisions.

Although poor walkability has a debilitating effect on people's willingness to use the metro, the adoption of walkable connections to stations has not yet received enough attention (67). Factors affecting metro catchment area walkability can be divided into mesoscale and microscale. Most previous studies on walkability have focused on built environment factors at the mesoscale, including land use diversity (68), density (69, 70), street design (71), connectivity (72), distance, and accessibility within the metro catchment (73). However, most of the studies are deficient in assessing pedestrian perceptibility of the walking environment at the microscopic scale. Microscopic factors of the built environment have an important influence on the walkability around metro stations (73), which can either facilitate or inhibit pedestrians (74). Moreover, the level of walkability also correlates to an individual's satisfaction with the perceived built environment (75, 76), including the quality and continuity of sidewalks (28), lighting (77), and the degree of obstruction on the walkway (78). Additionally, factors that are essentially subjective in nature, such as the degree of sidewalk cleanliness, social security around the station, traffic safety, and signage, are also found to have an impact on the walkability of the metro catchment area (79, 80).

In summary, although previous methods of evaluating walkability have involved objective spatial factors and subjective psychological factors, few studies have yet been conducted to combine subjective and objective evaluation variables. Meanwhile, the traditional methods of weight determination include correlation analysis and regression analysis, but they involve different subjective and objective dimensions. Further, such methods of pre-determined functional relationships may bring bias in the results. In addition, previous studies have not adequately combined the current built environment of the metro catchment areas with its importance to walkability, which is not conducive to accurately exploring the current shortcomings of the metro catchment area's walkability.

Data

Study area

Dalian, a tourist-oriented city, has a population of about 598.7 million and achieved a GDP of ∼703.04 billion RMB by the end of 2020. Dalian opened its first metro line in May 2003, making it the sixth city in mainland China with the operated metro system. As of December 2021, five lines have been put into operation with 201.03 km and 77 stations. The metro was widely used by commuters with an annual passenger volume of ∼156 million passengers and an average daily passenger volume of about 426.6 thousand passengers. Due to the transportation needs of foreign tourists and residents, Dalian Metro plays a very important role in passenger transportation.

This study is to investigate the influence of the built environment on the walkability of a metro catchment area, focusing on the environmental perception and the objective supportiveness of the built environment. Therefore, the location and function of the metro station itself are used as the two bases for the classification of metro stations, so that the selected stations are more typical. Additionally, the central city is treated as our study area due to a large proportion of pedestrian connections and the dense distribution of metro lines. A large number of pedestrian flows can ensure the diversity of basic attributes such as social characteristics and the travel purposes of pedestrians. To effectively reflect the variability of the pedestrian environment of the catchment areas, eight stations, namely, Dalian Railway Station (DR-S), Harbor Square (H-S), South China Square (SC-S), Exhibition Center (E-C), Tsingniwa Bridge (TNW-B), Xi'an Road (XA-R), Friendly Square (F-S), and Zhongshan Square (ZS-S), were selected as the sampled stations. These stations can be divided into several types on the basis of their functions related to land use, including residential-dominated, commercial centers, transportation hubs, and landscape open types (Table 1).

In addition, previous studies on the walkability of the station usually use the buffer zone with 800-m radius as the catchment area of metro station (17, 81). Meanwhile, the *Chinese official Guidelines for Planning and Designing Areas along Urban Railways* specify that the rail impact area is the region that is

TABLE 1 Overview of research sites.

Location	Site name	Site type	Classification criteria and characteristics	Station lines	Number of entrances and exits
Shahekou district	Xi'an road	Commercial center type	Located in the city center node; surrounded by commercial and entertainment offices; high flow of people and vehicles	Line 1/line 2	4
	Exhibition center	Open landscape type	Surrounded by famous attractions of the city; nearby buildings, roads, and environment are relatively well; significantly more people during holidays	Line 1	3
Xigang district	Dalian railway station	Transportation hub type	With subway interchange role; distribute various modes of transportation; high flow of people in the station;	Line 3/line 3 interval	2
Zhongshan district	Qingniwa bridge	Commercial center type	–	Line 2	3
	Friendship square	Commercial center type	–	Line 2	3
	Zhongshan square	Commercial center type	–	Line 2	6
	Harbor square	Open landscape type	–	Line 2	2
Ganjingzi district	South China square	Residence-led type	Surrounded by mainly residential areas; obvious residential group structure; commuter tide phenomenon	Line 1	3

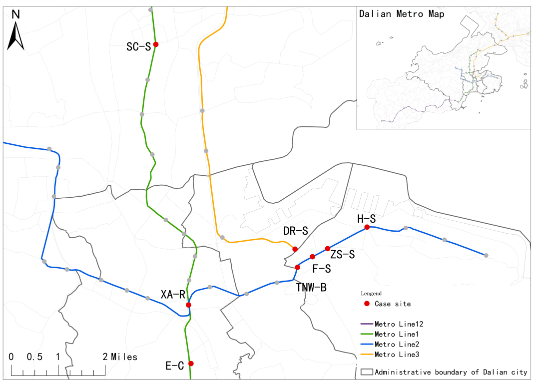

FIGURE 1
Case site location map.

about 500–800 m away from the station, within 15 min walking distance to the station entrance. Therefore, the area within 800 meters radius of the station (i.e., 10 min of walking time) is taken as the built environment background area for assessing walkability (Figure 1).

Data

Two types of data were used in this study: (1) objective measurement of the built environment of the metro catchment area and (2) subjective perceptions of the walkability of the metro catchment area. Objective data such as pedestrian paths within the built environment were obtained through web-based big data, street maps, and field observations. The subjective perception data was collected by distributing a questionnaire to respondents and quantifying the results with the help of the five-scale Likert approach. The variables in the questionnaire were selected based on the relevant built environment factors affecting station walkability as mentioned above, with consideration of previously studied sidewalk assessment tools (74) and sidewalk levels of service (76). The questionnaire was initially tested among 10 graduate students and reviewed by experts in the field, followed by several modifications on the basis of feedback. In addition, 29 micro-scale built environment factors that promote or inhibit the walkability of the metro catchment area were selected, taking into account the distinctive characteristics of Dalian as a local tourist city. The factors were classified according to their characteristics and hierarchical structure into six design qualities: connectivity, convenience, safety, comfort, pleasure, and diversity (Table 2).

Survey

The questionnaire and field survey was conducted from August 2021 to March 2022. The field survey was divided into two parts: pre-survey and formal survey. The format, clarity, and wording of the content of the questionnaire were improved through a pre-survey of 30 respondents who randomly distributed the questionnaire. The content of the questionnaire was divided into three parts: basic personal information, travel characteristics, and pedestrian satisfaction

TABLE 2 Built environment variable attributes.

Category	Variable	Description	Perspective	Data source	Expected direction
Connectivity	Pedestrian network density	Total walkway length/station area	Objective	Road data	+
	Walkway area rate	Total walkway area/station area	Objective	Road data	+
	Walkway continuity	Mean score of respondents' evaluation of walkway continuity	Subjective	Survey questionnaire	+
	Intersection density	Number of intersections/station area	Objective	Field surveys/street maps	+
	Average block length	Sum of the average lengths of blocks/number of blocks	Objective	Field survey/street map	+
	End-of-road ratio	The total length of end streets/total length of pedestrian walkways	Objective	Road data	-
Convenience	Ease of pedestrian crossing	The average score of respondents' evaluation of the convenience of pedestrian crossing	Subjective	Survey questionnaire	+
	Ease of crossing at flyovers	The average score of respondents' evaluation of the convenience of crossing the street on pedestrian bridges	Subjective	Survey questionnaire	+
	Ease of crossing at underpasses	The average age score of respondents' evaluation of the convenience of crossing the street at underpasses	Subjective	Survey questionnaire	+
	Signage facilities	Average rating of respondents' evaluation of signage facilities	Subjective	Survey questionnaire	+
Security	Signal light facilities	Mean score of respondents' evaluation of signalization facilities	Subjective	Survey questionnaire	+
	Street lighting facilities	The average score of respondents' evaluation of street lighting facilities	Subjective	Survey questionnaire	+
	Degree in traffic safety	Average rating of respondents' evaluation of traffic safety	Subjective	Survey questionnaire	+
	Degree in social security	The average score of respondents' evaluation of the degree of social security	Subjective	Survey questionnaire	+
Comfort	Walkway width of the access	The average width of pedestrian walkways	Objective	Field survey/street map	+
	Quality of paving of footpaths	The average score of respondents' evaluation of pavement quality	Subjective	Survey questionnaire	+
	Sheltering facilities	The average score of respondents' evaluation of sheltering facilities	Subjective	Survey questionnaire	+
	Degree of obstruction	The average score of respondents' evaluation of the degree of obstruction	Subjective	Survey questionnaire	–
	Rest seating facilities around the walkway	The average score of respondents' evaluation of resting seating facilities around the walkway	Subjective	Survey questionnaire	+
Pleasure	Open space density	Area of public space and green space/station area	Objective	Remote sensing image	+
	Public artwork	The average score of respondents' evaluation of public artwork	Subjective	Survey questionnaire	+
	Degree of walkway cleanliness	The average score of respondents' evaluation of the cleanliness of the walkway	Subjective	Survey questionnaire	+
	Degree in greening and landscaping	The average score of respondents' evaluation of the degree of greenery and landscaping	Subjective	Survey Questionnaire	+
	Degree of pedestrian congestion	The average score of respondents' evaluation of crowdedness	Subjective	Survey questionnaire	–
Diversity	Density of living facilities	Number of living facilities/total area	Objective	Baidu POI	+
	Density of commercial facilities	Number of commercial facilities/total area	Objective	Baidu POI	+
	Density of recreational facilities	Number of recreational facilities/total area	Objective	Baidu POI	+
	Density of transportation facilities	Number of educational facilities/total area	Objective	Baidu POI	+
	Transparency of buildings on both sides of the walkway	The average score of respondents' evaluation of the transparency of buildings on both sides of the pedestrian walkway	Subjective	Survey questionnaire	+

with the built environment of the metro catchment area. Personal characteristics included information on gender, age, occupation, monthly income, and home address. The travel characteristics include the purpose of travel, the number of trips per week by metro, and the feeder modes of connecting to metro stations. The final part of the questionnaire collected respondents' subjective satisfaction with the built environment factors of the station area. During the formal research process, the familiarity of the metro catchment area was identified on the spot by asking respondents in advance if they frequently traveled to and from the area by metro. Thus, the questionnaires obtained for this study were representative of respondents who regularly take the metro for various purposes and more than two times per week. The researchers distributed a total of 867 questionnaires in clear weather on weekdays and weekends, respectively, with a valid sample size of 800 and an effective rate of 92.3%, of which 486 questionnaires were collected on weekdays, accounting for 60.8%.

According to the statistics of personal attributes in Table 3, the gender ratio of the respondents was ∼50%. Teenagers and middle-aged people make up the majority of the total population. Nearly half of the respondents are commuters, followed by students. This shows the importance of the passengers who take the metro to work and school. Regarding income, most of the respondents are in the middle class, with 27.1% of the respondents in the 2,000–5,000 range and 30.8% in the 5,000–8,000 range. In addition, respondents take the metro about 4 times a week on average. 60.6% of the respondents choose walking as the mode to connect to the metro, which further demonstrates the validity of the sample. The purpose of travel is mainly shopping and dining, accounting for 39.9% of the total, followed by commuting to work, going home, and taking a leisurely walk, accounting for 29.1 and 20.8%, respectively. In summary, the survey sample has good representativeness in terms of both personal information and travel characteristics.

TABLE 3 Basic attributes statistics table.

Attribute	Subgroup	Numerical value
Gender	Male	51.4%
	Female	48.6%
Age	18–25 years old	30.1%
	26–35 years old	27.1%
	36–45 years old	20.2%
	46–55 years old	10.5%
	>56 years old	12.1%
Occupation	Students	22.5%
	Commuters	49.0%
	Freelance	11.4%
	Retired	10.6%
	Government employee	0.4%
	Others	6.1%
Income	<2,000	23.5%
	2,000–5,000	27.1%
	5,000–8,000	30.8%
	8,000–10,000	13.0%
	>10,000	5.6%
The average number of subway rides per week		4
Purpose of travel	Going to and from work, going home	29.1%
	Going to and from school	7.9%
	Shopping and eating	39.9%
	Leisurely walk	20.8%
	Other	2.3%
Connection method	Walking	60.6%
	Bicycle	2.8%
	Bus	23.3%
	Taxi, dropshipping	9.2%
	Electric car	0.9%
	Private car	3.2%

Methodology

A total of 867 valid questionnaires were generated during the research. Based on the available data collected, this study designs a machine learning-based prediction algorithm to assign weight to the variables. The algorithm consists of two modules: principal component analysis (PCA) and feedforward neural network.

Among them, PCA can effectively reduce the dimensionality of different types of data while maintaining multiple variations in data samples. It helps to eliminate the multicollinearity that destroys the statistical significance of independent variables in the data set, thus making the statistical results more accurate. At the same time, the value relationships among multiple data are explained more clearly by assigning variable weight labels. We use PCA to reduce the training time and avoid overfitting problems. When implementing PCA, our model's input is the original data, PCA transforms the data to a new subspace. Then we feed the output to the feedforward neural network. We designed the feedforward neural network with four fully-connected layers with 29, 128, 64, and 29 nodes in each layer. The feedforward neural network learns the relationship between the input and output manually. We use Adam Optimizer to train the feedforward model because Adam can tune the learning rates automatically. To compare the difference between the prediction and groundtruth. We leverage the MSE loss function. To get a stable neural network model, we train our model for 250 epochs. We can see from Figure 3, the model is stable when it is trained more than 50 epochs. The machine learning-based variable weight prediction algorithm effectively combines the objective and subjective to eliminate the scale effect and assign more objective weight to the variables. Based on the collected data, the correlation between different kinds of variables is explored with the help of PCA, the feedforward neural network is utilized to learn the weights variation of each variable with the guiding of the weights generated by PCA. Compared with the traditional correlation analysis and regression analysis, it effectively enhances the robustness of weight prediction and makes the research results of weights have the obvious advantages of being more objective and having higher credibility.

The weight of the variable represents the degree of the effect of the pedestrian environment factor on the walkability of the metro catchment area, and some variables even have a critical role. It is reasonable to discover the current problems and directions for improvement in the pedestrian environment by deeply exploring the individual factors that significantly affect the walkability of the metro catchment area. Therefore, this study combines the weighting results with the relevant built environment evaluation scores of the catchment area's current walkability to construct a "Score- Effectiveness" (S-E) two-dimensional quadrant diagram. This framework allows for a comprehensive analysis of the two-way correlation between the walkability performance of each built environment variable in the catchment area and its corresponding weight. This can fully illustrate the correspondence between the current status scores of variables and their effectiveness, to dig out the most sensitive existing problems related to walkability in the catchment area. In particular, for those built environment factors with low scores and high effectiveness, targeted improvement strategies that minimize the cost and maximize the benefit can significantly improve the walkability of the station catchment area. These strategies can precisely and effectively enhance the objective walkability and the subjective pedestrian friendliness of the station catchment area (Figure 2).

Due to the difference in the unit of selected data, the variables need to be normalized before entering the algorithm model. The evaluation results of the subjective variables are obtained by averaging the five-scale Likert scores of the eight stations, which ranged between 1 and 5 scores. For the objective variables, the scores vary in magnitude due to the existence of different scales. Therefore, the mean of the objective variables was normalized, followed by transferring into the same interval as the subjective scores, thus eliminating the problem of subjective and objective scales, as follows.

$$Y = y_{MIN} + \frac{y_{MAX} - y_{MIN}}{x_{MAX} - x_{MIN}} \times (\bar{x} - x_{MIN})$$

Where Y is the normalized mapped value; y_{MAX} is the maximum value of the mapped target interval; y_{MIN} is the minimum value of the mapped target interval; X_{MAX} is the maximum value in the original dataset; X_{MIN} is the minimum value in the original dataset; $\bar{x}$ is the average value in the original dataset.

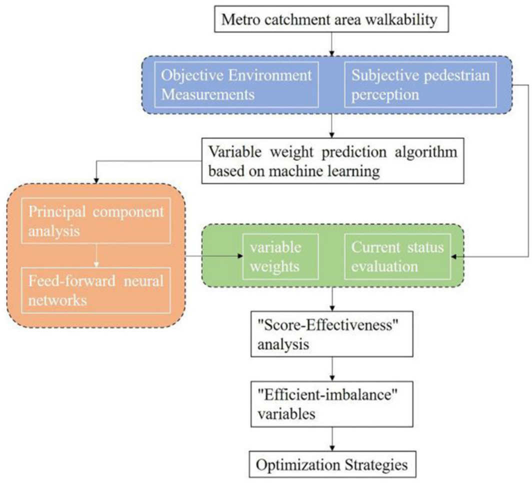

FIGURE 2
Research framework.

Results

Subjective and objective variable scores

The scores of each variable are shown in Table 4. Friendly Square (F-S) has 8 variables which ranked first (8), including the rate of walkway area, social security, walkway width, shade facilities, obstacle barrier, resting seat facilities around the walkway, and pedestrian congestion. By contrast, the Zhongshan Square (ZS-S) metro catchment area received 8 variables with the lowest value. It is possible that F-S is located in the financial and commercial center of Renmin Road, the busiest area in Dalian, and serves as an important node connecting transportation hubs and commercial areas such as Dalian Railway Station, Shengli Square, and Tianjin Street. Because of the strong pedestrian demand itself, the construction of pedestrian paths and various services in the catchment area provide pedestrians with high-quality, experiential walking spaces. Moreover, the characteristics of high pedestrian flow also make the two negative variables of obstacle barrier degree and pedestrian crowding degree score significantly larger than other stations. The ZS-S catchment area is one of the most famous squares in Dalian attributed to the circular square of ~168 meters in diameter. At the beginning of its planning and construction, a long and fatiguing walking path for pedestrians was designed. In addition, as a famous and historically significant square in Dalian, ten avenues radiate out from the area, which results in complex road conditions, high traffic flow,

TABLE 4 Evaluation indicator scores for each station area.

Indicator layer	Dalian Railway Station (DR-S)	Harbor Square (H-S)	South China Square (SC-S)	Exhibition Center (E-C)	Tsingniwa Bridge (TNW-B)	Xi'an Road (XA-R)	Friendly Square (F-S)	Zhongshan Square (ZS-S)	Objective interval value/subjective average
Pedestrian network density (a1)	35.66	27.91	26.01	33.52	37.43	37.92	37.65	34.07	3.61
Walkway area rate (a2)	16.10%	10.77%	12.98%	14.02%	17.35%	14.80%	17.88%	15.34%	3.33
Walkway continuity (a3)	4.03	3.86	4.00	3.55	3.86	3.38	3.79	3.72	3.78
Intersection density (a4)	51.23	35.81	12.43	51.23	64.66	45.76	89.71	90.52	3.19
Average block length (a5)	208.59	199.54	244.76	210.89	206.68	192.74	166.76	165.24	2.72
End-of-road ratio (a6)	2.32%	1.19%	1.64%	3.27%	2.13%	2.50%	2.25%	1.15%	2.71
Ease of pedestrian crossing (a7)	4.00	3.86	3.90	3.48	3.69	3.62	3.38	3.21	3.64
Ease of crossing at flyovers (a8)	4.00	3.18	3.47	3.29	3.14	3.18	3.18	2.00	3.18
Ease of crossing at underpasses (a9)	4.23	3.72	3.70	3.26	3.52	3.57	2.90	3.69	3.57
Signage facilities (a10)	4.00	4.03	4.10	3.26	3.79	3.86	3.48	3.83	3.79
Signal light facilities (a11)	4.00	3.59	4.10	4.03	4.17	4.17	4.00	3.59	3.96
Street lighting facilities (a12)	4.10	4.03	4.27	4.13	3.97	4.28	4.31	3.97	4.13
Degree of traffic safety (a13)	3.93	3.69	3.93	3.39	4.00	3.90	3.83	3.76	3.80
Degree of social security (a14)	4.20	4.10	4.37	4.42	4.31	4.14	4.48	3.97	4.25
Walkway width of the access (a15)	4.51	3.86	3.87	4.18	4.66	3.92	4.75	4.50	4.28
Quality of paving of footpaths (a16)	3.97	3.59	3.97	4.06	3.59	4.07	3.86	3.45	3.82
Sheltering facilities (a17)	3.63	3.59	3.40	2.84	3.14	2.38	3.86	3.48	3.29
Degree of obstruction (a18)	3.63	3.21	3.70	2.84	3.55	2.48	4.17	3.55	3.39
Resting seating facilities around the walkway (a19)	3.77	2.62	3.23	2.55	3.24	2.45	3.90	3.72	3.18
Open space density (a20)	2.69%	3.83%	5.71%	3.75%	3.60%	4.72%	4.71%	13.11%	1.99
Public artwork (a21)	4.03	4.10	3.53	4.06	3.24	2.90	3.86	4.17	3.74
Degree of walkway cleanliness (a22)	4.13	4.07	4.03	4.23	3.59	4.03	3.86	4.17	4.01
Degree of greenery and landscape (a23)	3.83	4.14	3.80	3.94	3.17	3.38	4.17	4.24	3.83
Degree of pedestrian congestion (a24)	3.67	3.52	3.60	3.48	3.66	3.10	3.90	3.72	3.58
Density of living facilities (a25)	95.49	77.59	129.31	46.25	153.68	253.65	206.90	239.73	3.01
Density of commercial facilities (a26)	188.50	126.83	268.57	283.00	250.17	346.16	262.11	271.06	3.24
Density of recreational facilities (a27)	3.98	3.98	4.48	28.35	8.46	23.38	6.47	6.47	2.10
Density of transportation facilities (a28)	14.92	5.47	7.96	3.98	14.42	8.95	14.92	13.43	3.39
Transparency of buildings on both sides of the walkway (a29)	3.90	3.31	3.80	3.23	4.03	4.38	4.03	3.79	3.81

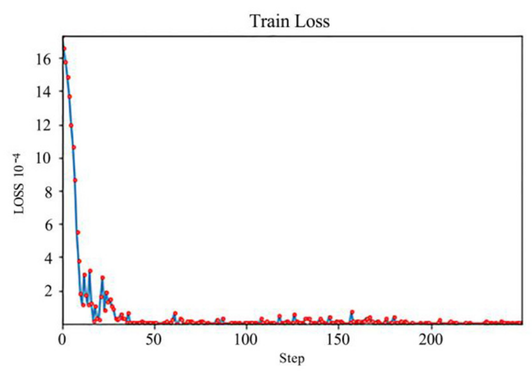

FIGURE 3
Convergence process of loss function of feedforward neural network.

and lack of signalization. As a consequence, it causes many concerns about pedestrian safety.

As for the subjective variables, the width of the pedestrian paths in the catchment area, the degree of social security, street lighting facilities, and the neatness of the pedestrian paths were generally recognized by the respondents; the scores of the rest seating facilities, shading facilities and the degree of barrier blockage around the pedestrian paths were significantly lower than the other variables. Combined with the field survey and interviews, most walking paths in the catchment area have problems such as a lack of service facilities, space encroachment, and unclear management.

Machine learning to determine variable weights

For the designed algorithm, the PCA is used to calculate the weights of each variable based on the collected data, the output of the weight calculated by the PCA is used as the data labels, and the feedforward neural network is used to learn the robust mapping from the variable samples to the weight labels. The loss function of this feedforward neural network gradually decreases during the training process until the network converges. The convergence process is shown in Figure 3, where the horizontal coordinate is the number of data iterations and the vertical coordinate is the loss value.

The modeling results of variable weights are shown in Figure 4. Factors related to walking connectively, include a1 (Pedestrian network density), a2 (Walkway area rate), a3 (Walkway Continuity), a4 (Intersection density), a5 (Average block length), and a6 (End-of-road ratio), are <0.01.

As a comparison, convenience and safety variables such as a7 (Ease of pedestrian crossing), a8 (Ease of crossing at flyovers), a9 (Ease of crossing at underpasses), a10 (Signage facilities), a11 (Signal light facilities), a12 (Street lighting facilities), a13 (Degree of traffic safety) and a14 (Degree of social security) have weights above 0.05, indicating the important role on affecting the walkability of metro areas. Among these convenience and safety factors, metro users may have many concerns about social security (a14 with the highest weight of 0.062) when connecting the metro transit.

Regarding the comfort and pleasure variables, only a15 (Walkway width of the access) and a20 (Open space density) have weights below 0.01, while the remaining factors have significantly greater weights than the previous two, including a16 (Quality of paving of footpaths), a17 (Sheltering facilities), a18 (Degree of obstruction), a19 (Resting seating facilities around the walkway), a21 (Public artwork), a22 (Degree of cleanliness of the walkway), a23 (Degree of greenery and landscape), and a24 (Degree of pedestrian congestion). Within the comfort and pleasantness variables, people may place more importance on the cleanliness of the walkway (a12 with the highest weight of 0.058).

On the contrary, most of the variables in diversity have weights below 0.01, such as a25 (Density of living facilities), a26 (Density of commercial facilities), a27 (Density of recreational facilities), and a28 (Density of transportation facilities). And the weight of a29 (Transparency of buildings on both sides of the walkway) is higher than 0.05, which is five times more than the weight values of other variables in the diversity. This indicates that metro users may care more about the façade form of buildings on both sides of the walkway than the density of various service facilities in the catchment area.

"Score-effectiveness" suitability analysis

In this study, we construct a framework of the "*Score-Effectiveness*" fit quadrant in which the horizontal coordinates are the weights obtained from the variable weight prediction algorithm and the vertical coordinates are the scores of the current variables. The baseline of the four quadrants is the mean value of the weights and satisfaction scores as the parallel axes of the horizontal and vertical coordinates, respectively. To form an effective, precise, and efficient optimization strategy based on field surveys and research.

As shown in Figure 5, both the weights and satisfaction results of variables in quadrant I are higher, indicating that pedestrians are more satisfied with the current situation of this variable, which belongs to the efficient and balanced type. The variables in quadrant II are low-efficiency and high-quality, meaning that pedestrians are also satisfied with these low-efficiency variables and only need to maintain the status quo for these aspects. The variables in quadrants III and IV are the inefficient and poor quality type and the efficient and imbalanced type, respectively. The variables in quadrant III have slightly less influence on satisfaction, and appropriate

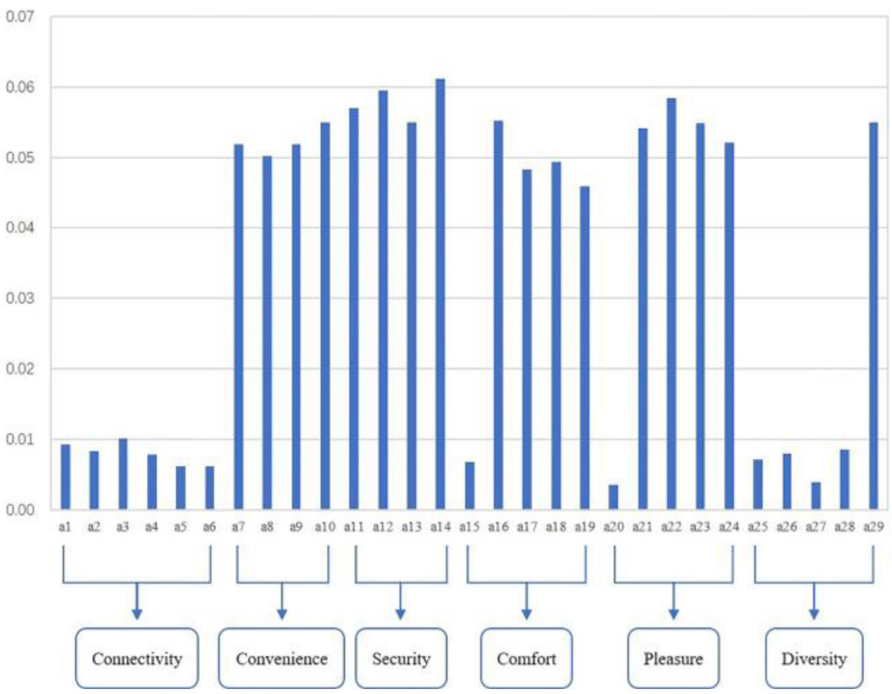

FIGURE 4
Distribution of variable weights.

optimization can be performed at appropriate time points for the weak points with low ratings. Variables in quadrant IV are characterized by high performance and low scores, which have a greater impact on satisfaction while scoring low. This indicates that the efficient imbalance-type variables are built at a relatively low level, but have a direct and important impact on the friendliness of supporting pedestrian walking. Therefore, the relevant variables need to be improved and optimized urgently to be able to improve the current level of metro catchment area walkability in a targeted and maximally effective way.

By counting the data from the questionnaire, as shown in Table 3 above, the respondents in the metro catchment area can be divided into commuting and leisure categories based on different travel purposes. Among them, 37% are commuters (commuting to and from work and school) and 60.7% are leisure people (leisurely walking, shopping and dining). Using the "Score-Effectiveness" model, the efficient imbalance-type variables under the three categories of full coverage, commuting, and leisure were identified by stratifying the purpose of the population trips, respectively. As shown in Figure 5, the efficient imbalance-type variables are consistent for full coverage and leisure populations, including a8 (Ease of crossing at flyovers), a17 (Sheltering facilities), a18 (Degree of obstruction), and a19 (Resting seating facilities around the walkway). For the commuter population, a9 (Ease of crossing at underpasses), a17, a18, and a19 are in low rating, high performance status. In general, a17, a18, and a19 are fixed efficient imbalance variables. While comparing the commuting and leisure population, the former cares more about the performance of a9 and the latter is focused on a8. Both a8 and a9 are crossing facilities, which also shows that the two types of people, commuters and leisure, have different needs for station domain walkability and have differential judgments on crossing forms. The flyover plays the role of outdoor landscape while assuming the traffic function. The leisure population prefers open crossing space, while the commuter population finds the underpass crossing more convenient.

Discussion

In this study, both subjective and objective perspectives are applied to evaluate the walkability of the metro catchment area. An approach of predicting the weight of variables based on machine learning technique is developed to accurately measure the importance of built environment factors that affect walkability. Among the selected built environment factors, the shade facilities, obstacle barriers, and resting seats around the pedestrian paths were found to be highly effective and imbalanced variables recognized as fixed by the population. indicating the necessity for improvement. Meanwhile, the ease of crossing the flyovers and underpasses are additional

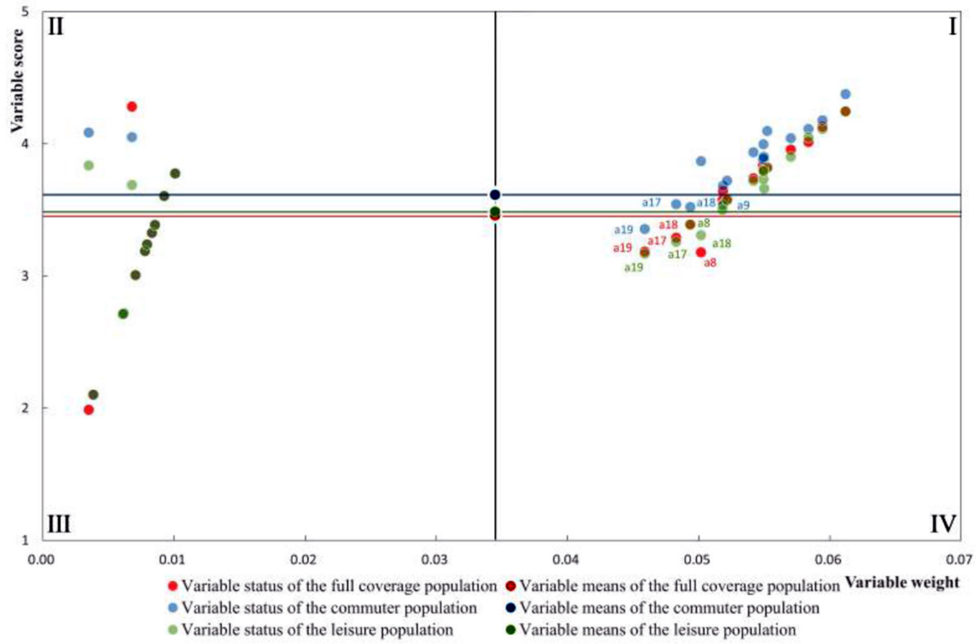

FIGURE 5
"Score-effectiveness" suitability quadrant.

efficient imbalance-type variables for the leisure and commuting populations. On the basis of the analysis in terms of the five efficient imbalance-type variables, this paper proposes targeted optimization strategies accordingly.

First, pedestrian bridges, an important measure to improve the convenience of walking, are suggested to be installed at traffic nodes such as main roads with high traffic flow and large safety hazards. In Dalian city, motorways, tramways, sidewalks, etc. are crisscrossed in the metro catchment area, causing major hidden dangers to the convenience and safety of pedestrians crossing the street. However, our field observation found that overpass crossing facilities in Dalian are extremely absent, which makes walkers inconvenient for crossing the road. Therefore, overpass crossing facilities should be added at appropriate locations around the catchment area to enhance walkability and form a friendly walking space to separate pedestrians and vehicles (76). In addition, the design of the overpass crossing should take care of the use of vulnerable groups such as the elderly. With the help of barrier-free designs (e.g., elevators and ramps), an effective and friendly pedestrian corridor is formed to eliminate the pedestrian's psychological barriers to walking caused by excessive slopes.

Second, during the interviews, most of the interviewees reported that the interior of the underpass was too dark, poorly tidied, and had a low level of security. It is recommended that large glass areas be used at the entrances and exits of underground passages to introduce a greater range of natural light. Strengthen the relevant management personnel to improve efforts, pay attention to health cleaning, post-maintenance and social security. Reduce the situation of mobile vendors occupying underground traffic sex paths and adopt time-sharing and centralized management. In addition, the underground passageway of the metro catchment area can and should be combined with the surrounding underground commercial space to maximize the use of the pedestrian flow and vitality brought by the station. The benefits are maximized while reducing the pressure of pedestrian flow in the ground commercial walkway.

Third, it is suggested to appropriately improve the ability of the shading facilities to cope with extreme weather. Possible measures include planting street trees along the avenues, building eaves, and setting corridors and canopies. According to the field study, there are very few sheltering facilities along the route to the metro stations, which makes metro users uncomfortable walking to the stations in bad weather. It is suggested to use some flexible sheltering facilities, such as folding devices similar to umbrellas on both sides of the walkway. In addition, shelter facilities can be also designed by integrating the functions of greening and rainwater collection collectively. These techniques will not only improve the overall environmental quality but also makes resources to be utilized more effectively.

Fourth, enhancing the environmental management and optimization in the metro catchment area is encouraged. The field survey also found that the pedestrian space in the catchment area is seriously encroached upon by commercial and advertising obstacles. Excessive space encroachment can directly lead to a significant reduction in walkability because of the increasing traffic chaos and safety risk. Therefore, it is recommended that the relevant authorities should develop management measures to prohibit commercial and advertising barriers in the pedestrian space, particularly around the entrance of metro stations where passengers are usually crowded, to reduce its negative impact on walkability.

Finally, the metro catchment area should be provided with public seating and resting space approximately. In this study, we found that resting seating facilities along the walkway have a positive impact on station area walkability, which is in line with the results of previous studies (77, 82). Dalian is a city with many open squares, and most of the metro catchment areas are accompanied by city squares spatially. However, squares with large sizes may cause fatigue to pedestrians and visitors, and that is why approximate allocation of resting facilities is particularly important to improve the willingness of walking. Therefore, increasing the number of resting seats along the pedestrian walkway can not only make walking less tiring but also improve the neighborhood vitality of the station area and enhance the attractiveness of the city.

Conclusion

Currently, the urban metro system in China is developing rapidly. However, the development of the metro catchment areas, particularly the planning and management of walking-related facilities, does not meet well with demands (i.e., comfort, convenience, and safety) of metro passengers. Considering that the land use has been planned, the optimization of the built environment of the metro catchment area is easier to implement and more effective than the reorganization of built environment factors. In this paper, subjective and objective variables of metro catchment area walkability are effectively combined. Through the innovative machine learning-based variable weight prediction algorithm, the weight value of each variable is obtained more scientifically and objectively. Based on this, this study further constructs a "Score-Effectiveness" suitability system to precisely identify the built environment factors that should be improved to enhance walkability in metro catchment areas.

The results of the study help to understand the priorities of built environment factors that affect the walkability of metro catchment areas, as well as to pinpoint the existing problems related to the walking connection to metro stations. A comparative analysis of the stratification of the population was conducted to find out the differentiated demand for metro catchment area walkability by populations who travel for both commuting and leisure purposes. This study provides relevant governments and planners with targeted and effective optimization strategies to make the metro areas more walkable. The major contributions of this study include: (1) to construct the "Score-Effectiveness" framework to identify the imbalanced factors in terms of the built environment, and hence, contribute to providing targeted policies to improve the walkability of metro areas; (2) to collectively identify the weight of objective and subjective built environment factors through developing a machine learning-based approach, which makes it possible to compare the importance of objective and subjective built environment factors.

However, there are limitations to this study. First, due to the difficulties in data collection, some built environment variables such as traffic congestion, noise, and air pollution (83) that may potentially affect walkability are unselected approximately. Further, we just selected eight sampled metro stations for analysis, which may cause some bias potentially. Future studies can expand the sample city size to enhance comparability.

Data availability statement

The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding author/s.

Author contributions

WX and YG: conceptualization. PZ and YG: funding acquisition, validation, and writing—review and editing. WX: formal analysis, supervision, methodology, and writing—original draft. BL and LS: investigation. MX: machine learning algorithm design and practice. All authors contributed to the article and approved the submitted version.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Publisher's note

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The built environment impacts on route choice from home to school for rural students: A stated preference experiment

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Introduction: Rural roads and built environment in China have been developed enormously, but it is not clear whether these roads fulfill the needs of school children as they need to travel long to school every day.

Objective: It is crucial to understand the influencing factors of their travel mode choices to better design future country roads and built environment, aiming to promote physical activities of school children in a safe built environment.

Method: This study thus attempts to explore the impacts of rural built environment attributes on children's school travel mode preferences. Eight rural built environment attributes are considered: distance from home to school; the number of intersections passed on the way to school; whether there are sidewalks/bicycle lanes; the traffic speed of school access routes; whether there are separation facilities between motor vehicles and non-motor vehicles; whether there are traffic lights and zebra crossings; availability of greenery such as lawns, flower ponds and street trees and whether there are shops on the way to school and at the school gate. Six hundred and thirty eight valid questionnaires were obtained through face-to-face interviews with school-age children in villages. A multinomial logit model was estimated to unravel the preferences and choices of rural school-age children in different models of school travel using the stated choice data.

Results: All the eight attributes have significant impacts on rural children's school travel choices on foot, bicycle, electric bicycle or motorbike. And four rural road design attributes have significant effects on rural children's school travel by private cars. A travel path with pavements or bike lanes, few intersections, low traffic speeds, greenery and shops can facilitate children's school travels on foot or by bike. The conclusions can provide reference for the further upgrading planning, designing and construction of rural roads, as well as enriching the theory and practice of child-friendly villages construction.

KEYWORDS

rural school travel built environment, stated preference survey, school travel, multinomial logit model, experiment

Introduction

At present, China has entered the stage of rapid development of new countryside and urbanization. Since 1995, the number of rural population in China has shown a gradual downward trend. According to the data of the seventh population census in China Rural Statistical Yearbook 2021, the number of rural population in 2020 will only account for 36.1% of the total population in China (1) (See Figure 1).

While the rapid urbanization of the countryside has contributed to its rapid development, it has also given rise to a series of problems, such as the destruction of the ecological environment due to the construction of roads, the overcrowding of the urban population, the inadequate supply of housing for low-income people in the cities, traffic safety and traffic congestion, etc. The original housing structure and transport structure of rural residents have also changed accordingly with the urbanization process (2).

With the rapid development of China's infrastructure and economic growth prompting the rapid development of rural road construction, The mileage of rural roads in China has increased significantly (3) (See Figure 2), rural roads cover both urban and rural areas, and household car ownership in rural areas of China has also changed dramatically in the past two decades or so (4). However, there are still many rural roads with weak traffic infrastructure (such as lack of greening, improper design of traffic lights and zebra crossings). At the same time, rural residents' weak awareness of traffic safety has also brought many safety problems.

Although the rural population in China is on the decline, according to the literature and previous rural research experience, the Chinese school-age children group still has a certain scale, which has generated huge travel demand. On the other hand, the number of rural schools has shown a trend of reduction due to concentration. At the beginning of the 21st century, the Ministry of Education of China launched the School Map Reorganization (SMR) plan, which involved closing small rural schools, opening large centralized schools in townships and counties, and shifting from "running schools in villages and villages" to integrating the resources from nearby schools. According to statistics, in the 20 years from 2000 to 2020, more than 350,000 primary schools have been canceled or merged. By the end of 2020, there are only 777 high schools, 14,241 junior high schools and 86,000 primary schools in rural China (See Figure 3), and the number of students enrolled has also decreased year by year (1) (See Figure 4).

The sharp drop in the number of schools due to the SMR plan has caused many children to lose the chance to study in their local schools (5). Some rural students and a small number of urban students can only choose boarding schools or take private cars to/from school to overcome the increasing home-to-school distance. All of these led to changes in the way of school travel (6).

The World Health Organization has made a survey and clearly pointed out that the number one cause of children's death in the world every year is traffic accidents, which accounts for a higher proportion in China. Globally, about 5 million people die each year from road traffic accidents. More than 70% of them occur in developing countries. And 80% of these accidents are related to children. This has become a serious social problem. In recent years, school age children have frequent traffic accidents. According to the statistics of China's transportation department,

FIGURE 1
Number and proportion of the country's population living in rural areas.

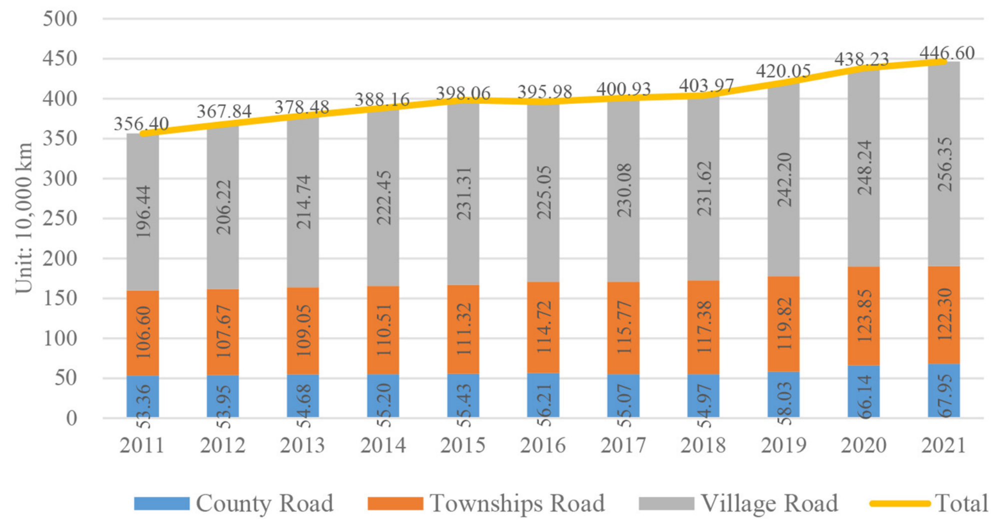

FIGURE 2
Mileage of national rural roads.

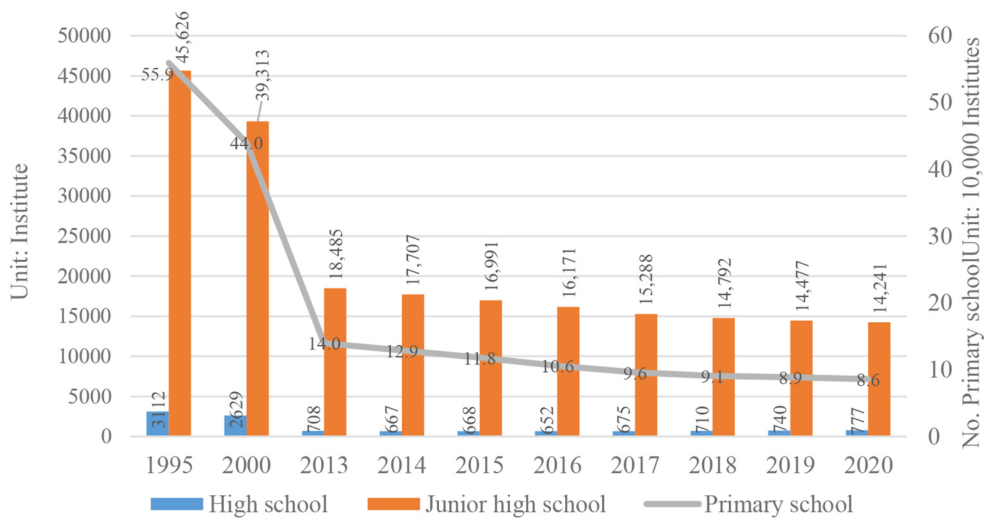

FIGURE 3
Number of rural schools in China.

more than 18,500 children die in traffic accidents every year in China. This mortality rate is 2.5 times that of European countries and 2.6 times that of the United States (7).

It is crucial to understand the preferences of children in rural areas and create a well and safe built environment for them to promote public health and active travels like walking and cycling. Most previous studies have explored the relationship between general built environment attributes and residents' preferences on different spatial scales, as reviewed by Saelens and Handy (8), Ikeda and Stewart (9), and Chen et al. (10), but failed to capture the micro-scale environmental factors like the detailed values of crossings on a road, the numbers of shops, etc. This research therefore aims to quantitatively study the relationship between children's preference and the micro-scale attributes of built environment travel paths for better design of the school path. In this study, declarative choice experiments were used to explore children's preferences, and discrete choice models were used to estimate the quantitative relationship

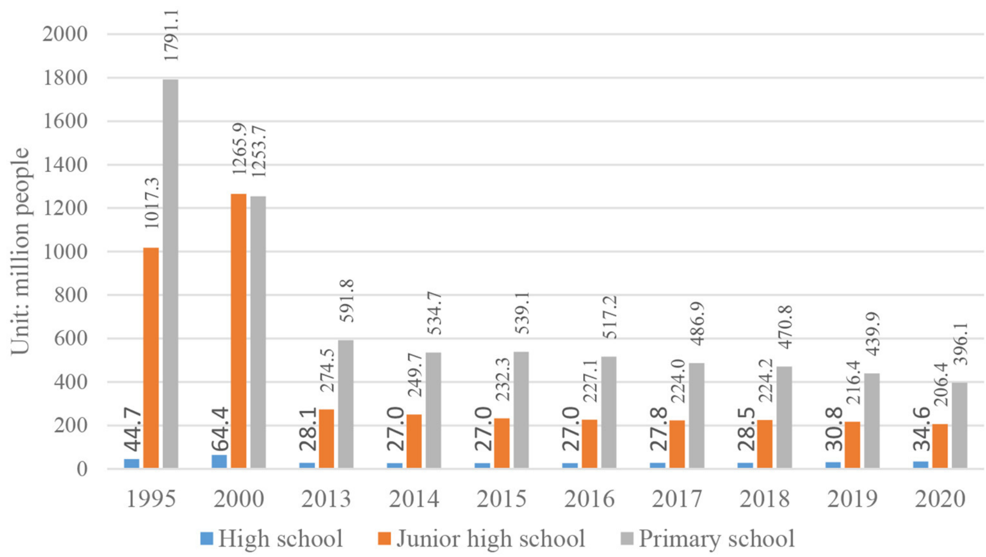

FIGURE 4
Enrollment of rural schools in China.

between micro built environment attributes (i.e., in this study eight travel path attributes) and children's overall preferences for travel modes.

Context-wise, at present, Chinese scholars have done much research on medium and large urban areas, but little research on rural children's school travel, especially in southwest China. Therefore, this study takes into account the current situation of rural development and the living habits of rural residents, and examines the attributes that influence children's school travel behavior and their influential relationships, and proposes practical strategies for planning and building child-friendly school travel roads in rural areas.

The rest of the paper is organized as follows: In Section Literature review, the selection of experimental design and data collection for the study are discussed. Section Stated choice design and data collection provides a discussion of the results of the model. Finally, section Results and discussion gives conclusions and policy recommendations.

Literature review

School travel is the main daily activity of children, and is also an important part of the daily life of many families. It mainly refers to the behavior of students commuting between school and home. The current modes of school commuting include walking, cycling, bus, car, public transportation, etc. Many countries refer to walking and cycling as "an active way of traveling," which is feasible in children's daily life and can increase children's physical health.

The factors affecting children's choice of school travel mode mainly include personal factors, family factors, travel characteristics factors, built environment factors and other factors.

Scholars studied on travel behavior earlier and made many achievements. At the same time, their focus gradually shifted from adults to children since 1980. The research on children's school travel behavior through school started late in China, and the research results are also relatively limited. In the existing literature, research on personal factors mainly includes age (11–14), gender (13, 15–18), race (19–21), etc. Family factors mainly include family income (22–25), family car ownership rate (26–29), family driver's license ownership rate, parents' convenience of transportation (12, 30, 31), parents' attitude toward students' travel (16, 32–34), number of brothers and sisters (32, 35), parents' education level (20, 29) and other family factors. The impact of travel characteristic factors on students' choice of commuting mode is mainly reflected in travel distance (36–42) and travel duration (28, 40). Compared with the first three types of factors, the built environment factors started late in the children's school travel and included a wide range of contents, so the impact on the choice of school age children's way of integration is also more complex. Traffic infrastructure conditions, the number of intersections, community resources, etc. will have an impact on children's school travel. For example, high pavement integrity of pedestrian roads (43), high bicycle lane coverage (44), and high shade tree density (45) all promote children's active school travel, while the increase in the number of street areas and intersections is not conducive to children's independent walking to school (45). Ikeda's research has shown that children's active school travel is positively related to their neighborhood safety perception. Obviously, compared with measurable objective factors, children's subjective perception of the environment is equally related to their learning behavior (34). In summary, the common factors impacting children school travel mode choices in the existing research include residential density (46–48), residential location (49, 50), pedestrian facilities (28, 51), travel safety (29, 52), etc.

Furthermore, Müller et al. (53) found that the closure of some schools (similar to China's policy of "removing points and merging schools") had a negative impact on the way students go to school. Khan et al. (54) survey of factors influencing students' choice of transportation to school revealed that students were more sensitive to factors such as the cost, time, and comfort in the school bus when choosing a school bus to school. Weather is also a major obstacle to children's active travel (55, 56). In addition to this, Grize et al. (57) found that cultural factors influence children's travel mode choice, and Dalton et al. (58) found a correlation between the frequency of active school travel and season in a study of rural children.

By retrieving relevant research literature on influencing factors of school age children's school travel, it is found that in recent years, scholars have discussed the travel characteristics of students in various countries and regions and the influencing factors of their travel modes, and gradually focused on the impact of built environment on children's school travel.

The combination of mature theoretical research and successful practical experience has an important guiding role in studying the influencing factors of Chinese rural children's school travel modes and improving the built environment for them. However, the influencing factors and related conclusions obtained by scholars from other contexts are not necessarily consistent with China's national conditions and cannot be directly copied.

Chinese scholars' research on children's travel modes and influencing factors is mostly concentrated in Hong Kong (49), Beijing (59), Shanghai (60) and other large cities, and some research on small and medium-sized cities (61), with little research for rural areas.

Although rural areas have been developing rapidly in recent years, there is still a large gap between urban and rural areas in terms of built environment, school layout and road scale (62). The research conclusions on the impact of urban built environment on children's school travel behavior cannot be fully applicable to the vast rural areas. Currently, Chinese scholars have conducted relatively few studies on children's travel to school in rural areas and the influencing factors exist, and these studies are still in the exploratory and initial stages, and rarely for the southwest of China. In-depth research should be conducted on the factors influencing children's school travel, taking into account the current state of rural development and the living habits of rural residents in southwest of China.

Stated choice design and data collection

Attribute selection

More specifically, for the travel path built environment attributes' impacts on travel mode selection, some scholars have found that distance has a great impact on transportation mode choice (17, 63–65), and the distance between home and school has a strong negative impact on the choice of walking to school (66). Otherwise, high traffic speeds (especially more than 30 km/h) and volume increase the risk of serious or fatal injuries to children and pedestrians, and may prevent parents from encouraging their children to walk to school (55, 67).The increase in the number of street areas and intersections also negatively affect children's independent walking to school (45).

For Chinese children in rural areas, parents often are concerned that their children will be involved in traffic accidents when walking in areas that lack facilities such as sidewalks. Scholars believe that the implementation of effective pedestrian interventions can reduce the traffic risks that hinder children from walking to school (68). For example, children have a higher proportion of walking to school in the built environment with high pavement integrity (43, 69).

Traffic lights and bicycle infrastructure are one of the main attributes that encourage cycling (70). Bicycle-specific facilities (SBFs), such as safety islands, raised curb pavement and other infrastructure separating motor vehicles and bicycles, can improve the safety of cycling, and such facilities play a good role in promoting cycling (68). Lin's observational study of adolescents found that high shade tree density and high sidewalk coverage encouraged children to walk to school independently (45), and Bosch's study found that the average density of convenience stores along the way was positively correlated with high positive traveling rate (71).

Therefore, on the basis of existing literature research and considering the actual situation of rural construction in Chengdu (in Southwest of China), this study selected eight built environment attributes, namely distance, number of intersections along the school path, sidewalk/bicycle lane, traffic speed, separation facilities between motor vehicles and non-motor vehicles, traffic lights and zebra crossings, green plants along the school path, and shops.

To design these eight attributes value levels, existing studies and the rural area conditions are combined to determine the tailor-made attribute levels for this research.

Several studies by scholars in other countries have shown that distance tends to be the primary concern of most parents. For most students, 1 mile is the maximum walking distance (72), and 2 miles is the maximum cycling distance (73). In addition, Kontou pointed out that walking was the most common way of school travel in urban and rural areas when the distance to

TABLE 1 Attribute levels.

Attributes	Levels			
Distance	**<0.5 km**	**0.5–1 km**	**1–2.5 km**	**>2.5 km**
Number of intersections passed	>5	3–5	1–2	0
Sidewalks/bike lanes	Yes		No	
Traffic speed of school path	High speed (≥30 km/h)		Low speed (<30 km/h)	
Machine non isolation facilities	Yes		No	
Traffic lights and zebra crossings	Yes		No	
Green plants	Yes		No	
Shops	Yes		No	

school was <0.5 mile, and the bicycle riding rate peaked when the home-school distance was between 0.5 and 1 mile (38).

Based on the previous research experience and data collection in nearly 100 rural areas in Sichuan Province (where the case area is located), the distance attribute in this study is divided into four levels: <0.5, 0.5 to 1 km, 1 to 2.5 km, and more than 2.5 km. At the same time, we set the attribute level of the number of intersections passing through as: >5, 3–5, 1–2, and 0.

Considering the different development conditions in rural areas and the limited awareness of rural children on traffic facilities; it is impossible to accurately quantify the traffic speed of rural school paths, lawn, flower beds, street trees and other green plants and shops on the way to school. Therefore, the level of five attributes of green plants such as sidewalk/bicycle lane, separation facilities between motor vehicles and non-motor vehicles, traffic lights and zebra crossings, green plants on the way to school, and shop is set as Yes or No, so as to facilitate the children interviewed to judge and answer.

The traffic speed of the school path is set to two levels: high speed (≥30 km/h) and low speed (<30 km/h). The attribute design level values are shown in Table 1.

Experimental design

There are many attributes that affect children's choice of school travel mode. Compared with judging directly a specific road segment, the statement choice experiment can control the covariance of the attribute level. Therefore, when other conditions are the same, the results reflect a more basic measure of children's preferences.

The application of stated choice experiments involves the creation of a design that combines the attribute levels in a particular manner. In this study, the two attributes with four levels and six attributes with two levels would result in $4^2 \times 2^6$ different profiles in a full factorial experimental design that involves all possible combinations of attribute levels. In order to make the questionnaire concise and reduce the dependence between different variables, the experimental design method was used for scenario combination. Orthogonal design and uniform design are two commonly used experimental design methods. However, orthogonal design was applied in the questionnaire because it could be used for experiments with a small number of levels (≤5).

In this study, Statistical Analysis System (SAS) statistical software was used to orthogonal combine eight attributes and corresponding levels in the design, and an orthogonal fractional factorial containing 32 attribute profiles was selected. Choice sets were created by randomly combining these 32 attribute profiles, thereby creating choice sets of two unlabeled alternatives. Each option added the option of "None" to allow the possibility that both options are lower than a certain selection threshold. The 32 choice sets were divided into eight blocks to reduce the burden on the respondents. In the end, each interviewee needed to answer the questions in four scenarios in a questionnaire. In each scenario, there are four different ways of school travel. The modes of transportation are: walking, bicycle, electric bicycle/motorcycle, and private car. The interviewees were asked to choose their favorite route scenario under each mode of transportation. If the interviewees chose "none," it means they did not like any of them. Table 2 shows an example of a selection set.

Data collection

Questionnaire design and survey administration

The questionnaire consists of three parts. The first part briefly introduces the research project and research purpose. The second part includes relevant variables of social population and rural children's school travel. The socio-demographic information involves children's gender, age, grade and whether they are the only children in the family. In order to supplement the information about children's families, the parents of the children interviewed were investigated by socio-demographic statistics. The variables include: gender, age, personal and total family income, education level, whether or not having a driving license, the number of private cars, motorcycles, electric bicycles and bicycles held by families. The third part includes four Stated Preference (SP) multiple-choice questions. The SP survey part of each questionnaire contains four combination scenarios, with a total of 16 designated choice questions. Under the premise of four modes of transportation: walking, cycling, electric bicycle/motorcycle, and private car, they can choose their preferred path to school.

TABLE 2 An example of a stated choice set for children.

	Street profile A	Street profile B	None
Distance	0.5–1 km	0.5–1 km	
Number of intersections passed	0	1–2	
Sidewalks/bike lanes	No	No	
Traffic speed of school path	Low speed	High speed	
Machine non isolation facilities	Yes	Yes	
Traffic lights and zebra crossings	Yes	Yes	
Green plants	Yes	Yes	
Shops	No	No	
If you walk to school, you choose	[ ]	[ ]	[ ]
If you go to school by bike, you choose	[ ]	[ ]	[ ]
If you go to school by electric bicycle/motorcycle, you can choose	[ ]	[ ]	[ ]
If you go to school by private car, you choose	[ ]	[ ]	[ ]

FIGURE 5
Distribution map of investigation areas.

Because children have not been exposed to such surveys, they may have misunderstanding and choose wrong options. Therefore, before asking the children to complete these 16 tasks, the investigators showed the children interviewed photos or videos of attributes involved, and explained all attributes and their levels. Then, the investigators made an example of selection to help the children to understand. The research team has organized a face-to-face questionnaire survey with rural children in July 2021. The preliminary selection of sample areas and villages was carried out by collecting information online and looking up maps. According to the distance from the center of Chengdu, the suburban areas were selected: Wenjiang District, Xindu District, Longquanyi District, Pidu District; Chongzhou City, Qingbaijiang District, Jianyang City, and Pengzhou City. The sample villages are selected from the eight regions. The regional distribution is shown in Figure 5.

Investigators learn about the situation of each village by communicating with residents, querying information online or searching maps, and select villages that are convenient, well-developed, and have schools in the village or nearby villages. The researchers also select several nearby villages to prevent insufficient sample size. Before the formal investigation, we conducted a pre-investigation, and selected 33 sample villages randomly according to the vigilance and cooperation of the villagers. The respondents all have agreed their participation in the research and all the data has been anonymized. For non-adults, their guardians have approved their participation as well.

Sample characteristics

Six hundred and thirty eight valid questionnaires were finally collected through household survey in 33 villages. In this study, the dependent variable travel mode is defined as walking, bicycle, bus, private car, electric bicycle and motorcycle. Among them, the proportion of choosing electric bicycle is the largest, 58.60%, followed by private cars, pedestrians and buses, 14.10, 13.20, and 9.20%, respectively. The proportion of students who choose bicycles and motorcycles for school travel is relatively less, 3.40 and 1.40%, respectively.

The detailed information of the selected socio-demographic variables' used in this research are shown in Table 3. According to the survey data, most of the surveyed children are boys, with 339 in total, accounting for 53.1% of the total surveyed children. 67.4% of the surveyed children are at the grade level of primary school. Most of the rural areas have built rural or township primary schools. It is easy for rural children to go to primary school, while rural school-age children may go to school in different places because of school choice when they go to junior high school. 52.2% of the surveyed children's parents are over 50 years old, and more than half of the parents are grandparents of the surveyed children. 51.3% of the surveyed parents have education level in primary schools and below. It can be seen that young and middle-aged workers are more willing to go out to work, while grandparents stay in the village to take care of children's life and study. The annual personal income of 48.2% of the interviewed parents was <10,000 RMB, and the percentage of children with total family income between 10

TABLE 3 Socio-demographic variables.

Personal attributes		Frequency	Personal attributes		Frequency
Gender	Male	53.1%	Only child	Yes	62.9%
	Female	46.9%		No	37.1%
Age	6–12 years old	69.0%	Grade	1–6	67.4%
	13–15 years old	22.0%		7–9	22.7%
	15–18 years old	8.9%		10–12	9.9%
Parental attributes		**Frequency**	**Parental attributes**		**Frequency**
Gender	Male	36.1%	Relationship with the children	Father	14.6%
	Female	63.9%		Mother	29.0%
Age	Under 30 years old	5.0%		Grandfather	24.3%
	31–40 years old	31.5%		Grandmother	31.8%
	41–50 years old	11.5%		Other	0.3%
	51–60 years old	35.5%	Annual personal income	<¥10,000	48.2%
	60 years old or older	16.7%		¥10,000–50,000	39.7%
Education level	Primary school and below	51.3%		¥50,000–100,000	11.1%
	Junior high school	24.3%		¥100,000–150,000	1.6%
	High school or junior college	20.1%	Driver's License	Yes	31.0%
	College degree	2.4%		No	69.0%
	Bachelor's degree	1.9%	Can ride a motorcycle	Yes	89.7%
	Master's degree and above	0.2%	/Electric bicycle	No	10.3%
Parental attributes		**Frequency**	**Parental attributes**		**Frequency**
Family members	3 and under	8.8%	Total household income	¥10,000–50,000	30.1%
	4	19.0%		¥50,000–100,000	46.0%
	5	41.1%		¥100,000–150,000	18.4%
	6 and above	31.1%		¥150,000–200,000	5.2%
				More than ¥200,000	0.3%
Number of cars	0	52.2%	Number of motorcycles	0	81.2%
	1	45.9%		1	18.5%
	2	1.7%		2	0.3%
	3 or more	0.2%		3 or more	0
Number of electric bicycles	0	6.0%	Number of bicycles	0	74.7%
	1	83.7%		1	24.8%
	2	8.9%		2	0.3%
	3 or more	1.4%		3 or more	0.4%

and 50,000 RMB was 46.0%. With the continuous promotion of the rural revitalization process and the development of the rural economy, 47.8% of the families owned a private car. The proportion of households with one electric bike was the highest, followed by private cars, bicycles and motorcycles. Compared with motorcycles, rural residents are more willing to choose light, flexible and affordable electric bikes for daily travel.

Data coding

After the questionnaire work was completed, the unfilled questionnaires were first screened and valid survey data were entered to test their reliability and validity. In addition, the study also coded the socio-demographic variables and micro-attributes of the built environment for school travel as required by the SP questionnaire data analysis. For example, male gender is coded as 1, female gender is coded as−1. For micro-graphic built environment attributes, three indicator variables were constructed for each attribute with four levels. Each indicator variable corresponds to a category coded as 1, the remaining categories are coded as−1 for all three indicator variables. For each attribute with two levels, two indicator variables are constructed, and the category corresponding to the "yes" indicator variable is coded as 1, and the category corresponding to the "no" indicator variable is coded as -1.

TABLE 4 Likelihood ratio test for independent variables.

Model	Chi-square test	
	Chi-square	Significance
The model of walking conditions	1523.014	0.000
The model of bicycle conditions	1220.765	0.000
The model of electric bicycle/motorcycle conditions	962.850	0.000
The model of private car conditions	1998.975	0.000

Results and discussion

Modeling analysis was conducted based on the SP survey to construct a functional relationship between transportation mode and influence attributes. In this study, multinomial logit model (MNL) was used (74) to analyze the preference of the interviewed children for school travel environment under different transportation modes, and all four models passed the chi-square test, and the significance was <0.05, meaning that the models fit well. And the test results and model fitting parameters are shown in Tables 4, 5, respectively.

Analysis of rural children's preference of walking in school travel environment

On the premise that walking is selected as the school travel mode, the influence of distance attribute on the first and second levels is 1% significant at the general level, with positive values. This indicates that when children choose to walk to school, they are willing to walk within a distance of <500 m and a distance between 500 m and 1 km, and the first rank coefficient is greater, indicating that the interviewed children prefer to walk to school within a distance of <500 m. The influence of distance on the third level is significant and negative at the normal level, which indicates that children do not like walking for the distance between 1 and 2.5 km.

The influence of the number of intersections on the first and second levels is 1% significant at the normal level, with negative values, indicating that children who walk to/from school do not like the sections with the number of intersections between 3 and 5 or more. This is consistent with existing findings that neighborhood built environment characteristics (i.e., major street intersections, retail density, and neighborhood density) are strongly associated with the odds of walking (75–78).

The partial value utility of sidewalks suggests that children who walk prefer the presence of sidewalks, which is consistent with existing research (43). Lack of sidewalks or intermittent sidewalks are considered a barrier because they make walking to school more dangerous, and discontinuous sidewalks force children to cross the street repetitively, increasing the number of children crossing intersections and posing a potential hazard (30). The installation/widening of crosswalks and sidewalk improvements would result in a significant increase in the number of children walking or bicycling to school (71). However, in the actual rural school travel built environment, most rural areas only have sidewalks near school sections, and in some rural areas even all sections are country roads, which indicates the need for sidewalks in future planning.

The effect of the first level of the vehicle speed attribute has a negative significance at the 1% level at conventional levels, indicating that children walking to/from school do not prefer environments with vehicle speeds >30 km/h. This may be due to the fact that a school travel built environment with high vehicle speeds can compromise children's walking safety. Carlson et al. (79) combined the effect of major roads on the odds of walking to school and found that children and parents may seek a route with lower traffic speeds to walk to school. As shown in Table 5, when children walk to school, they prefer facilities with road teeth, fences, green strips, and delineations that separate them from motor vehicle lanes. For children who walk, the effect of having traffic lights and crosswalks was significant at the 5% level, indicating that children who walk to/from school prefer crossing facilities. Greening facilities on the path to and from school indicate that children on foot prefer greenery such as lawns, flower ponds, and street trees on the path. In addition, the study finds that children who walk to/from school prefer to have shops on the way to school or in front of the school, probably because children are younger and like to stay and play at the shops on their way to/from school or buy small items such as snacks, toys, and stationery.

To summarize, for walking to school, the attribute that children care most about is distance, they are most likely to walk to school within 500 m. As the distance increases, their chances of choosing to walk to school decrease. The installation of sidewalk and isolation facilities between motor vehicles and non-motor vehicles will bring a sense of security. The green plants such as lawn and street trees along the school path will provide shade, isolation protection, and increase the sense of visual beauty for children who walk to school, thus promoting children to choose to walk to school, while the high traffic speed will hinder children from choosing to walk.

Analysis of rural children's preference of cycling in school travel environment

The effects of the distance attribute at the first and second levels were positive 1% significant at conventional levels, given the choice of bicycle to/from school, indicating that when children choose bicycle to pass school, they prefer to ride a bicycle at distances <500 m and at distances between 500 m and 1 km. Interestingly, the coefficient of the distance attribute is

TABLE 5 MNL model parameter estimation.

Attributes	Levels	Walk		Bicycle		Electric bicycle/motorcycle		Private car	
		Coefficient	Prob. |z|>Z*	Coefficient	Prob. |z|>Z*	Coefficient	Prob. |z|>Z*	Coefficient	Prob. |z|>Z*
Constant 1	1	−0.23602***	0.0000	0.55352***	0.0000	1.15344***	0.0000	0.19850***	0.0027
Constant 2	2	−0.33153***	0.0000	0.54682***	0.0000	1.05480***	0.0000	0.24947***	0.0002
Distance	<0.5 km	1.85974***	0.0000	0.73180***	0.0000	−1.42555***	0.0000	−2.68426***	0.0000
	0.5–1 km	0.73208***	0.0000	1.24804***	0.0000	0.24302***	0.0000	−0.70456***	0.0000
	1–2.5 km	−1.17038***	0.0000	−0.01883	0.7530	0.76149***	0.0000	1.27666***	0.0000
	>2.5 km								
Number of intersections passed	>5	−0.20194***	0.0045	−0.30775***	0.0000	−0.26279***	0.0000	−0.69916***	0.0000
	3–5	−0.24675***	0.0002	−0.09207	0.1290	−0.11990**	0.0267	0.02579	0.6998
	1–2	0.03199	0.6113	0.11466**	0.0421	0.00822	0.8837	0.13555*	0.0650
	0								
Sidewalks/bike lanes	Yes	0.15930***	0.0000	0.24438***	0.0000	0.14094***	0.0000	−0.01961	0.6201
	No								
Traffic speed of school path	High speed (≥30 km/h)	−0.10151***	0.0055	−0.37477***	0.0000	−0.20032***	0.0000	0.02775	0.4869
	Low speed (<30 km/h)								
Machine non isolation facilities	Yes	0.11928***	0.0010	0.22611***	0.0000	0.21501***	0.0000	0.00748	0.8481
	No								
Traffic lights and zebra crossings	Yes	0.09818**	0.0114	0.39925***	0.0000	0.39301***	0.0000	0.27501***	0.0000
	No								
Green plants	Yes	0.19735***	0.0000	0.32175***	0.0000	0.28826***	0.0000	0.23838***	0.0000
	No								
Shops	Yes	0.10227***	0.0077	0.22700***	0.0000	0.16474***	0.0000	0.06695	0.1027
	No								

***, **, * indicate significance at 1, 5, and 10% levels, respectively.

greater at the second level and the effect of the distance attribute at the third level is not significant at the conventional level, indicating that the interviewed children prefer to take the bicycle mode to pass school within the range of 500 m to 1 km. This is similar to the study by Kontou et al. (38) who found that the rate of bicycling peaked at home-school distances of between 0.5 and 1 mile.

The effect of the first of the number of intersections attribute is significant and negative at the conventional level, which indicates that children who cycle to/from school do not prefer road environments with more than five intersections. The effect at the third level is significant at the conventional level of 5%, indicating that children prefer to take the bicycle in a road environment with 1–2 intersections on the way.

Part of the value and utility of bicycle lanes show that children who travel to school prefer the road environment with bicycle lanes. The effect of the first level of the speed attribute had a negative significance of 1% at the conventional level, indicating that children do not prefer environments with speeds >30 km/h when choosing bicycles to get to/from school, which may be due to the fact that a built environment with too high a speed can affect children's safety through school.

The property of the isolation facilities between motor vehicles and non-motor vehicles shows that children prefer separated facilities from motorized lanes when bicycling to school, and that a built environment with separated facilities makes children feel safer.

For children who bicycle to/from school, the effect of having traffic lights and crosswalks was significant at the 1% level with a high significance coefficient, indicating that children who bicycle to/from school prefer cross-street facilities. The greenery on the path to school showed that children who bicycle to school prefer to have greenery such as grass, flower ponds, and street trees on the path to/from school. Children who bike to/from school prefer traveling paths with shops on their way or in front of the school. This is consistent with established research that higher average density of convenience stores is associated with higher odds of active traveling (71).

It is found that the maximum distance that rural children can accept is 1 km, and the distance they are most willing to ride a bike is between 500 m and 1 km. This may be because the distance of 500 m is short and it is not as convenient as walking to park a bike. During the visit, many children also said that they were not allowed to ride bicycles to/from school alone. Even though they had the ability to ride bicycles to/from school independently, parents do not allow children to ride bicycles to school independently for fear of children's safety. This is because that most of the rural roads have many intersections, with no special bicycle lane, and there is a lack of a safe bicycle environment.

Analysis of rural children's preference of electric/motorcycling in school travel environment

The effect of the distance attribute at the first level was 1% significant at the conventional level and negative when children chose to ride the electric bicycle/motorcycle to/from school, indicating that when children chose to ride the electric bicycle/motorcycle to and from school, they did not prefer to ride the electric bicycle/motorcycle at distances of <500 m. The effect of the distance attribute at the second and third levels was positively significant at the conventional level, indicating that children preferred to ride the electric bicycle/motorcycle at distances of 500 m or more. The effects of the first and second levels of the number of intersections attribute had a negative significance of 1% at the conventional level, indicating that children who ride to/from school by electric bicycle/motorcycle do not prefer road environments with more than three intersections; and the effect at the third level was not significant at the conventional level.

Some of the value utility of sidewalks/bike lanes suggests that children who go to school on electric bicycle/motorcycles prefer a road environment with bike lanes, possibly because children perceive that electric bicycle or motorcycles can be driven on bike lanes and that bike lanes provide them with safety and convenience.

The effect of the first level of the speed attribute has a negative significance of 1% at the conventional level, indicating that children do not like to choose electric bicycles or motorcycles to pass school in road environments where speeds are generally >30 km/h, and that driving environments with excessive speeds can be dangerous for children. The results show that when they go to school by electric bicycle or motorcycle, they liked to have such isolation facilities as curb, fence, green separation belt and scribing.

The school travel built environment with isolation facilities will enhance children's sense of security. The traffic light and zebra crossing attributes have a 1% level of significance at the first level of impact with a high significance coefficient, which indicates that children who ride to/from school on electric bicycles or motorcycles prefer to cross street facilities. The attributes of green facilities and shops on the path to school indicated that children who traveled by electric bicycle or motorcycle to school preferred the presence of shops and greenery such as lawns, flower ponds, and street trees on the path to/from school.

During the survey, the researchers found that most of the rural school-age children interviewed were transported to/from school by their parents on electric bicycles. In the survey on the preference of the built environment variables for children's school passages by electric bicycles, the highest significance was found for the range attribute of 1 to 2.5 km distance, and they also disliked the road environment with too high speed and too many intersections.

Analysis of rural children's preference of private car in school travel environment

The effect of the distance attribute at the first and second levels is significant at 1% at conventional level and both are negative, given the choice of private car to and from school, indicating that when children choose private car to go to school, they do not prefer to travel by private car at distances <500 m and distances between 500 m and 1 km, which may be due to children's consideration of factors such as time, cost, and convenience. The effect of distance attribute at the third level is positively significant at conventional level, when the distance to/from school is >1 km, they are willing to go to and from school willing to choose private car as the transportation. The effect of the first of the number of intersections attribute is significant at the conventional level of 1% and negative, indicating that children who travel to/from school by private car do not prefer road environments with more than five intersections and that too many intersections may prolong school travel time; the effects at the other two levels are not significant at the conventional level.

There is no significant difference in the attributes of sidewalks or bicycle lanes, speed, isolation facilities between motor vehicles and non-motor vehicles, and shops, which indicates that these attributes of the built environment for school travel have no impact on children taking private cars. The traffic light and crosswalk attributes have a 1% level of significance at the first level of impact with a high significance coefficient, which indicates that children who travel to/from school in private vehicles prefer to cross street facilities. The attributes of green facilities on the path to school indicate that children who

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travel by electric bicycle or motorcycle to school prefer to have greenery such as grass, flower ponds, and street trees on the path to/from school.

For children who go to/from school by private car, they prefer a built environment with fewer intersections, traffic lights with crosswalks and greenery, in addition to distance.

Analysis synthesis

The four multinomial logit models analyzing the preferences of the school travel built environment for the four travel modes showed two constant terms. Only the constant term of the choice experimental model in the walking condition was negatively significant, while the constant terms of the remaining three choice experimental models were positively significant. This suggests that in addition to the attributes and levels set by this study, there are other attributes of the school travel built environment that can affect walking or bicycle, electric bicycle, private vehicle, etc.

Conclusions and policy recommendations

The purpose of this study is to provide more insights on the relationship between the micro built environment attributes (like travel path attributes) and children's travel mode preference for school. To this end, a statement choice experiment was designed in rural areas of Chengdu, China. Supposing that rural school-age children want to walk, ride a bicycle, or take a private car to and from school, we invite them to point out which one they will choose under different street profiles. Compared with the judgment of specific road sections, the advantage of using the statement choice experiment is that we can control the covariance of attribute levels. Thus, all else being equal, the results reflect a more basic measure of children's preferences.

The research results show that, in addition to the general road related variables (distance, number of intersections passed, sidewalk/bicycle lane, traffic speed, isolation facilities between motorway and non-motorway, traffic lights and zebra crossings and other street crossing facilities), the greening and shop also have a significant impact on children who go to and from school by walking, bicycle, electric bicycle or motorcycle, and private car. For road related variables, the results show that children who commute to school on foot, bicycle, electric bicycle or motorcycle prefer to commute to school sections with sidewalks or bicycle lanes, few intersections, low traffic speed, green plants and shops.

In this study, children's preferences and differences for the school section under the four transportation modes are compared. For the distance attribute, children who walk to school or go to school by bike have a positive preference for shorter road sections, but children who walk prefer the road sections within 500 m, while children who go to school by bike prefer the road sections within 500 m to 1 km. For children who go to school by electric bicycle or motorcycle and private car, they will choose the road sections with larger distances. Children prefer a safer school travel built environment, such as a school travel roadway with fewer intersections, separated facilities, sidewalks or bike lanes, and well-developed crossing facilities.

Some of the results are consistent with the literature. Children who were physically exposed to environmental passages were more sensitive to green plants. Children's nature also leads them to have a significant positive preference for the school path with shops. The literature also shows that shops (retail stores) are having an impact on children's school travel (75, 80). In this study shops were found to be a highly preferred attribute level for children who walked, biked, or commuted to school by electric bicycle/motorcycle. The presence of greenery and sidewalks/bike lanes also influence children's school travel styles, which have been studied in most past studies (81–85). In this study, greenery and sidewalks/bike lanes were studied at both the presence and absence levels to show the impact on children's school travel styles. The traffic lights as one of the crossing facilities have been studied in past studies (86–89). However, zebra crossing, an important crossing facility, have been little studied together with traffic lights. This study includes both crossing facilities together and provides two preferences for them. The purpose of this study is to explore a healthy built environment for rural school-age children and to reduce parents' commuting pressure to and from school by improving the built environment for school travel and promoting public health. However, the results of the study may not comprehensively reveal the implied pattern of the built environment impacts on road choice for rural students due to long-standing constrains for a single case study (90, 91), more cases are suggested to further explore the pattern to acquire more insights in future studies.

Some advice based on the empirical results are listed here: relieving traffic congestion and chaos caused by private cars and electric bicycle to the vicinity of the school; providing a built environment for children to go to/from school alone; promoting active school traveling for rural children; increasing social interaction opportunities for children, and promoting low-carbon travel for rural residents. This research can provide some inspiration and reference for future rural road planning and design practice.

Data availability statement

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

Ethics statement

Ethical review and approval was not required for the study on human participants in accordance with the local legislation and institutional requirements. Written informed consent to participate in this study was provided by the participants' legal guardian/next of kin.

Author contributions

Conceptualization and formal analysis: LH and YW. Data curation: LH, XD, and ML. Funding acquisition and writing—review and editing: TW. Investigation: LH and XD. Methodology and project administration: YW. Supervision: YW and TW. Writing—original draft: LH, XD, and TW. All authors have read and agreed to the published version of the manuscript. All authors contributed to the article and approved the submitted version.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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Designing for the post-pandemic era: Trends, focuses, and strategies learned from architectural competitions based on a text analysis

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The COVID-19 pandemic has made the built environment an important source of prevention and control, architects and scholars have thus been seeking countermeasures since the beginning of the outbreak. As design and construction cycles are long, only a few completed cases and evidence-based studies are available for reference. However, massive architectural competition works have emerged, which always been the soil for discussion and practice of cutting-edge design issues. These contain a vast number of ideas for solutions from various design dimensions—including cities, buildings, and facilities—and provide a great deal of materials worth analyzing and summarizing. Therefore, the exploration of competitions will provide us with public health intervention directions, strategies and a rethinking of the built environment. Using a text-mining approach, we analyzed 558 winning entries in architectural competitions related to the pandemic response, exploring specific issues, populations involved, coping strategies, and trends that emerged as the pandemic evolved. Our results show that the strategies proposed can be grouped into 17 keywords, with modularization being the most frequent strategy and related strategies like rapid assembly, flexible space, etc. are also took a significant percentage of the use. Further, we explored the technical orientation, year, territory, target groups, and target problems of the works which lead to a series of cross-comparison relationships. The results indicate that indirect impacts caused by the pandemic gained more attention and flexible Solutions were used more often highlighted the consensus when adapting to the uncertainties. The focus on the spiritual dimension is increasing year by year reflected the spiritual influences were gaining traction and the indirect impacts gradually showed up over time. The research will provide a strategy reference for the design response to the pandemic, as well as help understand the influence and significance of social factors behind the divergence of issue focuses and strategic tendency in different regions and times.

KEYWORDS

COVID-19, architectural competitions, text mining analysis, statistical analysis, design strategies, social focuses, design trends

Introduction

The coronavirus disease 2019 (COVID-19) outbreak has had a massive impact on all of society and has triggered a major public health crisis (1). Despite the implementation of measures such as social distancing, lockdowns, border closures, and human tracing having effectively controlled the spread of COVID-19 (2), there were concurrently multiple secondary impacts (3, 4), such as psychological effects (5, 6) and changes to physical activities, functions, and quality of life (7).

The transmission of infectious diseases among the populace is related to epidemiology and even more closely to the built environment. The intersection of the two fields was noticed as early as the Middle Ages when controlling environmental factors helped bring an end to the bubonic plague (Black Death) in the 14th century. This launched related research on the built environment as an intervention in public health (8). The cholera outbreak in London in the 19th century brought awareness of the geographic linkages of the disease (9), which led to changes in the approach to urban planning. These included the creation of larger public spaces between buildings and more organized layouts, governance of dirty and overcrowded neighborhoods, and introduction of additional parks and green spaces in the city center (10). The urban design of Paris incorporated extensive amounts of lengthy streets and open spaces to establish a well-developed infrastructure for the sewage system (11). In the 1950s, building designs incorporated terraces, balconies, and flat roofs to curb the spread of tuberculosis and other respiratory diseases (12).

Thus, public health issues have major impacts on urban planning, design, and development, and the related crises have resulted in the restructuring and optimization of urban spaces (13). These historical experiences of integrating the built environment and public health fully demonstrate that urban design is an integral factor in improving public health (14, 15) and plays a critical role in the prevention of disease outbreaks; the control, isolation, and mitigation of pandemics; and the formulation of countermeasures after such events (16).

The COVID-19 pandemic has persisted for nearly 3 years. During this period, there have been enthusiastic discussions in academia and the industrial sector, leading to diverse perspectives on related issues and countermeasures. These include the influence of different environments on wellbeing during the COVID-19 period (17, 18), the need to develop a resilient urban system of the future (19), and a paradigm shift toward the built environment to consider the effects of pandemics and informatization (20). However, building and urban development involve lengthy construction cycles, and evidence-based research on optimizing the built environment for pandemic conditions is limited. Most existing research aimed to uncover the principles and discuss the related impacts (21–25). However, designers are practitioners and work mostly based on their accumulated experience and the relevant specifications of their current projects. The impact of the pandemic on design goals and methods is enormous, and it will take years to develop new design guidelines based on experience and post-occupancy evaluations (POE) of completed works. In response to the pandemic, a large number of new construction or renovation optimization projects have emerged. While the final structures will be used for decades after their completion, these programs often involve short-term cycle and heavy design tasks, leaving little opportunity for architects to explore existing social needs and solutions. Nevertheless, unearthing existing needs and responding to them is an important challenge for the industry today that directly affects the long-term influence of the built environment on public health in the post-pandemic era.

In the academic and industry sectors, architectural design competitions have always facilitated thought experiments and free expression of ideas on social issues. Architectural design in a broad sense encompasses a wide range of content, from urban planning to building design to landscape and interiors, all within the larger architectural context (26); in short, the built environment, and therefore the architectural design competition entries, often include a discussion of all aspects of the built environment. Previous research on this topic often focused on the presentation and analysis of one or several such competitions, such as compiling the competition works into publications to showcase the results, discussing the issues faced during the process of the competitions (27–30), performing comparative analyzes of various series of competitions (31–33), and discussing the strategies derived from specific designs presented in the competitions (34–37). Similarly, there was a flourishing of ideas on various issues related to the pandemic after its outbreak. There were numerous discussions on the use of design strategies for the built environment as interventions for the pandemic, as well as thoughts and reflections on the pandemic from various perspectives. Architects generated a large number of cases and refined design methods in a short period of time in response to the changes in the environment. Cumulatively, these are valuable resources for design practices and constitute a good opportunity for comprehending the variations in focus across different geographic regions and over time. By analyzing these works we hope to obtain a series of inspiring solutions for architects and decision makers, but also to explore the commonalities and differences and the reasons behind them.

Following from the above, the issues being examined in this study were as follows:

RQ1: What specific social issues did the competition works focus on as a result of the pandemic? What were the proposed solutions to those issues?

RQ2: Have the attitudes and focus on social issues changed over time with the progression of the pandemic? Have the strategies proposed for resolving the issues been revised accordingly?

RQ3: Do the focus and proposed strategies differ from a geographic perspective?

Materials and methods

Data sources and processing

To gather as many competition works related to the pandemic as possible, the research team conducted searches at two levels: competitions and design works. Given that the COVID-19 infection first appeared at the end of 2019, we searched within the timeframe of 2020 until August 2022. This would include all architectural competitions held in 2020–2022. First, the team screened competition themes posted on websites within and outside China pertaining to renowned architectural design competitions. This included more than 10 websites such as ArchDaily/Architecture Competitions, Arc race, Archinect, Bustler, Archi Competition, and the competitions blog, which are specialized websites that collect and publish information on architectural design competitions or professional websites that share winning works. The relevant competition information was found through searches using keywords such as "pandemic" and "COVID-19" with the winning works being directly added to the database.

Second, the massive changes brought on by the pandemic throughout society led to many design works intending to deal with and solve the related problems. The award-winning works were manually identified according to the well-known series of competitions that have been held for many years. The pandemic was not the sole competition theme being considered; any design work that dealt with the topic was collected. Finally, general Internet searches were conducted using keywords such as "pandemic," "COVID-19," and "competition" to supplement the database with a small number of competitions and works not found in earlier searches.

Review data collection

We compiled 553 winning works from 56 competitions (Figure 1). Among them, 33 competitions had themes that were clearly limited to COVID-19, and the remaining 23 had winning works produced within this scope. There were 20 and 36 competitions hosted within and outside China, respectively. From the annual distribution, in 2020, 2021, and 2022, there were 318, 219, and 16 works, respectively.

A search of the related competitions led to the discovery of five works in 2015 related to the pandemic theme. These works focused on infectious diseases such as cholera and Ebola, which broke out in Africa. Considering that works with similar concerns at different times could provide useful comparisons, these were also incorporated into the overall database of winning works, giving a total of 558 works. Of all the studied works, 201 and 357 were from within and outside China, respectively. A categorization was made according to the geographic location of the competition organizers. Asia had the highest number of works at 388, followed by Europe (131), America (29), and Africa (10).

The various competitions had different ways of ranking the winning works. Thus, in addition to the explicit first, second, and third prizes, which were recorded as Award Levels 1–3, respectively, a fourth category of Award Level 4 was added to include works with excellence awards and shortlisted finalists.

A preliminary database was prepared by sorting out the recorded information on the name, theme, year, and other textual information on the competitions, as well as the regions the competition winners were from, their award levels, and descriptions of their works.

Methods

The four steps of graphic language conversion, text mining, data coding, and text analysis were applied sequentially to transform the drawing works from graphic to textual languages for the purpose of statistical analysis. After key information was extracted from large amounts of textual data, the unstructured textual information was encoded before the meaning and lessons learned were obtained. These constituted the four portions of the research contents.

An important preliminary task was to convert and break down the competition drawings into the textual language required for subsequent research. Some works had textual descriptions provided on the winning pages or drawings. After a manual inspection to determine that all information required for the study was covered, the texts were directly extracted and entered into the database. The tasks of image recognition and textual description had to be manually completed for works with no or incomplete information provided. All researchers involved are professionals, and accuracy during conversion was ensured by their ability to parse and extract the design ideas and key information from the drawings. In addition to the corpus required for text mining after conversion of the design descriptions, other details such as the target population and selected building types were included separately in the database.

The contents of text mining in this study were divided into two parts: competition themes and introduction of the works. Further exploring the themes set by the competition organizers helped us understand the focus and guiding direction of these institutions or organizations in the context of the pandemic. Delving into the introduction of the works also allowed us to grasp the observations and responses that were prominent in the design perspectives. In other words, the first part pertained to

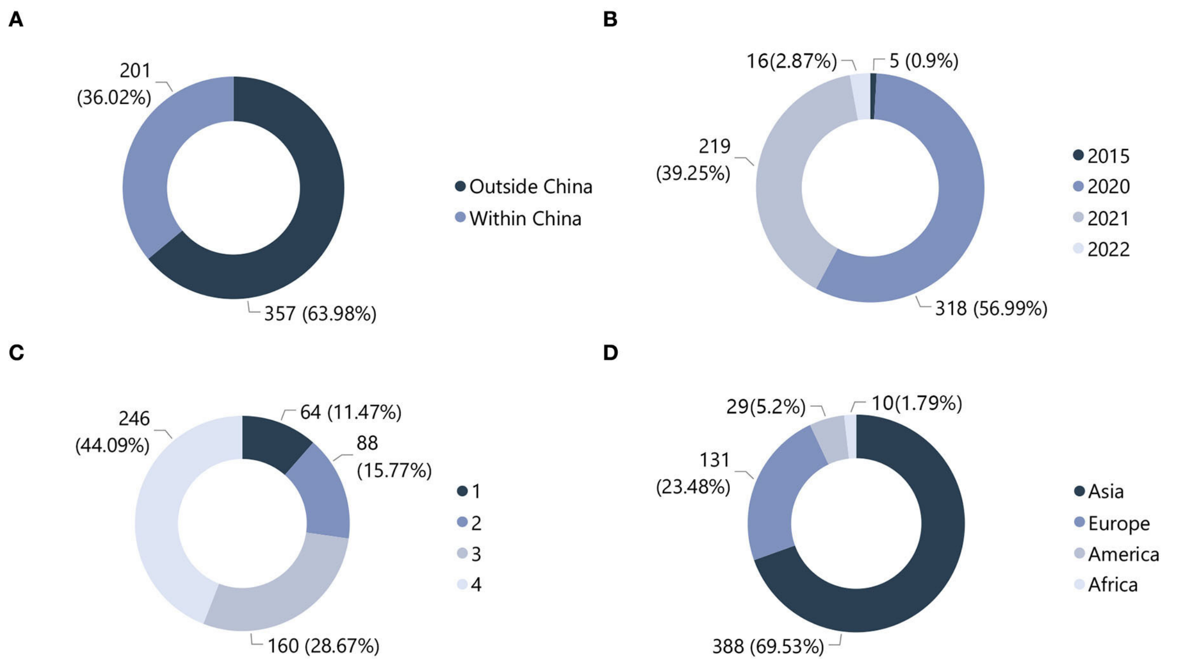

FIGURE 1
Distribution of collected competition works. **(A)** Territory. **(B)** Year. **(C)** Award level. **(D)** Country.

observations at the social level, and the second part related to ideas at the individual level.

Text mining as a mainstream methodology has a wide range of applications in many fields (38–40), which involves techniques such as distribution analysis, clustering, trend analysis, and association rules, etc., (41). In this study, the NLPIR Big Data Semantic Intelligent Analysis Platform 1.0.0.1 (42) and WordArt (https://wordart.com/) were used for text mining and visualization of the results, respectively. First, all the competition topics and work descriptions with the pandemic theme were compiled into one document to form a source folder for the corpus. After accessing the NLPIR platform and launching the "New word discovery" tab, the corpus was imported for the extraction of new words and keywords (43). The extracted results were entered into a user dictionary, together with labeled keywords that were manually summarized. Next, the user dictionary was imported to the "Batch word segmentation" tab for word segmentation of the corpus. Following this step, the common stopword list was imported to the "Language statistics" tab for compiling the statistics on word frequency. The meaningful and meaningless words were screened and categorized accordingly, with the latter placed in the stopword list. The statistics on word frequencies were then compiled again. The entire process was repeated to increase the accuracy of the word frequency data. After one round of manual screening, the word frequency data were entered into WordArt to generate word clouds.

The word frequency results obtained through text mining were classified into two groups: issues and solutions. These formed the main basis for data encoding. The core focus of this study was to identify the issues that the competition works highlighted in the context of the pandemic and the proposed solutions. The first step was coding the issues toward which the works were oriented. Descriptions of the issues gathered during the previous step of graphic language conversion were summarized into five primary and seven secondary categories. The primary categories were (1) original building and space form non-adapted to the normalization of pandemics, (2) spiritual needs in the context of a pandemic, (3) medical resource supply shortage, (4) medical building optimization, and (5) unreasonable resettlement of floating personnel.

Under Category (1) were two secondary categories: unreasonable function and organization of human living space in a pandemic situation and unreasonable urban public space in a pandemic situation. Under Category (2) were two secondary categories as well: commemoration of people and events related to the pandemic and restoration of the psychological impact of the pandemic. After extraction from the converted text, the strategies of the competition works in response to the pandemic were coded to form 17 strategy labels. These covered the design contents highlighted by the high-frequency words. There was also a small number of labels that were not high-frequency words, some of which could be grouped under similar keywords according to their contents.

A work might correspond to more than one strategy label owing to the complexity of the works and the various foci under the scope. For example, Work No. 275 integrated eight strategies to enhance the adaptability of urban public spaces as its response to the pandemic. After the coding was completed, information on the works, including the year, territory (within or outside China), continent, award level, technical orientation, and target group, was treated as the input variables. Following this step, the graphic language was completely converted into label information, and the complete database of 558 works was finally formed for subsequent analysis.

The statistics and description of the data were of great significance in this study. We used these numbers and proportions to understand the designers' thoughts and solutions to the pandemic, as well as the common and evolutionary characteristics. IBM SPSS Statistics 26 software was used to conduct statistical computations of the frequency and percentage of each variable in the database. After the chi-square test, pair-wise cross-tabulation analysis was performed on those variables with significant differences to determine the variations in data under different conditions of variable classifications.

Results

Results of text mining

The acquired data were divided into two parts: information on the competition themes and that on drawing works information. After NLPIR and manual processing, 29 new words and 92 keywords were obtained for information on the competition themes, and 36 new words and 89 keywords were obtained for drawing works information. The new words and keywords were imported into the word segmentation dictionary to obtain more accurate results for word segmentation, leading to the statistical results for single and binary word frequencies. There were 39 single word frequencies on competition themes, and 79 single word frequencies and 20 groups of binary word frequencies for drawing works information. Table 1 shows the top 30 words with the highest frequency extracted from the themes and works.

The visualization results indicated that the parties designating the competition themes emphasized the pursuit of a healthy life (Figure 2). "Complex system," "fitness products," and "comfort" appeared multiple times in the list of new words, whereas "fitness," "health," "sports," and "isolation" featured frequently among the keywords. Among the single words, the word frequencies of "community" and "health" had greater weights. The discussions of space presented diversified and cutting-edge designs among the drawing works information, concerned issues such as "healthcare," "flow lines," "social," "infrastructure," etc., buildings and spaces such as "community," "hospital," "public space," "square," "roof," etc., resorted to strategies such as "modularization," "elasticity," "resilience," "mobility," "prefabrication," "improving living quality," "intelligence," etc. All these reflected the competitors' positive thinking during the unusual period. Where modularity appears most frequently as a strategy.

Results of the descriptive statistics

Results of frequency analysis

There was a wide range of competition works dealing with architectural/design carriers, with the scale ranging from the macroscopic level of cities to the microscopic level of facilities. These could be grouped into seven categories (Figure 3), with public buildings occupying the largest proportion at 28.7%. The other categories were residential buildings (26%), facilities (18.8%), communities (12.2%), public spaces (5.7%), cities (4.5%), other building types (4.1%), and works at the non-building level accounted for 41.4% of the total. Works dealing with the population were divided into 12 categories; the populace and residents categories accounted for 37.6 and 37.8% of the total, respectively (Figure 4). Doctors and patients accounted for 13.4%, and the remaining categories each accounted for ∼3% or less of the total: refugees (3.2%), teachers and students (2.7%), floating personnel (1.6%), elderly adults (1.3%), deceased individuals (1.3%), white-collar workers (0.5%), low-income individuals (0.2%), adolescents (0.2%), and athletes (0.2%).

The target problems could be broadly divided into direct and indirect impacts of the pandemic (Figure 5A). The indirect impacts accounted for 80.2% of the total; 72.2% were concerns over the original building and space form non-adapted to the normalization of the pandemic situation. Unreasonable function and organization of human living space in a pandemic situation and unreasonable urban public space in a pandemic situation accounted for 40.9 and 31.2% of the total, respectively. The proportion of works focusing on spiritual needs in the context of a pandemic situation was 8.2%, and those for the commemoration of people and events related to the pandemic and restoration of the psychological impact of the pandemic were 5.7 and 2.5%, respectively. The proportion of works on the direct impacts of the pandemic was 19.8%, with the medical category receiving the most attention (17%). The medical resource supply shortage, medical building optimization, and unreasonable resettlement of floating personnel accounted for 12.5, 4.5, and 2.7% of the total, respectively (Figure 5B).

Statistics on technical orientation were used to examine whether the solutions envisaged in the face of the pandemic were high- or low-tech to better understand their orientation. High-tech solutions referred to the use of technologies and even fantastical methods, such as information intervention, construction of virtual worlds, and applications of advanced

TABLE 1 High frequency vocabulary of competition themes and works.

Themes word frequency		Themes key words			Works word frequency		Works key words		
Words	Freq.	Words	Weight	Freq.	Words	Freq.	Words	Weight	Freq.
City	123	Complex system	19.28	9	Modularization	79	City	73.02	124
Society	68	Sports	15.29	22	Unit	60	Community	68.99	128
Epidemic situation	65	Quarantine	14.41	15	Public space	40	Modularization	45.41	79
Community	58	Body building	14.23	24	Medical treatment	31	Public space	30.15	40
Health	51	Health	13.71	52	Pandemic era	31	Vertical	25.79	34
Health	22	Public space	12.81	13	Roof	30	Medical treatment	24.82	32
Sports	21	Fitness products	12.64	4	Device	30	Roof	22.31	30
Body building	20	Comfort	12.48	5	Elastic	26	Move	21.84	43
Architect	17	Memorial hall	10.92	12	Hospital	25	Flat and pandemic combination	21.11	4
Epidemic era	16	Facade system	10.89	5	Streamline	25	Street	20.66	23
Certainty	13	Education	10.56	10	Facilities	24	Hospital	19.99	25
Public space	13	Medical treatment	10.55	12	Security	23	Ecology	19.63	23
Medical treatment	12	Park city	10.36	3	Street	23	Elastic	19.05	27
Ecology	12	Memorial device	9.31	3	Ecology	23	Improve living quality	17.47	11
Family	12	Social distance	9.25	6	Health	21	Green	16.47	15
Memorial hall	12	Daily life	8.78	11	Socializing	18	Health	16.35	44
Daily life	11	High-rise buildings	8.76	6	Toughness	18	Sharing	16.25	23
Green	10	Green	8.69	10	Exchange	18	Landscape	16.16	20
Density	10	Density	8.69	10	Vertical	16	Social distance	16	16
Normal	10	Multidimensional	8.64	3	Green	15	Balcony	15.46	13
Planning	9	Urban and rural	8.51	8	Social distance	15	Commemorate	15.4	16
Elastic	9	Office	8.47	6	Square	15	Synthesis	15.34	6
Sharing	9	Elastic	8.33	9	Sharing	15	Facade	14.72	5
Complex system	9	Basic needs	8.26	3	Open	14	Toughness	14.36	19
Originality	8	Public transit	8.26	3	Transport	14	Infrastructure	13.75	10
Emergency	8	Dynamic response	8.26	3	Balcony	13	Chinese tradition	12.89	5
Solution	8	Shelter space	8.26	2	Courtyard	12	Spatial folding	12.5	12
Significant contribution	8	Outdoor space	8.26	2	Commemorate	12	Pandemic resistance	11.49	7
High-rise buildings	6	Security	8.1	29	Park	12	Life module	10.75	3
Social distance	6	Population mobility	8.07	4	Wisdom	12	Streamline	10.69	25

Freq., frequency.

technologies. Low-tech solutions were based on existing or routine methods. Considering that the pandemic itself is a public health event, interventions in the built environment were often physical, resulting in a relatively high proportion of low-tech solutions for real life. After analyzing the samples, the proportions of low- and high-tech solutions were 71.7 and 28.3%, respectively (Figure 6A).

The quantity of strategies applied in the works ranged from 1 to 8, with the highest number of works (151, or 27.1% of the total) having applied two strategies. Only four works (0.7%) applied eight strategies. The mean and median of the quantity of strategies were 2.81 and 2, respectively (Figure 6B). Modularization and flexible space were the strategies that appeared the most frequently, at 262 and 229 times, respectively. These two strategies were adopted by almost half of the works, with 116 works (20.8%) adopting both strategies concurrently, making them the most recommended solutions by designers (Figure 6C). These various solutions highlighted the strategic directions being considered, which included adaptability of space, attention to social distancing, discussions on public vs. private spaces, immediate methods to solve needs, and spiritual needs. Notably, the application of building digitalization accounted for 20% of all the works. The pandemic has provoked designers to engage in in-depth thinking over the application of digital resources to solve real problems or even replace partial realities.

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FIGURE 2
Competition themes and works high frequency words word cloud. **(A)** The themes word cloud. **(B)** The words word cloud.

Results of cross-analysis

After the chi-square test, a pairwise test of the 11 variables was conducted. The test results for the strategic variables are shown in Figure 7. Next, cross-analysis was carried out between those variables that presented significance, and a comparative analysis of the differences was performed using the percentage as the main object.

Cross-analysis targeting the "territory" variable

Six variables were significant for the "Territory" variable: technical orientation ($p = 0.01$), architecture category 2 ($p < 0.001$), target problem label level 1 ($p = 0.006$), target problem label level 2 ($p = 0.004$), target group ($p < 0.001$), and quantity of strategies ($p < 0.001$). The proportion of works that selected high-tech solutions was significantly higher within China than outside China (34.83 vs. 24.65%), meaning that more competitors within China chose high-tech solutions to handle the pandemic (Figure 8A). Similarly, the proportion of works that focused on public buildings and communities was significantly higher within China than outside China (33.83 vs. 25.77%, 18.41 vs. 8.68%). There were significantly more works from outside China than within China that focused on residential buildings (29.13 vs. 20.40%).

For the target problem, 81.59% of works from within China selected original building and space form non-adapted to the normalization of pandemics, which was significantly higher than the proportion of works from outside China (66.67%). By comparison, works from outside China focused on the medical resource supply shortage, the proportion of which was

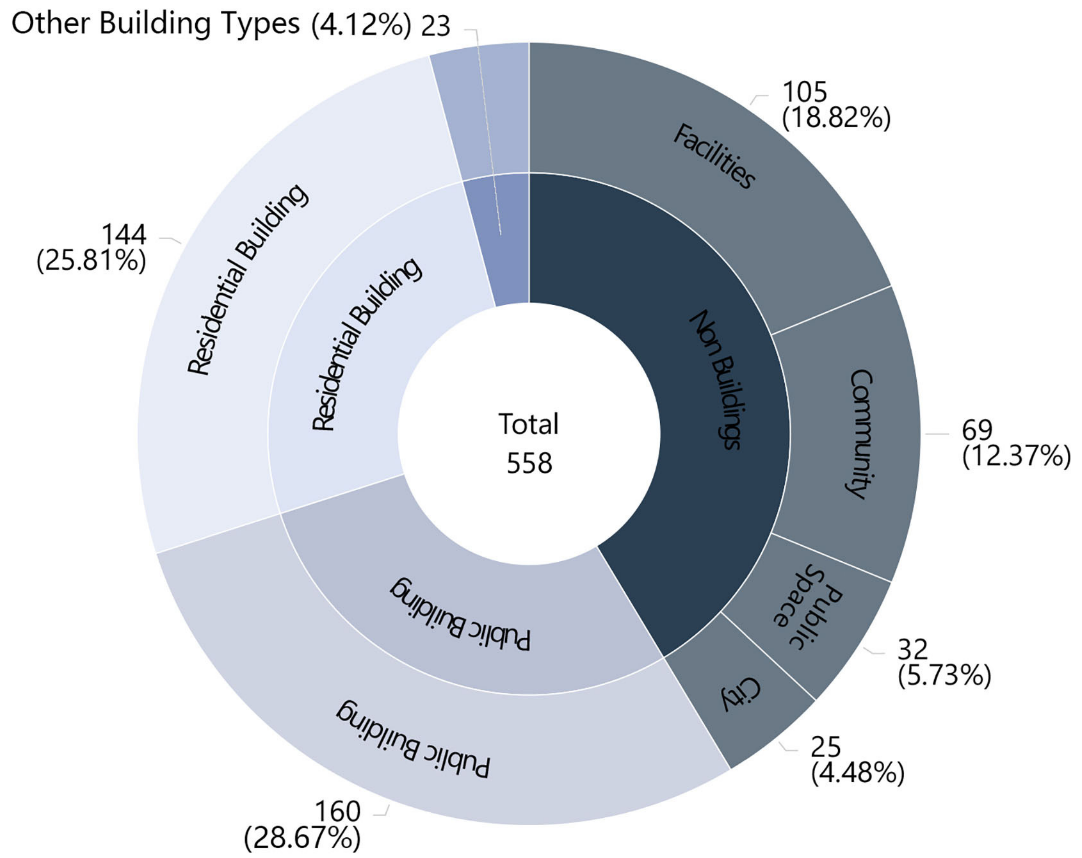


FIGURE 3
Distribution of building types.

significantly higher than that of works within China (14.57 vs. 8.96%) (Figure 8B). For the target group, 46.27% of works from within China selected the populace, which was significantly higher than the proportion of works from outside China (32.77%). However, the proportion of the latter choosing doctors and patients was significantly higher than that of works from within China (17.37 vs. 6.47%) (Figure 8C).

After analyzing the quantity of strategies, the proportions of works from outside and within China that selected a single strategy were 29.69 and 13.43%, respectively. The former region had a greater tendency to use one strategy to solve problems, whereas the latter had a higher proportion of works that applied a combination of methods to solve problems. In terms of specific strategies, works from within China had significantly more applications of the following strategies compared with works from outside China: modularization (54.23 vs. 42.86%), rapid assembly (37.8 vs. 8.68%), three-dimensional space (67.66 vs. 17.65%), flexible space (67.66 vs. 26.05%), space regeneration (19.40 vs. 5.04%), building digitalization (34.33 vs. 10.92%), and movability (15.42 vs. 8.96%). Works from outside China had significantly more applications of the following strategies compared with works from within China: social distancing (28.85 vs. 12.44%), psychological healing (14.01 vs. 7.46%), spatial linear organization (3.36 vs. 0.5%), improving the accessibility of green space (20.45 vs. 9.95%), and improving living quality (14.01 vs. 7.96%) (Figure 9).

Cross-analysis targeting the "year" variable

The following variables were significant for the "Year" variable: technical orientation ($p = 0.001$), architecture category ($p < 0.001$), target problem label levels 1 & 2 ($p < 0.001$), target group ($p < 0.001$), and quantity of strategies ($p = 0.001$). In 2020, the proportion of works using high-tech solutions was 34.59%, which was significantly higher than the mean of 28.32%. In 2021 and 2022, the proportion decreased to 20.1 and 12.5%, respectively. For architecture category, the proportion of other buildings (parks, gates, bridges, monumental buildings, and structures) in 2022 was significantly higher than the mean (43.75 vs. 4.12%) (Figure 10A). In the 3-year period from 2020 to 2022, the proportions for the original building and space form non-adapted to the normalization of the pandemic, which was under the target problem label level 1, decreased annually from 78.9 to

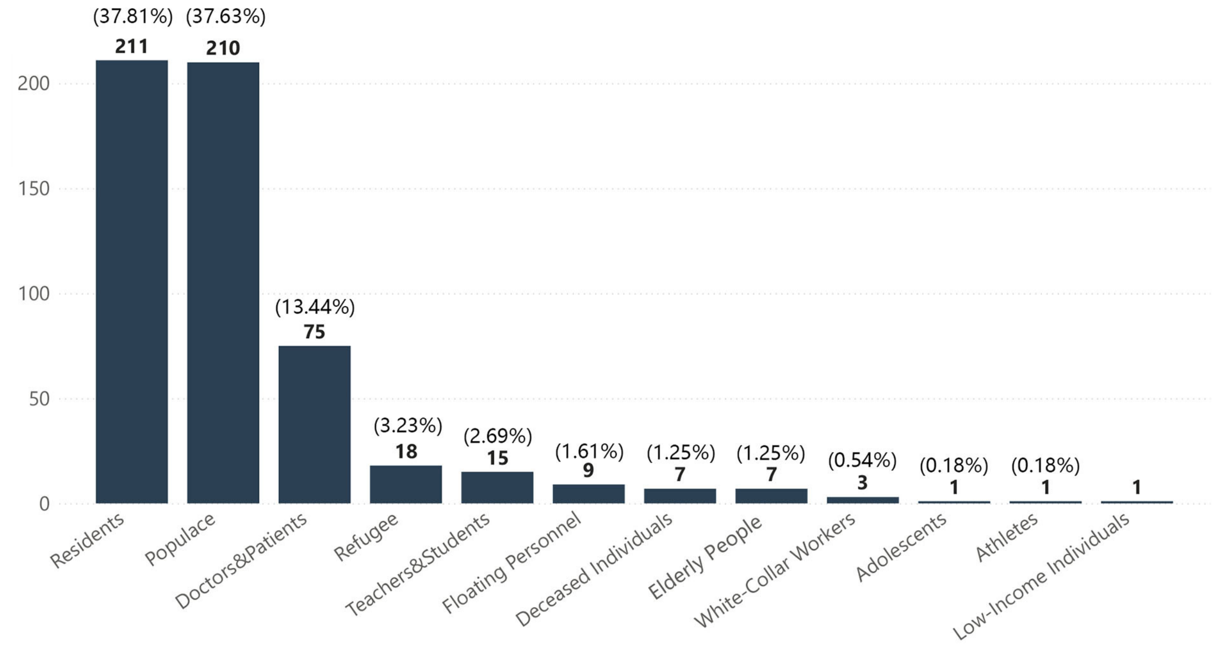
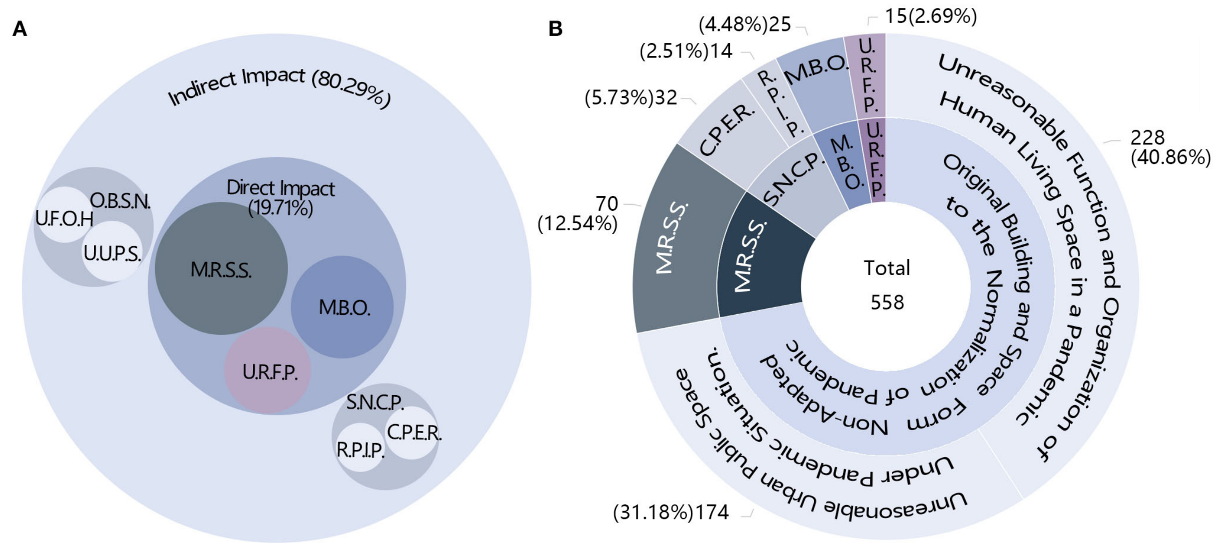


FIGURE 4
Distribution of target groups.



Notes : Problem Label Level 1
O.B.S.N. : Original Building and Space Form Non-Adapted to the Normalization of Pandemic. M.R.S.S. : Medical Resource Supply Shortage.
S.N.C.P. : Spiritual Needs in the Context of a Pandemic. M.B.O. : Medical Buildings Optimization.
U.R.F.P. : Unreasonable Resettlement of Floating Personnel
Problem Label Level 2
U.F.O.H. : Unreasonable Function and Organization of Human Living Space in a Pandemic Situation.
U.U.P.S. : Unreasonable Urban Public Space Under Pandemic Situation.
C.P.E.R. : Commemoration of People and Events Related to the Pandemic.
R.P.I.P. : Restoration of the psychological impact of the pandemic.

FIGURE 5
Distribution of targeted problems.

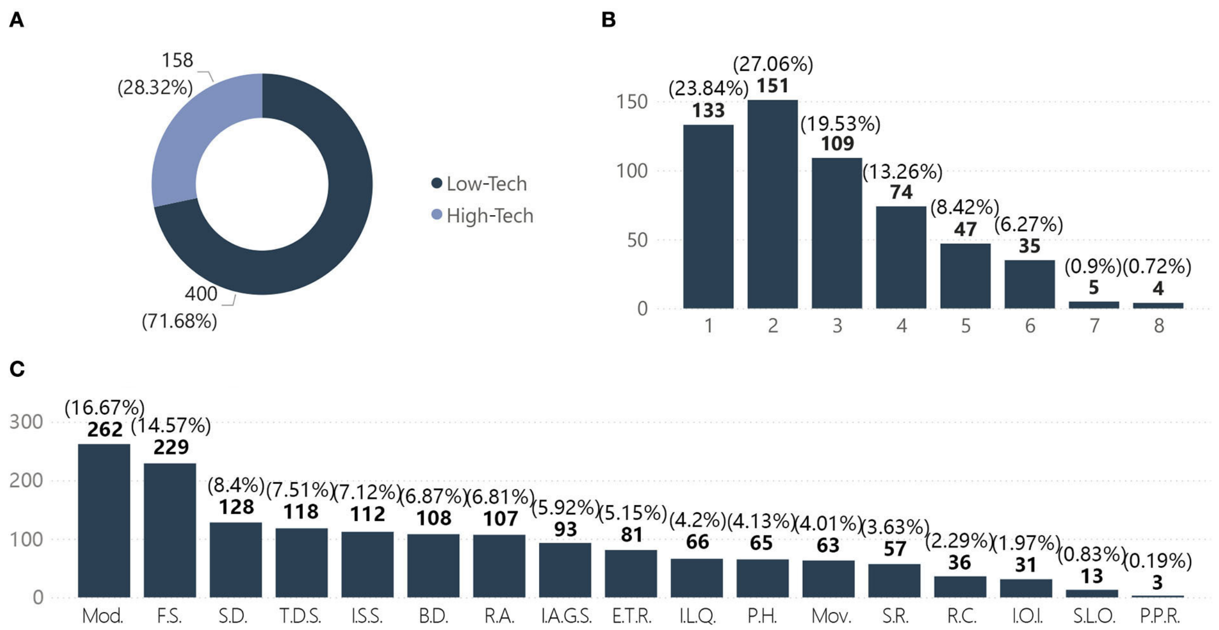


FIGURE 6
Distribution of strategies. **(A)** Technical orientation. **(B)** Quantities of strategies. **(C)** Strategies categories.

64.4% and then to 62.5%. Over the same period, explorations of spiritual needs in the context of a pandemic situation were 3.5, 13.2, and 37.5%, respectively, increasing annually (Figure 10B). In 2022, 75.00% of the target group selected populace, which was significantly higher than the mean of 37.63%. In 2021, the proportion of doctors and patients as the target group was 20.55%, which was significantly higher than the mean of 13.44%. By comparison, the proportion of works targeting doctors and patients in 2015 was as high as 100%. The proportion increased from 7.9% to 20.5% in the period 2020–2022 (Figure 10C).

The modularization strategy was used by 50.31 and 43.84% of works in 2020 and 2021, respectively, but dropped sharply to 6.25% in 2022. The situation was similar for rapid assembly, with proportions of 20.75, 16.44, and 0% in 2020, 2021, and 2022, respectively. As the most basic and effective strategy for pandemic prevention and control, the yearly distribution of works on social distancing was consistent with that of the two aforementioned strategies: 27.36% in 2020, 17.35% in 2021, and only 6.25% in 2022. Over the same period, the use of the following two strategies similarly decreased annually: movability (15.41, 6.39, and 0%) and improve the accessibility of green space (23.58, 7.76%, and 6.25). In contrast, the use of psychological healing as a strategy increased annually at 6.92, 16.89, and 31.25%, respectively (Figure 10D).

A comparison was made between the competition works submitted in 2015 and those during the COVID-19 period. One hundred percent of works used the strategies of modularization and rapid assembly in 2015, 40% used social distancing, and 20% used psychological healing. These were all significantly higher than the mean. However, the following strategies, which occupied relatively high proportions subsequently, were not recorded: flexible space (41.04%), three-dimensional space (21.15%), improve or increase social space (20.07%), and building digitalization (19.35%).

Cross-analysis targeting the "target problem" variable

Target problem label levels 1 & 2 were significant for the target group ($p < 0.001$) and quantity of strategies ($p < 0.001$). The characteristics of emergency needs during the pandemic being prominent were revealed in the cross-analysis of strategies and target problems. To address the issues of medical resource supply shortage and unreasonable resettlement of floating personnel, the proportions of strategies involving modularization (81.43, 73.33%), rapid assembly (37.14, 53.33%), movability (20.00, 33.33%), and emergency treatment and resettlement (57.14, 73.33%) were significantly higher than the means (46.95, 19.18, 11.29, and 14.52%, respectively). The use of above strategies reflected the need for flexible emergency functions when dealing with the issues of provision of medical care and temporary resettlement. For the issues of the original building and space form non-adapted to the normalization of a pandemic situation and medical building optimization, applications of the social distancing strategy (27.11, 32.00%) were also significantly higher than the mean of 22.94% (Figure 11A).

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	Territory	Year	Award Level	Technical Orientation	Architecture Category 1	Architecture Category 2	Target Problem Label 1	Target Problem Label 2	Target Group
Year	.059								
Award level	.068	.446							
Technical orientation	.001**	.001**							
Architecture category 1	.087	.000**	.002**	.024*					
Architecture category 2	.001**	.000**	.001**	.008**					
TARGET Problem label 1	.006**	.000**	.027*	.339	.000**	.000**			
TARGET Problem label 2	.004**	.000**	.016*	.284	.000**	.000**			
Target group	.000**	.000**	.004**	.356	.000**	.000**	.000**	.000**	
Modularization	.010**	.000**	.025*	.000**	.055	.000**	.000**	.000**	.000**
Rapid Assembly	.000**	.000**	.009**	.000**	0.24	.000**	.000**	.000**	.008**
Three–Dimensional Space	.007**	.562	.335	.892	.015*	.000**	.000**	.000**	.000**
Flexible Space	.000**	.106	.024*	.020*	.004**	.000**	.000**	.000**	.000**
Resilient City	.075	.937	.082	.145	.000**	.000**	.005**	.020*	.043*
Improve / increase Social Space	.885	.203	.008**	.946	.002**	.000**	.000**	.000**	.001**
Social Distancing	.000**	.013*	.838	.003**	.000**	.000**	.000**	.000**	.003**
Psychological Healing	.021*	.000**	.091	.946	.000**	.000**	.000**	.000**	.000**
Publicization of Private Resources	.268	.979	.755	.275	.034*	.198	.883	.627	.933
Indoor–outdoor Integration	.268	.729	.112	.05	.000**	.003**	.089	.012*	.028*
Space Regeneration	.000**	.247	.000**	.965	.005**	.001**	.089	.001**	.007**
Building Digitalization	.000**	.319	.103	.000**	.236	.153	.136	.28	.103
Movability	.021*	.004**	.122	.000**	.091	.153	.001**	.002**	.186
Spatial Linear Organization	.031*	.046*	.66	.842	.22	.449	.003**	.005**	.051
Emergency Treatment and Resettlement	.296	.006**	.517	.001**	.000**	.000**	.000**	.000**	.000**
Improve the Accessibility of Green Space	.001**	.000**	.005**	.064	.085	.000**	.000**	.000**	.001**
Improve Living Quality	.034*	.078	.003**	.064	.000**	.000**	.000**	.000**	.000**
Quantity of Strategies	.000**	.001**	.346	.000**	.046*	.092	.000**	.000**	.000**

FIGURE 7
Pairwise cross-tabulation analysis results.

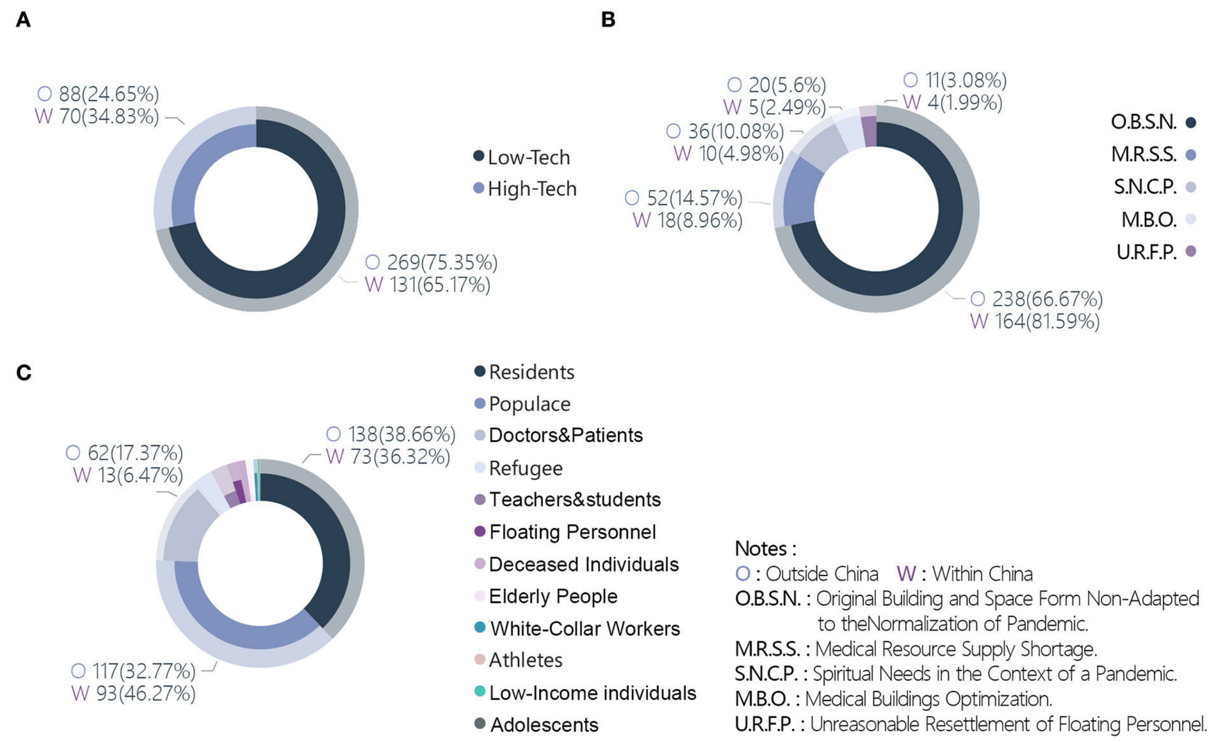

FIGURE 8
Cross-tabulation results with territory. **(A)** Territory and technical orientation. **(B)** Territory and target problem. **(C)** Territory and target group.

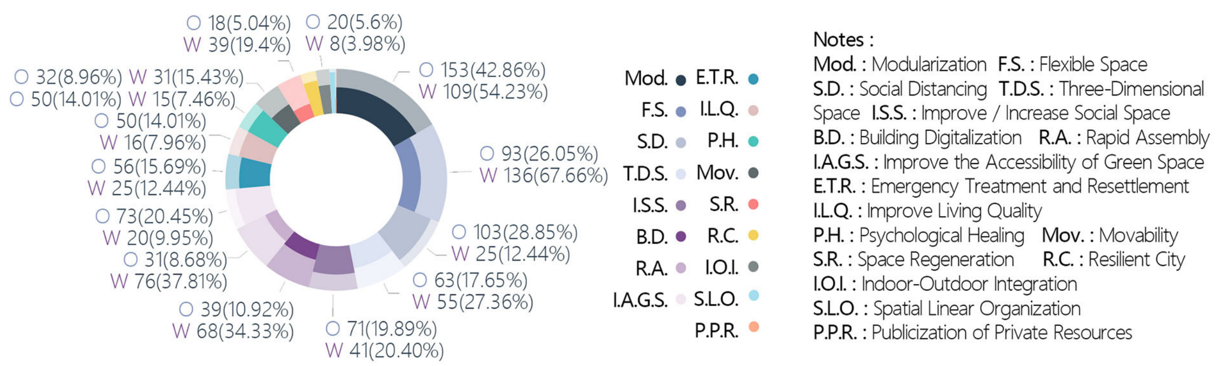

FIGURE 9
Cross-tabulation results with territory and strategies.

For medical resource supply shortage and medical building optimization, the proportions of works applying the spatial linear organization strategy and related to medical problems (5.71, 12.00%) were significantly higher than the mean (2.33%). These reflected the importance of effective solutions for streamlining in medical issues. The proportions of works under spiritual needs in the context of the pandemic situation and medical building optimization that selected a single strategy were 71.74 and 40.00%, respectively. This was significantly higher than the mean of 23.84%. For commemoration of people and events related to the pandemic, which was under spiritual needs, the proportion of works choosing a single strategy was high and reached 87.50%. This was significantly higher than the mean of 23.84% (Figure 11B). Comparing the research results with other problems illustrated that issues related to spiritual needs and medical buildings were mostly addressed using a single strategy, whereas complex strategies were required to solve conflicts in the supply of medical resources and unreasonable functional organization.

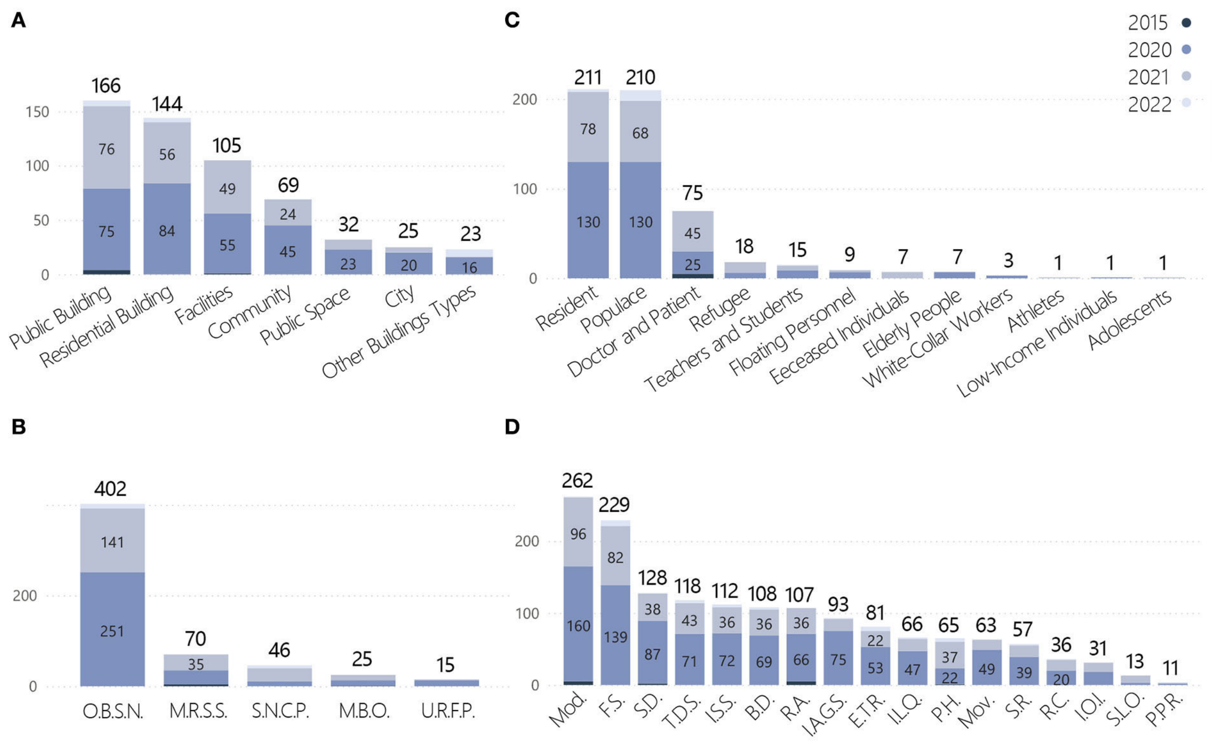

FIGURE 10
Cross-tabulation results with year. **(A)** Year and architecture category. **(B)** Year and target problem. **(C)** Year and target group. **(D)** Year and strategies.

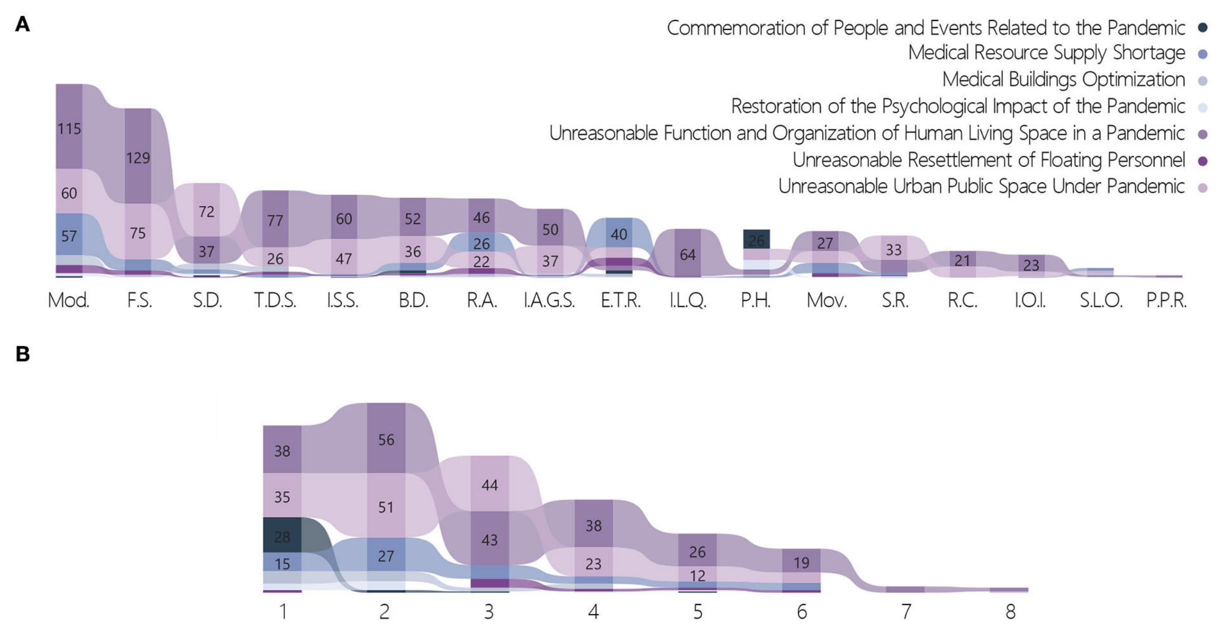

FIGURE 11
Cross-tabulation results with target problem. **(A)** Target problem and strategies. **(B)** Target problem and target problem label level.

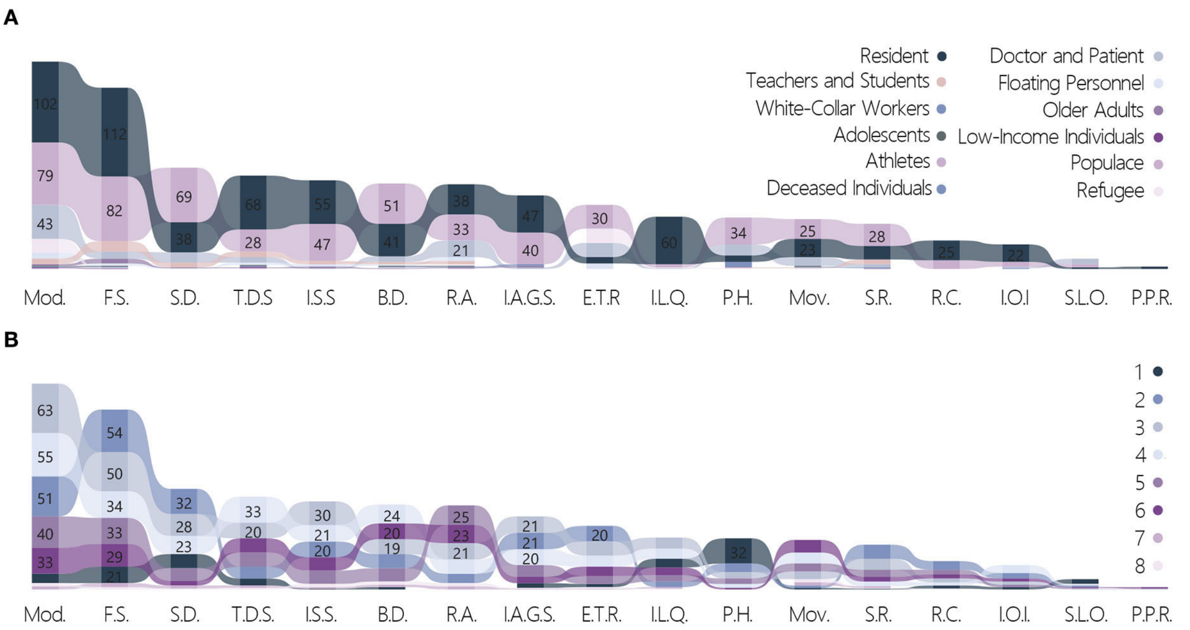

FIGURE 12
Cross-tabulation results with target group & quantity of strategies and strategies. **(A)** Target group and strategies. **(B)** Quantity of strategies and strategies.

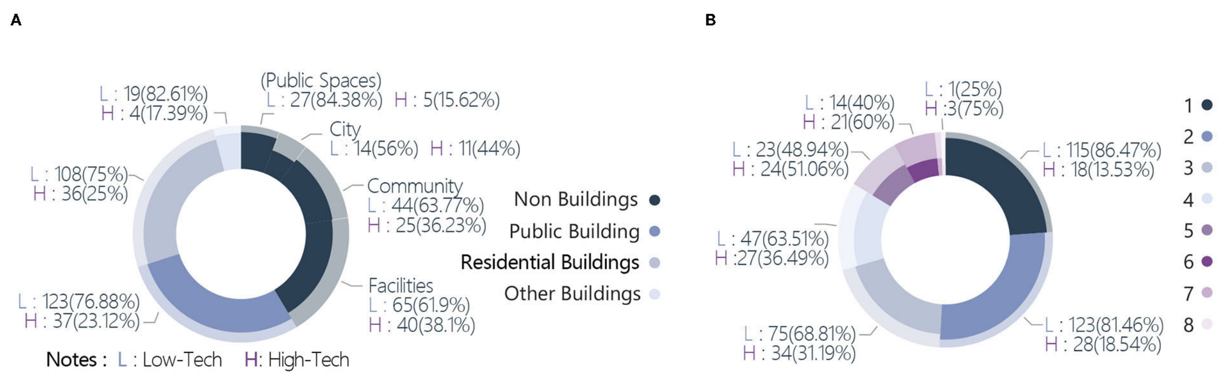

FIGURE 13
Cross-tabulation results with technical orientation. **(A)** Technical orientation and architecture category. **(B)** Technical orientation and quantity of strategies.

Cross-analysis targeting the "target group" variable

The cross-analysis of the target groups and strategies showed that (Figure 12A) only one strategy was selected in all works dealing with deceased individuals. The proportion of works that chose four strategies to manage teachers and students was 26.67%, which was significantly higher than the mean of 13.26%. The countermeasures at the spiritual level often applied a single strategy; the combination of multiple strategies was often considered for teachers and students, who constituted a complex and diverse group.

The percentages of strategies used for different groups were analyzed, and several conclusions were arrived at after comparing the average proportions of each item. First, all strategies were included for use on the populace, which is the most general sense of a group. Social distancing accounted for 53.08% of the total, which was significantly higher than the mean of 41.04%. This has also been proven to be an effective strategy for pandemic prevention and control worldwide.

All strategies were similarly included for residents as a group. The application rates of five strategies—three-dimensional space, flexible space, indoor–outdoor integration, improving the accessibility of green space, and improving living quality—were significantly higher than the mean. These strategies were approaches that targeted the living conditions

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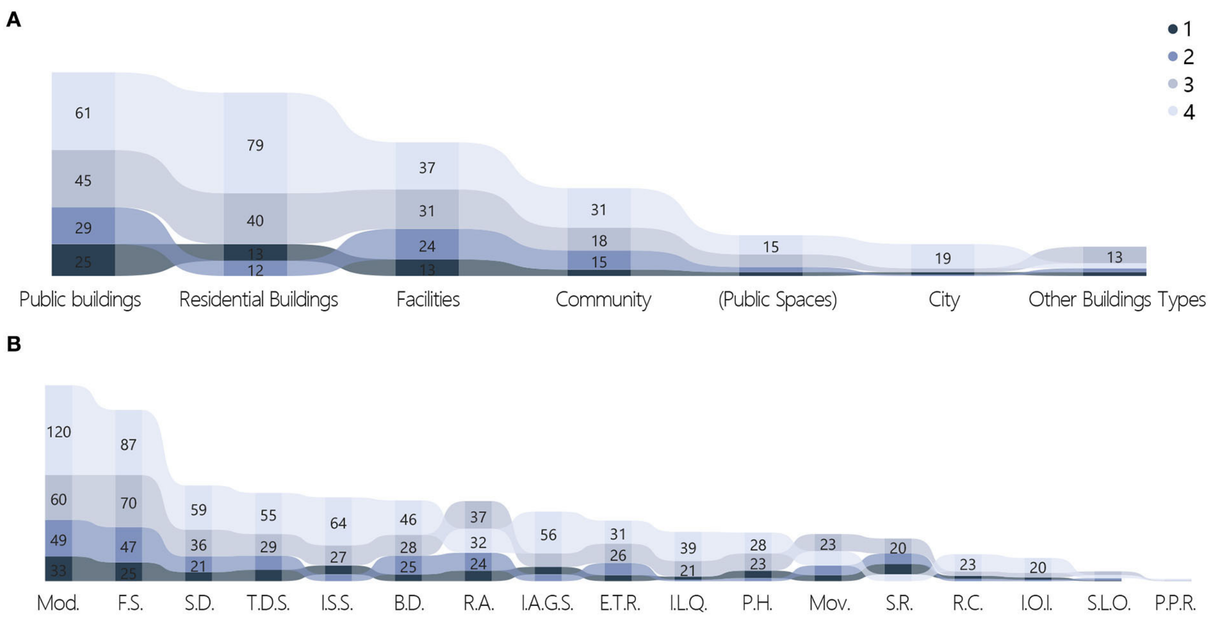

FIGURE 14
Cross-tabulation results with award level. **(A)** Award level and architecture category. **(B)** Award level and strategies.

of residents to deal with the pandemic environment. For the four strategies of modularization, rapid assembly, psychological healing, and emergency treatment and resettlement, the focus on doctors and patients was significantly higher than the mean. This was mainly reflected in responses to the instantaneous surge in the demand for medical resources and psychological relief.

Cross-analysis targeting the other labels variable

The "Quantity of strategies" variable showed that, works on psychological healing constituted the highest number with only one strategy applied, amounting to 32 out of 133 works. This was followed by flexible space, which appeared in 21 works (Figure 12B). When multiple strategies were combined for application in one work, the following 11 strategies were often grouped together: modularization, rapid assembly, three-dimensional space, flexible space, improving/increasing social space, space regeneration, building digitalization, movability, emergency treatment and resettlement, improving the accessibility of green space, and improving living quality. All works applying eight strategies used the following five strategies: modularization, rapid assembly, improving/increasing social space, building digitalization, and movability.

The "Technical orientation" variable was significant in architecture categories 1 & 2 ($p = 0.024$, $p = 0.008$) and quantity of strategies ($p < 0.001$). In the architecture category, the proportion of works on non-buildings with high-tech solutions was 35.06%, which was significantly higher than the mean of 28.32%. Under the secondary label, the proportions of works on the city (44.00%) and facilities (38.10%) were significantly higher than the mean of 28.32%. The proportion of works on public spaces and public buildings with low-tech solutions was significantly higher than the mean (84.38 & 76.88% vs. 71.68%) (Figure 13A). These statistics indicated that high-tech solutions are more applied to the categories of cities and facilities, whereas more low-tech solutions are proposed for public buildings.

In the cross-analysis between quantity of strategies and technical orientation, the proportions of works that incorporated one and two strategies involving low-tech solutions were 86.47 and 81.46%, respectively, significantly higher than the mean of 71.68%. The proportions of works using six and eight strategies and involving high-tech solutions were 60.00 and 75.00%, respectively, significantly higher than the mean of 28.32% (Figure 13B). The implication was that the lower the number of strategies used, the higher the tendency to use low-tech solutions, and the higher the number of strategies used in the works, the more likely that these strategies contained high-tech solutions.

The following variables were significant for the "Award level" variable: architecture categories 1 & 2 ($p = 0.002$, $p = 0.001$), target problem labels 1 & 2 ($p = 0.027$, $p = 0.016$), technical orientation ($p < 0.001$) and target group ($p = 0.004$). Winning works related to public buildings or facilities did not necessarily have more options to choose from within the buildings category. For example, 39.06% of works with Level 1 awards covered public buildings, which was significantly higher than the mean of 28.67%. For Level 2 awards, 50.00% of the works dealt with non-buildings, of which the proportion that selected facilities was 27.27% and the mean was 18.82%. In the selection of issues to respond to, the winning works emphasized the issue of contrast of medical resource supply; it was the focus of 18.75% of works granted Level 1 awards, which was higher than the mean of 12.54%.There was a significant difference between award levels for the strategy of space regeneration. The proportions of works with awards at Levels 1 and 2 that adopted this strategy were 21.88 and 15.91%, respectively. These were significantly higher than the mean of 10.22%. By comparison, only 3.66% of works with Level 4 awards applied this strategy (Figure 14).

Discussion

Focus

There were equal numbers of works dealing with the populace and residents, jointly accounting for 75.4% of the total. Most works addressing people affected by the pandemic chose to cover a broad scope. Among them, nearly 40% focused on residents, clearly revealing a perception of the vast impact of the pandemic on daily living. The proportion of works for doctors and patients was significantly higher for other occupations/groups of people, and this group was also the most directly affected by the pandemic. Other groups—teachers and students, white-collar workers, and athletes—accounted for a relatively small proportion from the occupational perspective. Attention was paid to elderly people and adolescents as members of vulnerable age groups. Other originally vulnerable groups in society, such as refugees, the poor, and floating personnel, combined to form the subjects of 5% of the total works. At the same time pandemic also redefines the vulnerability population (43).

Secondary health impacts include economic stability, education, healthcare, neighborhood and built environment, and social and community contextual factors (44). The indirect impacts of the pandemic on life constituted the main issue of focus, accounting for 80.2% of the total. Incompatibility with the physical space was a primary consideration. The concern over issues related to people's living spaces was greater than that for public spaces, and living space issues were also the biggest problems experienced by the base population during the pandemic. Attention to spiritual needs also exceeded 8%. These showed that, although issues with the physical space were predominant during the pandemic, impacts at the spiritual level were also great and could not be ignored. Further evidence of the dramatic psychological impact of COVID-19 and the urgency for intervention (45–47). The direct impacts of the pandemic were relatively concentrated, with the greatest emphasis being on medical care. The most prominent problem was medical resource supply, which was related to the critical demand placed on the medical system for pandemic control. Unreasonable resettlement of floating personnel was also a concern for the vulnerable populations in society.

Among the strategies used in the studied works, modularization and flexible space were the most popular, applied in nearly half of the works. The proportion of works with simultaneous applications of both strategies was also high. For the statistics on text mining, modularization was also the most mentioned strategy in terms of word frequencies and keywords. This highlighted the consensus among designers to be flexible when adapting to the uncertainties brought about by the pandemic. Social distancing has been widely discussed in Pandemic Influenza (48, 49), and simulation validation of targeted social distancing design has been performed (50). Improving/increasing social space and social distancing seemed to be a pair of mutually exclusive strategies (51, 52), which implied the dilemma that the pandemic created for people: they not only had to maintain a social distance for effective pandemic prevention and control but also had to improve social health through interactions (53, 54). A variety of solutions to this dilemma were provided by these works through their specific forms of realization.

Differences

Among the collected works, those from within China accounted for nearly 40% of the total. China was the first country to report cases of COVID-19 infections. In the subsequent 3 years, the government imposed the general policy of dynamic eradication of infections to deal with the pandemic. The similarities and differences between the situations within and outside China could be examined by comparing the works from both regions. From the perspective of the building types involved, works from within China during the pandemic paid more attention to meso- and community-level issues and those related to public buildings. Works from outside China focused on issues related to residential buildings. For issues related to the pandemic, works from within China emphasized the indirect impacts, whereas those from outside China were more interested in the problems with the medical system that were exposed by the pandemic.

In parallel, there was a contrast between works from within and outside China in terms of the target groups: the former included more works dealing with broad scopes, such as the populace, whereas the latter focused on doctors and patients, who were the most closely associated with the pandemic. From the perspective of the strategies used, works from within China involved adjustments in the construction of physical space; works from outside China that applied strategies for the spiritual space accounted for a larger proportion. The proportion of works from outside China that applied social distancing was much larger than those from within China. As early as 100 years ago, during the 1918–19 influenza pandemic, the New York City Department of Health enforced several social distancing policies at the same time, including staggered business hours, compulsory isolation, and quarantine, which likely led to New York City suffering the lowest death rate from influenza on the eastern seaboard of the USA (55). In terms of the technical orientation, a greater proportion of works from within China chose high-tech solutions to deal with the pandemic.

Trends

It has been nearly 3 years since the COVID-19 outbreak. The findings of the cross-analyzes relating to the year as a variable showed substantial variations, which led to evident trends in terms of the questions and groups of people that the works dealt with, as well as the use of strategies. Over the 3-year period of 2020–2022, the original building and space form non-adapted to the normalization of the pandemic constituted the largest proportion of works. The highest number was in 2020, when nearly 80% of the works discussed this issue. Although 60% of the works still focused on this issue in 2022, the proportion declined annually. In contrast, discussions of psychological needs during the pandemic increased annually from 3.5 to 37.5%. In the early stage of the pandemic, the issue of incompatibility with the physical space accounted for the absolute majority of works, and it was the most prominent and influential issue. As the pandemic progressed, its impacts on the spiritual level gradually emerged and received more attention. Correspondingly, there were more explorations of commemoration and restoration, both aspects of spiritual needs. The variable of people was initially dominated by the populace and residents, but both aspects declined in 2021. Instead, the focus on doctors and patients was on the rise.

The use of high-tech solutions in works decreased over the 3 years and was replaced by works with low-tech solutions. Strategies that focused on adaptability—modularization, rapid assembly, and movability—accounted for a high proportion of all works. However, their use showed a declining trend over the 3 years, as did use of strategies involving social distancing. After a comparison with the 2015 competition works, the core strategies adopted in the 2020–2022 works were found to be very similar and related to adaptations to emergencies and flexibility. Therefore, it was surmised that modularization, rapid assembly, movability, and social distancing were important strategies to rapidly address the changing needs in the early stage of the pandemic. However, discussions of these conventional strategies gradually declined with the progress of the pandemic. Instead, there was a shift to the discovery of and solutions to diverse secondary social problems. Notably, the strategy of building digitalization had consistently maintained a mean of nearly 20%. The pandemic had further promoted the space and form in which online activities occurred and also prompted people to make more extensive use of digital technologies to avoid pandemic risks. This would undoubtedly accelerate the development of related technologies such as digital twin (56, 57). In essence, the pandemic has pressed the fast-forward button on the growth of the "Metaverse."

Conclusion

To explore ways to intervene public health in the post-pandemic era and to provide a rethinking of the built environment, this study launched research on the issues and solutions presented by architectural design competitions and drawing works under the COVID-19 theme, as well as the variations in their characteristics and the evolutionary trend. The findings indicated that the direct impacts revolved around the medical system and temporary resettlement; the indirect impacts, which accounted for a relatively high proportion of works, were related to the incompatibility between the existing environment and spiritual needs. This corresponded with the broad scope in terms of the target groups of the works—namely, the populace and residents. These strengthened the perception of the extensive impacts that the pandemic has had on life. Flexible emergency adaptations featured predominantly among the strategies extracted from the works, among which modularization and flexible space were the most important solutions. Once again, the extensive use of modularization was in response to concerns about the incompatibility between the existing environment and emergency problems such as medical care and settlement of people affected, and it also highlighted the general trend of prefabricated buildings.

Cross-analysis of the works indicated multiple differences in terms of territory, target group, target problem, architecture category, technical orientation, and strategies, which produced a series of meaningful conclusions. Works from within China applied more high-tech solutions, paid more attention to the populace, and focused more on the impact of the pandemic on the people's lives; by comparison, works from outside China paid more attention to direct issues such as medical resource supply and spiritual needs. A single strategy was often used to deal with issues related to spiritual and medical needs, and these issues were more frequently discussed in works that won high-level awards.

After analyzing the changes with the passage of time, we found declining attention to issues pertaining to physical space but increasing attention to spiritual issues annually. The use of strategies involving emergency flexible adaptations decreased, but the proportion of strategies encompassing psychological healing increased. The application of high-tech solutions declined overall, but the application of building digitalization remained stable. These reflect the change in people's awareness, concerns, and reflections on the pandemic as it develops and evolves.

This pandemic presents a common challenge to all systems in society. Architectural design, as a critical undertaking of intervening in the built environment, should take the responsibility of actively combating the pandemic. The analysis of architectural design competitions under the theme of the pandemic enabled us to better understand its impacts on society in a more diverse way, leading to responses and suggestions within the field of construction that can deal with public health issues in the context of the pandemic and which are proposed in a more rapid and timely manner compared to the relatively lengthy design–build–use–evaluate cycle involved in evidence-based research.

Implications

This research aimed to explore the patterns, differences, and trends of the themes and works submitted for architectural design competitions and to provide additional public health interventions and directions by rethinking the built environment. The impacts of the pandemic on society as a whole will be long-lasting and usher in permanent changes in the fields of public health and architectural design. In the early stage of the pandemic, social management and control methods were relied upon for effective prevention and control. This further confirmed that the pandemic not only affected the medical system but had impacts radiating to all aspects of society. The effectiveness of the environment at suppressing the pandemic was also clearly demonstrated. The field of public health gradually attracted attention as an intervention method. Considering that architectural design can provide additional methods with far-reaching influence, competition works based on the theme of public health should be treated as important knowledge resources for management and decision-making.

Architectural design is a creative process. There is often insufficient time for substantial preliminary research because of the engineering requirements. New problems arising from the impact of the pandemic require vast accumulation of experiences and thoughts. The targeted problems and strategies for solutions compiled in this study can provide perspectives and ideas for design practice. The myriad types of strategies and solutions form a valuable database of case studies, which will provide designers with comprehensive ideas for problem solving. Concurrently, city managers receive decision-making suggestions that prompt them to pay attention to the impact at all levels, organize a diverse design team, and consider the wellbeing of various groups of people.

Limitations

Although as many competition entries as possible were sampled from the Internet in this study, the generalizability of the findings remains limited. First, the number of competitions and works compiled from 2022 was significantly lower than in the other years. This was because the samples were collected in the current year. More importantly, the relevant sample size had indeed shrunk significantly. This situation was most likely due to the long time span, during which the tracking of the pandemic and the attention of society and individuals varied with the changes in the pandemic itself. Design competitions typically revolve around the prevailing social focus receiving the most attention. The violent shock to society in the early stage of the pandemic led to the emergence of intensive thematic discussions in the past 2 years, resulting in a huge base number of works and a wide variety of perspectives.

The impacts of the pandemic have gradually become clear after in-depth discussion, such that the attention of organizers and contestants of design competition have gradually been diverted to other social issues. For example, several important series of competitions held in China in 2022 had begun discussing topics such as "urban connectivity," "landscape folding," and "connecting tradition and the future." Such topics no longer led participants to the pandemic perspective.

At the same time, the use of only Chinese and English in our online searches omitted competition information posted in other languages and increased the proportion of works from within China. Finally, because competition works were adopted as the samples, there was no information on post-use evaluation after implementation of the proposals. Objectively, this was a limitation faced between balancing the prevailing urgent needs and the long cycle inherent in the implementation of architectural designs. Nevertheless, this study has provided the basis for follow-up verification and comparative research that we plan to undertake.

Data availability statement

The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding author/s.

Author contributions

PH contributed to conception and design of the study and wrote the first draft of the manuscript. LW, YS, and XZ organized the database. PH and YS performed the statistical analysis. LW drew the charts. All authors contributed to manuscript revision, read, and approved the submitted version.

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Conflict of interest

PH was employed by Harbin Institute of Technology Architectural Design and Research Co.

The remaining authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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The spatial pattern and influencing factors of tourism eco-efficiency in Inner Mongolia, China

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Background: Tourism eco-efficiency is a performance basis for evaluating green total factor productivity and sustainable development.

Objective: The objective of this study was to measure tourism eco-efficiency in Inner Mongolia and explore its influencing factors. The aim was to provide an accurate reference for improving the quality and efficiency of tourism in Inner Mongolia and promoting the sustainable development of the regional economy and society.

Methods: Tourism eco-efficiency in Inner Mongolia from 2009 to 2019 was calculated using a super-slacks-based measure (SBM) model with an undesirable output. The spatial variation function was used to explore the spatial evolution pattern of tourism eco-efficiency in Inner Mongolia, and the influencing factors of the spatial evolution were analyzed by geographically weighted regression.

Results: Tourism eco-efficiency in Inner Mongolia is relatively low. Eco-efficiency values among cities in Inner Mongolia vary, and their distribution is not balanced. The structural eco-efficiency of tourism in Inner Mongolia has been consistent from 2009 to 2019. The degree of homogenization in the overall direction is relatively good. Furthermore, its spatial distribution form and internal structure evolution show a certain regularity and continuity. The pattern evolution of tourism eco-efficiency in Inner Mongolia is jointly driven by the economic level, environmental regulation, industrial structure, traffic conditions, resource endowment, and tourism reception facilities. These influencing factors show obvious spatial heterogeneity.

Conclusion: From the perspective of Inner Mongolia, the difference in the tourism eco-efficiency value from 2009 to 2019 was relatively large, but the number of effective areas in the efficiency frontier generally showed a fluctuating growth trend. The range parameters of tourism eco-efficiency showed a decreasing trend, and the spatial correlation effect of tourism eco-efficiency in Inner Mongolia showed a decreasing trend under the influence of structural and spatial differentiation.

KEYWORDS

tourism eco-efficiency, spatial evolution, influencing factors, Inner Mongolia, sustainable development

Introduction

Tourism is one of China's strategic pillar industries. In addition to helping regional economic growth and poverty alleviation, tourism contributes significantly to aesthetics and ecological civilization in China (1). In recent perspectives, the tourism industry is growing at a fast pace, which has resulted in extensive industrial development, ecological damage, and environmental pollution (2). With the rapid development of the tourism economy, the impact of carbon emissions generated by tourism activities on the environment is expanding annually and smokeless industries have ceased to exist. This necessitates consideration of the environmental problems caused by the development of tourism (3). Sustainable tourism was first proposed by the International Conference on Sustainable Development in 1990 and basically advocates for consideration of the ecological environment while promoting economic development and increased attention to collateral environmental effects during the development of the regional tourism economy to allow for the sustainability of the tourism industry. The evaluation of tourism eco-efficiency is a feasible method to measure the sustainable development of tourism, and an important research method is to start with tourism eco-efficiency (4). Therefore, this study, which is based on tourism eco-efficiency, can provide a reference to optimize the allocation of tourism elements and improve the use of tourism resources. Furthermore, it can provide a reference to promote the quality and efficiency development of tourism and practice sustainable tourism (5). Tourism eco-efficiency is a principal indicator to determine the sustainable development of tourism; it considers the ecological environment while meeting the tourism demands. Tourism eco-efficiency can be used to evaluate the sustainable development of tourism in a relatively scientific manner because it summarizes industrial, economic, and environmental indicators (6).

Schaltegger first proposed the concept of eco-efficiency in 1990 (7), and then the World Business Council for Sustainable Development proposed a method for measuring the ratio of eco-efficiency (the ratio of the economics of a product or service to its environmental impact) (8). Afterward, they explored its efficiency in industries such as agriculture, forestry, and the service industry. Tourism eco-efficiency is derived from ecological efficiency. Due to the continuous enrichment of tourism products, the types of tourism activities are increasing, and the tourism economy is developing rapidly; therefore, the negative impact of tourism on the environment is gradually emerging. For example, the surge in the number of tourists will lead to increased carbon emissions in tourism destinations. The energy consumed by tourists and the solid waste generated will cause different degrees of damage to the ecological environment (9, 10). Gössling proposed the concept of tourism eco-efficiency in 2005 (11). Since then, an upsurge in research on tourism eco-efficiency has been observed. It is mainly developed from five aspects: concept definition (12), model construction (13), level measurement (14, 15), mechanism of action (16, 17), and countermeasures (18). In terms of research content, scholars mainly regard the estimation of carbon emissions as the core content of eco-efficiency measurement (19–22). For example, Guo analyzed the spatial pattern of provincial tourism eco-efficiency under the constraints of energy conservation and emission reduction (23). Wang studied the spatial evolution of the tourism eco-efficiency industry and the impact environmental regulations had on the industry (24). Huang explored the monitoring and evaluation of carbon footprint and ecotourism in Wuyuan County (25).

There are two main types of calculation methods for tourism eco-efficiency: single index and model methods (26–29). Because existing statistical data do not include carbon emissions attributed to tourism, the single index measurement of tourism eco-efficiency should be determined using the tourism peeling coefficient model based on carbon emissions from other industries. That is, the ratio of the environmental impact index and the tourism economic index is used to express tourism eco-efficiency. Liu used the single ratio method to calculate tourism eco-efficiency and compared the differences between provinces (30). Li used the single index to calculate tourism eco-efficiency and analyzed its consistent relationship with regional ecological security (31). However, the eco-efficiency measurement of the single index method was slightly inaccurate due to the limited selection of variables. Many scholars prefer the multi-index method of measurement, which is mostly based on the input–output model and calculates tourism eco-efficiency by means of data envelopment analysis (DEA) [super-DEA, super-slacks-based measure (SBM)] and other methods. Lu used the super-SBM model with an undesirable output to calculate tourism eco-efficiency, and used the Tobit model to analyze influencing factors (32). Li measured tourism eco-efficiency in Wuling Mountain using the DEA method and analyzed its spatial pattern and influencing factors *via* exploratory spatial data analysis (33).

From the perspective of eco-environmental protection, studies on tourism eco-efficiency are in line with China's goal of constructing an ecological civilization and high-quality economic development. This is of great significance for the sustainable development of tourism (2). Located in northern China, Inner Mongolia is an important ecological security barrier. Inner Mongolia is also one of the provinces with relatively rich grassland and forest resources in China. It is particularly important for safeguarding China's ecological security and constructing an ecological civilization (34, 35). However, the rapid economic growth of Inner Mongolia mainly depends on energy, metallurgy, and other resource-based industries, which has caused great pollution to the environment. Thus, the ecological environment of Inner Mongolia needs urgent improvement (36). Also, the special geographical location, natural conditions, and industrial development mode make the ecosystem of Inner Mongolia very fragile. Therefore, it is urgent to provide countermeasures and suggestions for constructing an ecological civilization and the sustainable development of Inner Mongolia (37). In the face of the increasing energy consumption of tourism and the deterioration of the ecological environment, the evaluation of tourism eco-efficiency in Inner Mongolia can effectively reflect the relationship between the economic activities of tourism and its ecological environment. This will play a positive role in effectively dealing with the deterioration of the ecological environment caused by tourism development and promoting the construction of an ecological tourism civilization in Inner Mongolia (4, 10). This study measures tourism eco-efficiency in Inner Mongolia. The conclusions obtained not only help the government and tourism enterprises to effectively avoid the mismatch caused by blind investment and the loss of resources and environmental efficiency, but also provide countermeasures and suggestions for the government to make targeted tourism development planning, according to the temporal and spatial evolution of tourism eco-efficiency in Inner Mongolia (16, 17). In short, tourism eco-efficiency is the weather vane of green tourism development. The measurement of tourism eco-efficiency in Inner Mongolia can provide more scientific policies and guidance for the development of tourism in Inner Mongolia, so as to promote the coordinated and sustainable development of regional tourism (30, 31).

A sound ecological environment is the material basis for human survival and development, and also an important condition closely related to human health. A healthy urban physical environment is an important factor for the sustainable development of human settlements in the future. Research on tourism eco-efficiency in Inner Mongolia is helpful to provide a reference for the ecologically sustainable development of Inner Mongolia. This will not only promote Inner Mongolia to a resource-saving and environmentally-friendly society but also promote Inner Mongolia to implement a strict ecological and environmental protection system. The exploration of tourism eco-efficiency in Inner Mongolia is conducive to solving the prominent environmental problems affecting people's health and can provide a reference for the construction of ecological civilization, green development, and human healthy life.

Most of the studies focus on the concept of tourism eco-efficiency and the calculation of the tourism carbon footprint. Research on the measurement index of tourism eco-efficiency is lacking. In addition, there are only a few evaluations and spatial evolution analyses of provincial tourism eco-efficiency. To fill this research gap, this study aims to construct an index system to measure tourism eco-efficiency based on the eco-efficiency theory and the actual background of China. Therefore, this study evaluates tourism eco-efficiency in Inner Mongolia and analyzes the spatial pattern and influencing factors of tourism eco-efficiency of different cities in Inner Mongolia. The research questions of this study are as follows:

1. What indexes and models can measure tourism eco-efficiency in a relatively reasonable way?
2. What is the spatial pattern of tourism eco-efficiency in different regions of Inner Mongolia?
3. Are there spatial differences?
4. If there are spatial differences, what are their causal factors?
5. What are the rules of spatial distribution and evolution?

These issues reflect the empirical measurement of tourism eco-efficiency at different scales and the dynamic mechanism behind its temporal and spatial evolution. Research on tourism eco-efficiency is essential for the sustainable development of tourism in Inner Mongolia. To answer the abovementioned research questions, we established three subgoals.

First, this study established the evaluation index system of tourism eco-efficiency in Inner Mongolia based on previous studies. The super-SBM model with an undesirable output was used to calculate tourism eco-efficiency in Inner Mongolia.

Second, the spatial variation function was used to analyze temporal and spatial evolutionary features of tourism eco-efficiency in Inner Mongolia.

Third, the factors influencing tourism eco-efficiency in Inner Mongolia were assessed using the geographically weighted regression (GWR) method.

Materials and methods

Study area

The Inner Mongolia autonomous region is located in the northern region of China, across northeast, north, and northwest China, adjacent to Heilongjiang, Jilin, and eight other provinces, bordering Russia, Mongolia, located at 37.24–53.23°N, and 97.12–126.04°E. The entire region consists of nine cities and three leagues, and covers an area of 1.18 million km^2, with abundant grasslands, forests, mountains, rivers, and deserts among other natural resources and Manchu and Mongolian culture, ethnic customs, border ports, and other human tourism resources. In recent years, Inner Mongolia has made a significant effort to create the brand image of "bright Inner Mongolia is in the north of the motherland." In 2020, Inner Mongolia planned to promote epidemic prevention and control and cultural tourism, the year-round reception of domestic tourists and domestic tourism revenue reached 125 million people and 240.406 billion yuan (RMB), indicating that the development of tourism has developed well (38). Therefore, it is representative to research tourism eco-efficiency in Inner Mongolia. In terms of the ecological environment, Inner Mongolia has a superior resource endowment, vast territory, huge reserves of natural resources, and rich types. Inner Mongolia ranks first in China for grassland, forest area, and per capita arable land, and its reserves of rare earth metals rank first in the world. The ecological status of Inner Mongolia is not only related to the survival and development of the people of all ethnic groups in the region, but also to the ecological security of its neighboring areas. Therefore, protecting the ecological environment of Inner Mongolia is of great significance for its green and sustainable development (34). At the beginning of the twentieth century, the exploitation of non-renewable resources, such as coal and oil, and extensive development caused serious harm to the ecological environment of Inner Mongolia. However, with the effective implementation of ecological protection policies in Inner Mongolia in recent years, various ecological indicators have been restored, which have promoted the sustainable ecological development of Inner Mongolia (35). A good ecological environment is the material basis for human survival and development. It is also an important condition closely related to human health. A healthy urban physical environment is an important factor for the future sustainable development of human settlements. Eco-tourism in Inner Mongolia began with the development of tourism in the early 1980s. Relying on the rich eco-tourism resources, such as grasslands, deserts, forests, lakes, wetlands, wild animals, and plants, eco-tourism in Inner Mongolia has achieved rapid development. Eco-tourism is a form of tourism to protect the ecological environment, and its biggest characteristic is protection (36). Research on tourism eco-efficiency in Inner Mongolia not only promotes Inner Mongolia as a resource-saving and environmental-friendly society but also promotes the implementation of a strict eco-environmental protection system in Inner Mongolia (37).

Data sources

Given the availability and integrity of data, this study of 12 union city in Inner Mongolia in 2009–2020 data analysis, data mainly comes from China city statistical yearbook from 2010 to 20120, Inner Mongolia statistical yearbook, or from Inner Mongolia ecological environment agency's website or with partially missing data interpolation processing.

Index construction

Tourism eco-efficiency is a derivative of the concept of eco-efficiency applied to tourism, which refers to the use of a small environmental impact in the development of the tourism industry to obtain a high economic output. Based on the reference of the index systems reported by Wang (24) and Li (33) among other scholars, this study combines the available data on Inner Mongolia and the characteristics of the tourism industry (Table 1). The input of tourism products [composed of the sum of the number of star hotels, travel agencies, and weighted scenic spots (3A or above scenic spots)], labor input (the number of employees in the tertiary industry), and capital are considered as input indicators (investment in tourism fixed assets, that is, the ratio of the total tourism income to the gross national product (GNP) is used for conversion). The total tourism income (the domestic tourism revenue and inbound tourism revenue) and total tourism person-times (domestic tourism person-times and inbound tourism person-times) are considered as the expected output indicators. Wastewater and sulfur dioxide emissions from tourism are considered as undesirable output indicators (there are no statistical data on tourism carbon emissions at the present stage, so industrial wastewater and sulfur dioxide emissions are collected, and the ratio of tourism revenue to GNP is used for conversion measurement) (39, 40).

Research methods

Super-SBM model with an undesirable output

The SBM model proposed by Tone is an improvement of the traditional DEA model. It addresses radial and angular deviations and allows a more accurate assessment of the relationship between the input and output. Based on this, the effective ranking of decision-making units can be realized. The super-SBM model with an undesirable output was used to measure tourism eco-efficiency in Inner Mongolia (24) through the following formula:

$$\begin{cases} \min p = (1 - \frac{1}{m}\sum_{i=1}^{m}\frac{s_i^-}{x_{ik}}) / \left[1 + \frac{1}{q_1+q_2}(\sum_{r=1}^{q_1}\frac{s_r^+}{y_{rk}} + \sum_{r=1}^{q_2}\frac{s_t^{b-}}{y_{ik}}) \right] \\ s.t. x_k = X\lambda + s^-, y_k = Y\lambda - s^+, b_k = b\lambda + s^{b-} \\ \lambda \geq 0, s_i^- \geq 0, s_r^+ \geq 0, s_i^{b-} \geq 0 \end{cases}$$

Where p is the efficiency; m, q_1, and q_2 are the number of indicators for inputs, desired outputs, and undesired outputs; x_k, y_k, and b_k are input, desired output, and undesired output variables; x_{ik}, y_{rk} and y_{tk} are the elements of input and output vectors; X, Y, b are input–output matrices; and s_i^-, s_r^+, and s_t^{b-} are the slack variables of input, desired output, and undesired output; and λ indicates column vectors.

Spatial variation function

The spatial variation function proposed by the geostatistician Matheron can analyze the spatial correlation and heterogeneity of geographic variables. It can also reasonably and effectively analyze the spatial variation law and describe the spatial correlation between random fields and random processes (41–43). The formula is expressed as follows:

$$\gamma(k) = \frac{1}{2N(k)}\sum_{i=1}^{N(k)}\left[Y(x_i) - Y(x_i + k)\right]^2$$

TABLE 1 The tourism eco-efficiency measurement index system of Inner Mongolia.

Category	Index name	Index characterization
Input indicators	Tourism products	The sum of star hotels, travel agencies, and weighted scenic spots
	Labor force	Number of workers in the tertiary industry
	capital	Investment in fixed assets for tourism
Desired output indicators	Total tourism Revenue	Domestic tourism revenue and inbound tourism revenue
	Total number of visits	Domestic tourism arrivals and inbound tourism arrivals
Undesired output indicators	Tourism wastewater discharge	Tourism as a percentage of industrial wastewater discharged
	Sulfur dioxide emissions from tourism	Tourism as a percentage of industrial sulfur dioxide emissions

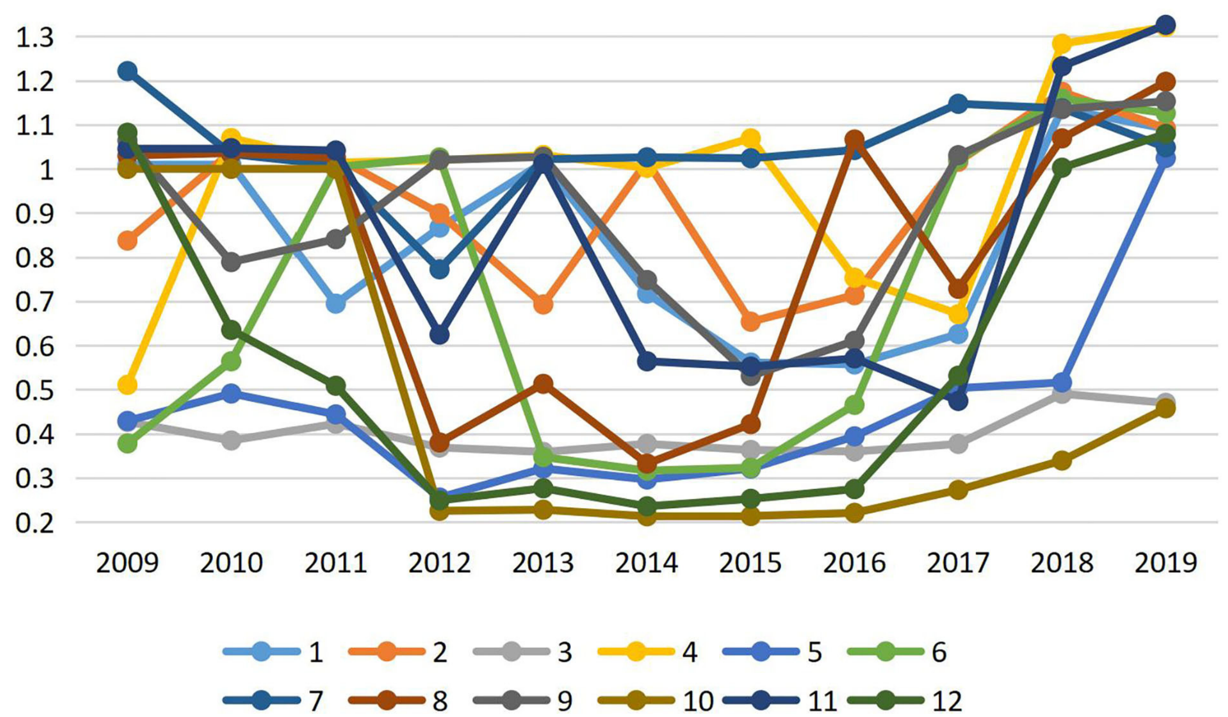

FIGURE 1
Tourism eco-efficiency in Inner Mongolia from 2009 to 2019. Hohhot City, Baotou City, Hulunbuir City, Xing'an League, Tongliao City, Chifeng City, Xilin Gol League, Ulanqab City, Ordos City, Bayannur City, Wuhai City, and Alxa League are represented by numbers 1–12.

$Y(x_i)$ and $Y(x_i + k)$ are the observed values $Y(x)$ of the geographic variables at the points x_i and $x_i + k$,$N(k)$ are the sample sizes of the k segmentation distance.

Geographically weighted regression

Geographically weighted regression focuses on the local effects of spatial objects. Based on the principle of regression, it attempts to explore the relationship between spatial variables under the premise of considering the spatial correlation of the samples. Based on this, the spatial variation and driving factors of the research object are extended forward, and the characteristics and laws of spatial variation are analyzed (44–46). The formula is expressed as follows:

$$y_i = \beta_0(u_i v_i) + \sum_k \beta_k(u_i, v_i)x_{ik} + \varepsilon_i$$

Where y_i refers to the global dependent variable; x_{ik} is the independent variable; $(u_i v_i)$ is the coordinate of the capital city of the i region; $\beta_k(u_i, v_i)$ is the spatial unit value of the continuous function in the i region; ε_i is the random error term,β_0 and $\beta_k$are the parameters; and $k$is the number of regions.

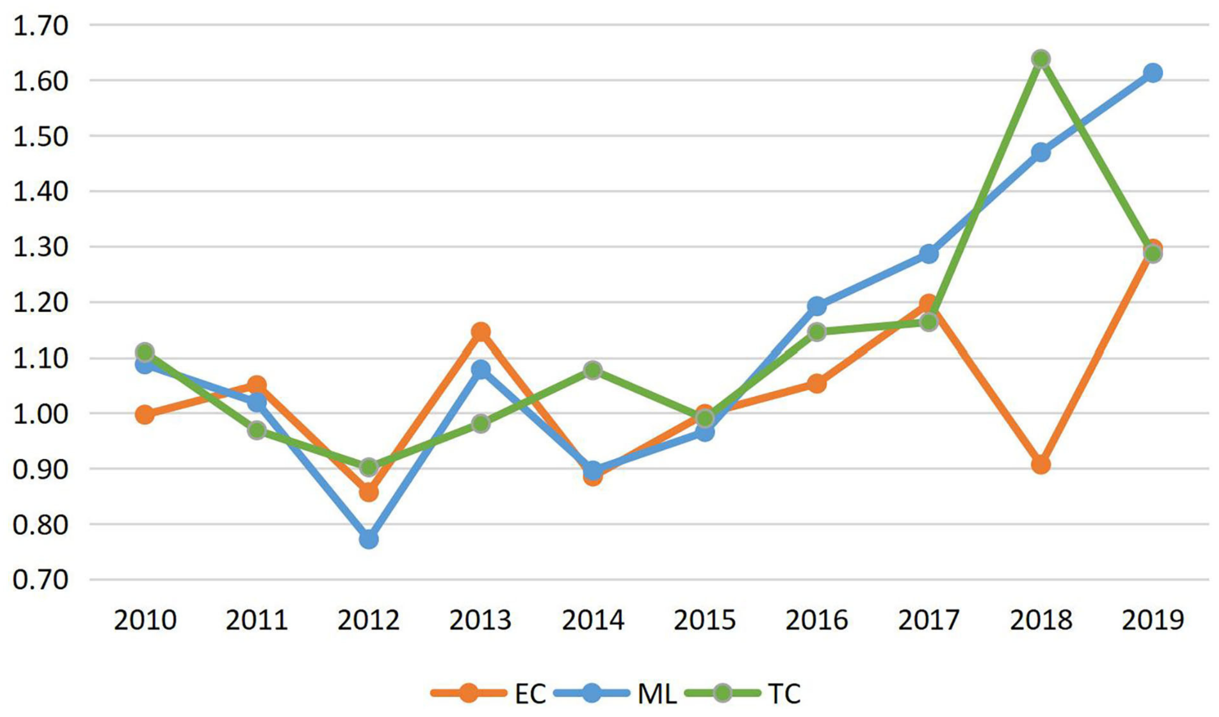

FIGURE 2
Tourism machine learning (ML) index and its decomposition in Inner Mongolia from 2009 to 2019.

Results

Measurement and overall characteristics of tourism eco-efficiency in Inner Mongolia

Tourism eco-efficiency in Inner Mongolia

Based on the super-SBM model of the variable return scale (VRS) with an undesirable output, tourism eco-efficiency in Inner Mongolia from 2009 to 2019 was statically evaluated and obtained (Figure 1). Overall, tourism eco-efficiency in Inner Mongolia from 2009 to 2019 was generally low, with an average of only 0.74, indicating the presence of environmental pollution and resource waste in the tourism industry in Inner Mongolia, and there is a relatively wide scope to improve tourism eco-efficiency. From the perspective of Inner Mongolia, the difference in tourism eco-efficiency from 2009 to 2019 was relatively large, but the number of effective areas in the efficiency frontier generally showed fluctuating growth dynamics. From 2009 to 2019, the mean value of tourism eco-efficiency in Hohhot City, Baotou City, Ordos City, Hinggan League, and Xilin Gol League in Inner Mongolia reached the effective level, but tourism eco-efficiency in Alxa League, Wuhai City, Tongliao City, and Bayannur City was relatively low, and there was a significant margin of improvement. In short, tourism eco-efficiency in Inner Mongolia needs to be improved. The overall level of tourism eco-efficiency in Inner Mongolia is relatively low, and regional differences are relatively large. Tourism eco-efficiency in the central region of Inner Mongolia ranks first in the whole region. This is mainly due to the high level of economic development in the central region of Inner Mongolia, which has enough ability to invest in ecological construction and provides good conditions for its own green development.

Tourism eco-efficiency machine learning index

Tourism eco-efficiency is a static measure that is independently measured yearly. Therefore, to determine the mobile changes in the tourism eco-efficiency levels in Inner Mongolia from 2009 to 2019, it is necessary to measure its growth rate. In this study, the VRS model was used for the measurement analysis considering the machine learning (ML) index, which refers to the growth rate of tourism eco-efficiency when the desired output is increased and the undesired output is reduced in equal proportion. The ML index includes two indicators: tourism eco-technical efficiency growth rate (EC) and tourism eco-technical progress growth rate (TC) (Figure 2). The ML index of an undesired output from 2009 to 2019 was greater than one in most years, indicating that tourism eco-efficiency in Inner Mongolia showed a trend of optimization. In terms of the average value of each year, the average growth rate of tourism eco-efficiency in Inner Mongolia is 13.80%,

TABLE 2 Fitting parameters of the variation function of tourism eco-efficiency in Inner Mongolia.

Year	Model	Co	Co+C	Co/(Co+C)	Range	R^2
2009	Gaussian	0.001000	0.540000	0.001851852	2809386.41	0.594
2013	Gaussian	0.027600	0.231200	0.119377163	1519008.56	0.374
2019	Gaussian	0.020300	0.253600	0.080047319	1293841.95	0.459

TABLE 3 The fractal dimension of the variation function of tourism eco-efficiency in Inner Mongolia.

Year	Omnidirectional		N-S (0°)		EN-WS (45°)		E-W (90°)	
	D	R^2	D	R^2	D	R^2	D	R^2
2009	1.420	0.620	1.091	0.229	1.521	0.670	1.174	0.652
2013	1.400	0.449	1.896	0.005	1.633	0.044	1.292	0.500
2019	1.459	0.339	1.868	0.006	1.537	0.089	1.990	0.000

among which the contribution rate of technical efficiency and technological progress is 0.1 and 10.81%, respectively. The contribution rate of technological progress is significantly higher than that of technical efficiency, indicating that technological innovation plays an essential role in tourism eco-efficiency in Inner Mongolia. Due to a variety of factors, including the international green barrier, energy constraints, tightening in the "environmentally reversed transmission mechanism," and the "five-sphere integrated plan" development philosophy, the government employs an active energy structure optimization strategy to boost capital investment, energy conservation, and emissions reduction. Technology research and development, as well as fiercely promoting technological innovation in its critical role in the development of the tourism industry, are all priorities.

The spatial-temporal evolution of tourism eco-efficiency in Inner Mongolia

First, the projection coordinate system of Inner Mongolia was measured, then the spatial variation function of 2009, 2013, and 2019 Inner Mongolia tourism eco-efficiency was measured, and finally, the optimal model for measuring the fractal dimension of each direction was selected. Ultimately, the Kriging interpolation simulation was performed to comprehensively analyze the evolution process of the spatial pattern of tourism eco-efficiency in Inner Mongolia. According to the results of the spatial variation value of tourism eco-efficiency in Inner Mongolia (Table 2), the Gaussian model was selected as optimal for analysis. In addition, the structural features of tourism eco-efficiency in Inner Mongolia were consistent over the years, and its coefficient of determination tended to initially increase and then decrease, but overall it remained relatively stable. The range parameters of tourism eco-efficiency decreased from 2,809,386.41 m in 2009 to 1,293,841.95 m in 2019, indicating that the spatial correlation of tourism eco-efficiency in Inner Mongolia showed a narrowing trend under the influence of structural and spatial differentiation. Due to the vast territory and large east-west span of Inner Mongolia, there are huge differences in the economic foundation, resource endowment, infrastructure, and traffic conditions among the allied cities, which lead to limitations in their spatial correlation, core area radiation, and interregional spillover.

From the fractal dimension of the spatial variation function (Table 3), the overall direction of tourism eco-efficiency in Inner Mongolia exhibited a relatively good degree of homogenization, and the spatial difference in the overall direction fluctuated and increased, while the spatial difference in the local direction was relatively obvious. The dimension value in the overall direction increased from 1.420 in 2009 to 1.459 in 2019 but showed a transient decline in 2013. The south-north fractal dimension continued to increase, and the coefficient of determination was small and decreased continuously, indicating that the spatial difference in tourism eco-efficiency decreased in this direction, and the scale of differentiation was small and continuously decreased. The gap between tourism eco-efficiency in northern and southern Inner Mongolia is decreasing. The fractal dimension and the coefficient of determination in the northeast and southwest do not change significantly, indicating that the spatial difference and divergent scales of tourism eco-efficiency in this direction show a stable trend with little change and relatively balanced development. The fractal dimension increased from east to west, while the coefficient of determination shows a decreasing trend, indicating that the spatial difference in tourism eco-efficiency in this direction and the scale of differentiation tended to decrease. In short, the evolution of each direction exhibited unique properties. From the perspective of historical development, the eastern region of

Inner Mongolia is dominated by the primary industry, while the western region has a certain first-mover advantage in the development of secondary and tertiary industries. However, the natural resources and rich cultural heritage of the east provide a prerequisite for the development of leisure tourism. All cities in Inner Mongolia pay attention to the development of tourism and the improvement of ecological efficiency. However, due to differences in the economic foundation, infrastructure, and the universality of policy coverage, the improvement of tourism eco-efficiency in Inner Mongolia is characterized by an overall improvement, but the local advantages are not obvious.

The Kriging interpolation simulation of the variation function of tourism eco-efficiency in Mongolia (Figure 3) shows that the spatial distribution form and internal structure evolution of tourism eco-efficiency in Inner Mongolia have some regularity and continuity. In 2009, 2013, and 2019, the low-value areas of tourism eco-efficiency showed a trend of low-value dispersion and concentration, with Bayannur City and Alxa League being the low-value core and low eco-efficiency valley, respectively. At the same time, the high-value polar core areas were mainly focused on Hohhot City, Ulanqab City, and Xilin Gol League, and the siphon effect was the most significant. This is mainly due to the high level of economic development in the central region of Inner Mongolia, which has enough ability to invest in ecological construction and provides good conditions for its own green development. Due to geographical location, infrastructure, and other reasons, the eastern and western regions of Inner Mongolia have not achieved coordinated development of economic growth, environmental protection, and tourism development. Tourism eco-efficiency of the core cities in Inner Mongolia should have the positive effects of radiation and agglomeration and brings about the balance and coordinated development of the entire region.

The influencing factors of tourism eco-efficiency in Inner Mongolia

Based on the objectivity of the spatial heterogeneity of the influencing factors of tourism eco-efficiency, the GWR method was used to measure the regression coefficients of the influencing factors in each region. Data from 2009, 2013, and 2019 were selected to construe the spatial evolution law of the influencing factors on the eco-efficiency level. Considering (u_i, v_i) as a i coordinate, the GWR model of tourism eco-efficiency is expressed as follows:

$$TECO_{ij} = \beta_0(u_i, v_i) + \beta_1(u_i, v_i)\,pGDP_y + \beta_2(u_i, v_i)TIP_y$$
$$+\beta_3(u_i, v_i)CHU_y + \beta_4(u_i, v_i)SWS_{ij} + \beta_5(u_i, v_i)EPE_{ij} + \varepsilon_{ij}$$

Where $TECO_{ij}$is the tourism eco-efficiency level of the i region in the period j; $pGDP_{ij}$, TIP_{ij}, SWS_{ij}, and EPE_{ij} represent the economic development (per-GDP), industrial structure (tertiary industry share), traffic condition (ratio of the length of graded highways to the urban area), resource endowment (the weighted score of high-level scenic spots), and environmental regulation (expenditure on energy conservation and environmental protection), respectively, in the period J of the region i.

ArcGIS10.4 was used to calculate GWR, and the regression coefficients of each influencing factor were divided into five levels ranging from the high-value area to the low-value area based on five levels of natural fracture points (Table 4). In terms of economic factors, from the perspective of space, tourism eco-efficiency in Hulunbuir City, Xing'an League, Tongliao City, and Chifeng City, among other cities was found to be greatly affected by the economic level, while tourism eco-efficiency in Bayannur City, Wuhai City, Alxa League, and other cities were less affected by the economic level. From the temporal perspective, the pattern of tourism eco-efficiency affected by the economic level of each year was basically the same. The spatial and temporal patterns of the impact of environmental regulation on tourism eco-efficiency were generally consistent with those of economic factors. Spatially, the tourism eco-efficiency factors in Wuhai City, Alxa League, and Bayannur City are greatly affected by industrial structure, while those in Bayannur City, Hulunbuir City, Xing'an League City, Tongliao City, and Chifeng City and other tourism eco-efficiency factors are less affected by industrial structure factors. With respect to time, the pattern of tourism eco-efficiency affected by industrial structure in different years is basically the same; however, certain patterns exhibit slight variations. The spatial and temporal patterns of the influence of traffic conditions and resource endowment on tourism eco-efficiency are generally consistent with the spatial and temporal distribution pattern of the influencing factors of industrial structure. Summarily, tourism eco-efficiency in Inner Mongolia should be improved according to the heterogeneity of different countermeasures and suggestions.

Discussion

This study uses a super-SBM model with an undesirable output to assess and analyze tourism eco-efficiency during 2009–2019 in Inner Mongolia. Then, using the spatial variation function analysis of the spatial and temporal evolution characteristics of tourism eco-efficiency in Inner Mongolia and based on the GWR analysis of the influence of factors of tourism in Inner Mongolia on eco-efficiency, the following conclusions were drawn.

The average tourism eco-efficiency in Inner Mongolia is 0.74, which is relatively low. Furthermore, the tourism eco-efficiency values of the provinces vary significantly, and their distribution is unbalanced. In addition, technological progress contributes significantly to the growth rate of

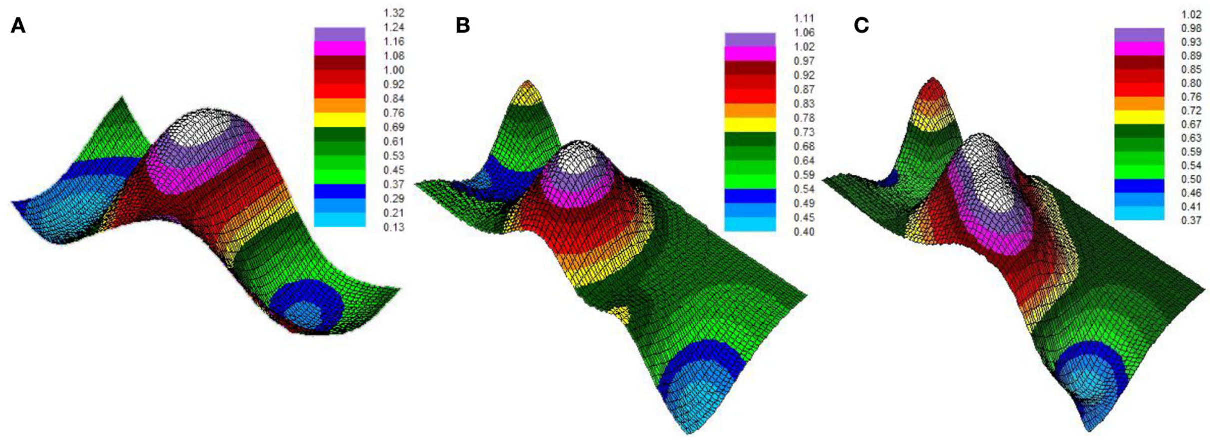

FIGURE 3
The Kriging interpolation simulation of the tourism eco-efficiency variation function in Inner Mongolia in 2009, 2013, and 2019. **(A)** 2009, **(B)** 2013, and **(C)** 2019.

TABLE 4 Natural fault zone division of each parameter in the geographically weighted regression (GWR) model.

	Year	High-value area	Re-High-value area	Median value area	Re-Low-value area	Low-value area
Economic development	2009	3,4,5	6,7	1,8	2,9,11	10,12
	2013	3	4,5,6,7	1,2,8	10	9,11,12
	2019	3,4,5	6,7	1,2,8	9,10	11,12
Industrial structure	2009	11,12	2,8,10	1,7,9	5,6	3,4
	2013	10,12	2,7,11	8,9	1,3,4	5,6
	2019	10,12	2,9,11	1,7,8	3,6	4,5
Traffic conditions	2009	10,12	2,9,11	1,8	7	3,4,5,6
	2013	12	2,9,10,11	1,8	3,7	4,5,6
	2019	12	9,10,11	1,2,8	6,7	3,4,5
Resource endowment	2009	10,12	2,11	1,8,9	7	3,4,5,6
	2013	9,11,12	1,2,10	8	5,6,7	3,4
	2019	11,12	1,9,10	2,8	6,7	3,4,5
Environmental regulation	2009	3,4,5,6	7	1,9	2,8,11	10,12
	2013	4,5,6	3	1,7,8	2,9,10,11	12
	2019	3,4,5	6,7	1,2,8	9,10,11	12

Hohhot City, Baotou City, Hulunbuir City, Xing'an League, Tongliao City, Chifeng City, Xilin Gol League, Ulanqab City, Ordos City, Bayannur City, Wuhai City, and Alxa League are represented by numbers 1–12.

tourism eco-efficiency in Inner Mongolia, indicating that technological innovation has a relatively high impact on tourism eco-efficiency. The differences in tourism eco-efficiency from 2009 to 2019 in Inner Mongolia were relatively large, but the number of effective areas in the efficiency frontier generally showed a fluctuating growth trend. The results of this study echo previous studies. Jun shows that the extensive economic growth mode restricts the improvement of tourism eco-efficiency in Inner Mongolia (47). The improvement of Inner Mongolia's technological level and the realization of scale efficiency are the fundamental ways to improve eco-efficiency and realize energy saving and emission reduction. On the whole, the value of tourism eco-efficiency in Inner Mongolia is generally low, indicating the occurrence of environmental pollution and resource waste in the development process of tourism in Inner Mongolia, and there is a relatively large room to improve tourism eco-efficiency (18, 32).

The range parameters of tourism eco-efficiency showed a decreasing trend, and the spatial correlation effect of tourism eco-efficiency in Inner Mongolia showed a decreasing trend under the influence of structural and spatial differentiation. Tourism eco-efficiency in Inner Mongolia showed consistent structural characteristics in different periods. The general homogenization degree of tourism eco-efficiency is relatively good, and the spatial difference in the local direction is relatively obvious. The spatial distribution pattern and internal structure evolution of tourism eco-efficiency have a certain regularity and continuity, showing a high-value concentrated distribution, and low-value scattered contiguous distribution. Yuanyuan and Yuxiang pointed out that the spatial variation function can deeply describe the randomness and structure of regional variables and measure the degree of variation of the spatial pattern of economic units (48). The structural characteristics of tourism eco-efficiency in Inner Mongolia are consistent over the years, and its coefficient of determination first increases and then decreases, but in general, it is relatively stable. The spatial difference in tourism eco-efficiency is decreasing from the south to the north, and the scale of differentiation is small and continuously decreasing. The gap between tourism eco-efficiency from the south to the north in Inner Mongolia is narrowing. The fractal dimension of tourism eco-efficiency in the east-west direction of Inner Mongolia shows an increasing trend, while the coefficient of determination shows a decreasing trend, indicating that the spatial difference of tourism eco-efficiency in Inner Mongolia is decreasing in this direction, and the scale of differentiation is smaller and continuously smaller. In short, the evolution of each direction has its own characteristics (41, 42).

The pattern evolution of tourism eco-efficiency in Inner Mongolia is jointly driven by the economic level, environmental regulation, industrial structure, traffic conditions, resource endowment, and tourism reception facilities, and there is obvious spatial heterogeneity among the influencing factors. The spatial and temporal patterns of the impact of environmental regulation on tourism eco-efficiency are generally consistent with those of economic factors. The spatial and temporal patterns of the influence of traffic conditions and resource endowment on tourism eco-efficiency are generally consistent with those of the influencing factors of industrial structure. Zhilong and Diyun emphasized that the economic level, industrial structure, resource endowment, infrastructure, and environmental regulation are the key factors affecting tourism eco-efficiency (33, 41). The regional economic level is closely related to the development of the tourism industry, which affects the development level of regional tourism to a certain extent. The optimization of the industrial structure is conducive to the healthy development of the tourism industry, thus affecting tourism eco-efficiency (44). Tourism resources are the foundation of tourism development, and resource endowment will inevitably have an important impact on tourism eco-efficiency. Infrastructure, such as traffic conditions, is an important objective condition for the smooth development of regional tourism activities, which will also have a certain impact on tourism eco-efficiency (45).

Implications

This study first constructs a tourism eco-efficiency evaluation index system based on Inner Mongolia and then explores the evolutionary path and spatial pattern of tourism eco-efficiency in Inner Mongolia from the perspective of the geographic spatiotemporal dimension. To provide an accurate reference for improving tourism quality and eco-efficiency in Inner Mongolia and the sustainable development of the regional economy and society.

Theoretical implications

First, the study presents research on tourism eco-efficiency from the perspective of ecological and environmental protection, which conforms to the connotation of developing an ecological civilization and meets the requirements of high-quality economic development. This is of great significance for enriching the theory of ecological civilization construction and expanding the applicable category of ecological civilization construction. Second, tourism eco-efficiency is the application of the theory of tourism eco-efficiency. Tourism eco-efficiency can combine the development of the tourism economy with its environmental impact, which can also provide some academic reference for the study of eco-efficiency in other industries. Finally, this study tries to determine the temporal evolution path and spatial pattern of tourism eco-efficiency, which is the basic paradigm of geographic spatiotemporal analysis. With respect to research, this study incorporated the undesired output in the tourism eco-efficiency measurement and constructed a relatively scientific, systematic, and perfect tourism eco-efficiency evaluation index system. In addition, the rules of spatiotemporal evolution and the characteristics of tourism eco-efficiency based on Inner Mongolia were analyzed. This provides additional insight into the correlation between geographical spatial patterns and the ecological environment, and promotes the cross-integration of tourism economics and tourism geography and other marginal disciplines. With respect to research methods, this study adopts the super-SBM model with the undesirable output to calculate tourism eco-efficiency in Inner Mongolia from 2009 to 2019, and comprehensively uses the Malmquist–Luenberger index to break down tourism eco-efficiency. The spatial variation function and GWR analysis describe its spatiotemporal evolution characteristics and allow the integration of econometrics, spatial geography, and other disciplines.

Management implications

Tourism eco-efficiency is an essential index for the formulation of a tourism development plan, the evaluation of tourism management, and the promotion of the sustainable development of the tourism destination. The evaluation of tourism eco-efficiency, the description of the time evolution path, the outline of the spatial distribution pattern, and the discussion of its dynamic correlation with the development of the tourism economy have significant practical value. In the face of increasing tourism energy consumption and the worsening of the ecological environment, Inner Mongolia tourism eco-efficiency evaluation can effectively reflect the relationship between economic activities and the ecological environment. This is validated by the development of the worsening situation of the tourism ecological environment, can boost sustainable blossom of the province tourism such as national macro policy takes root provides the beneficial reference. The exploration of the time evolution model and the outline of the spatial pattern of tourism eco-efficiency in Inner Mongolia elucidate the sustainable development of the entire region's tourism in Inner Mongolia from a macro perspective and provide scientific guidance for the "top-down" decision and "bottom-up" policy of tourism ecological protection in Inner Mongolia. Moreover, this study explores the spatial and temporal patterns of tourism eco-efficiency and its influencing factors in Inner Mongolia, which provides a reference for the optimization of tourism eco-efficiency and the sustainable development of tourism in other regions.

Under the national macro context of constructing an ecological civilization, Inner Mongolia should change its tourism development model, enhance tourism eco-efficiency, and promote the sustainable development of tourism. Therefore, this study proposes the following. In view of the performance of tourism eco-efficiency in Inner Mongolia, the environmental ecology of tourism in Inner Mongolia needs to be improved, and environmental protection needs to be considered while developing the tourism industry, to enhance the sustainable development of tourism (17, 18). First, the government can stipulate relevant laws and regulations, formulate the ecological red line for tourism development, limit carbon emissions from tourism-related enterprises, and reduce environmental pollution from tourism activities. We need to focus on changing the tourism development model and enhancing tourism eco-efficiency in Inner Mongolia. The black linear development mode characterized by high energy consumption, high pollution, and low income should be gradually discontinued, and a green circular development characterized by low consumption, low pollution, and high income should be formed (49). Second, tourism eco-efficiency among cities in Inner Mongolia was observed to be heterogenous; therefore, targeted development countermeasures and suggestions based on local conditions are required to strengthen their cooperation, learn from each other's advanced experience, take the resource-efficient and environmental-friendly tourism development path, and jointly promote the sustainable development of tourism in Inner Mongolia. Inner Mongolia should continue to strengthen intra-provincial cooperation and actively draw on advanced experience from other provinces, adhere to the basic principle of strengthening external cooperation and internal communication, promote the transformation of the tourism development mode, and improve tourism eco-efficiency through knowledge and technology spillover as well as capital and talent radiation (50). Finally, the tourism development strategy should be constantly adjusted to promote the two-way synergistic improvement of the tourism economy and tourism ecology. As the global economy enters a new normal, the blind pursuit of tourism industry expansion should be abandoned, and the continuous improvement of tourism development quality should be promoted, in order to provide the funds, talents, information, and technology required to ensure tourism ecological protection.

Limitations

This study explores in depth the spatial pattern and influencing factors of tourism eco-efficiency in Inner Mongolia. The study provides a reference for future research on tourism eco-efficiency and sustainability in Inner Mongolia and other regions. However, this study has certain shortcomings that should be addressed. First, regarding the design of the index system, carbon emissions as an undesirable output of tourism eco-efficiency reflect the negative impact of tourism on the environment. However, related theoretical and empirical research is insufficient; the travel coefficient of carbon emissions for Inner Mongolia has not been evaluated. Therefore, the measurement results of tourism eco-efficiency may be slightly conservative (21, 22). Secondly, given the ease of access to data, this study analyzes tourism eco-efficiency in a single province of Inner Mongolia, which can reflect the actual development status of tourism eco-efficiency. In future research, the perspective can be extended to a large-scale analysis of the region and the entire country (32, 33). In addition, this study analyzes the spatial layout and influencing factors of tourism eco-efficiency in the tourist attractions of Inner Mongolia and proposes recommendations for the optimization of their spatial structure. Therefore, future research should deeply analyze the reasons for the unreasonable spatial structure of tourism eco-efficiency, and should propose reasonable recommendations for the optimization of the tourism eco-efficiency structure, for the improvement of tourism eco-efficiency in similar areas (51).

Conclusion

This study first constructs the tourism eco-efficiency evaluation index system and then explores the evolution path and spatial pattern of tourism eco-efficiency in Inner Mongolia from the perspective of the geographic spatiotemporal dimension. Inner Mongolia has a relatively low tourism eco-efficiency value, with an average value of 0.74. Furthermore, the tourism efficiency values of the provinces vary and their distribution is unbalanced. The range parameters of tourism eco-efficiency and the spatial correlation effect of tourism eco-efficiency in Inner Mongolia under the influence of structural and spatial differentiation showed a decreasing trend.

Data availability statement

The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding author.

Author contributions

XW contributed to all aspects of this work. YW wrote the main manuscript text and analyzed the data. Both authors reviewed this manuscript, read, and agreed to the published version of the manuscript.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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Spatial accessibility analysis of green space from a health-benefit perspective: Implications for healthy urban development

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The spatial accessibility of urban park green space (UPGS) plays a crucial role in promoting the healthy development of cities and their residents. However, previous studies have overestimated the accessibility of UPGS and failed to adequately consider the impact of variegated parks on residents' needs. To fill this gap in the research, we first propose an improved two-step floating catchment area (Huff-2SFCA) method that takes into consideration the trade-offs between supply, demand, and walking time to calculate the UPGS accessibility index for the built-up area of Mianyang, China. Next, we assess the spatial characteristics of UPGS accessibility from both partial and overall points of view and further explore the relationship between accessibility and population size. Our results show that (1) every street area has a different form of UPGS construction, and most of these spaces are of poor quality; (2) municipal-level parks are significantly more accessible than district-level parks, community-level parks, or neighborhood-level parks; (3) the overall distribution of accessibility is generally characterized by a decreasing trend along both sides of the river, with poor overall accessibility; and (4) 243 residential districts are located in high-demand–low-supply areas that need improving. This study can be employed to identify areas that are underserved by UPGS and can provide a basis for improving the accessibility of UPGS and promoting its health benefits.

KEYWORDS

health benefits, park quality, Huff-2SFCA model, spatial accessibility, urban park green space

Introduction

The novel coronavirus (COVID-19) pandemic has affected individuals' mental health, leaving them with increased physical and emotional wellness needs (Ifdil et al., 2020). As the only natural or semi-natural land-use form within the city, urban park green space (UPGS) plays a prominent role in maintaining biodiversity, improving the urban microclimate, and absorbing pollutants (Yang et al., 2015). Moreover, UPGS provides urban residents with opportunities to interact with nature, encourages outdoor activities, and promotes physical and mental health (Shaohua and Wanmin, 2007). Research has shown that the health-promotion benefits of UPGS are directly linked to public health recovery and urban sustainability in the post-pandemic era (Lopez et al., 2021).

However, due to rapid urbanization, an increasing number of people are living in complex environments with many high-rise buildings, high population densities, and low levels of green space (Li et al., 2015; Zhang and He, 2021). In addition, the pandemic forced cities to face the challenge of meeting the growing demand for a limited quantity of green space (Venter et al., 2021). Therefore, improving the quality of existing urban parks in cities has become a goal to be addressed by planners and policy makers to restore residents' physical and mental health in the post-pandemic era (Reid et al., 2022).

Urban park green space provides health-promotion benefits by attracting visitors (King et al., 2015). Studies have explored the planning and construction of UPGS by exploring eco-cultural services, ecological regulation services, ecological support services, and other factors affecting UPGS visits (Gibson, 2018; Xie et al., 2018; Tu et al., 2020; Zheng et al., 2020). Of these factors, accessibility substantially affects visits to and the health benefits of UPGS (Gidlow et al., 2012). For example, residents' mobility was influenced by UPGS accessibility while the COVID-19 controls were in place to reduce the probability of disease transmission (Liu, 2015). Accessibility indicates the ability of residents to obtain park services and then receive the health benefits of UPGS (Hegetschweiler et al., 2017). Therefore, accurate assessments of UPGS accessibility to identify underserved areas can guide the planning and construction of urban parks and provide a basis for improving and optimizing the health-promotion benefits of urban parks in the post-pandemic era.

Most studies have evaluated the accessibility of public service facilities in terms of spatial accessibility (Fan et al., 2017). The spatial accessibility model is affected by three parameters: supply, demand, and connection (Xing et al., 2020; Zhang et al., 2021). Supply refers to the ability of the destination to fulfill demand, demand refers to the differentiated characteristics of the population, and connection refers to the distance or time between supply and demand (Giles-Corti et al., 2005; Wolch et al., 2014; Rigolon, 2016). Accessibility analysis methods mainly include buffer analysis, kernel density estimation, network analysis, the Voronoi diagram, the gravity model, and the two-step floating catchment area method (2SFCA). Buffer analysis, kernel density estimation, and network analysis can be used to identify a population within a specified distance as an alternative coverage method, which is considered somewhat random due to the difficulty of determining a predefined distance (Nicholls, 2001; Moore et al., 2008; Miyake et al., 2010). The Voronoi diagram method assumes that citizens choose the park closest to their residence and is used to evaluate the carrying capacity of UPGS in a certain area (Sister et al., 2010). The gravity model combines the attraction and distance-decay effect of the park and solves the problem of the assumed service range to a certain extent (Chang and Liao, 2011). These models consider only a single factor as affecting accessibility. In contrast, the 2SFCA method, based on the principle of the gravity model, which comprehensively considers the three factors, is now used and has been improved as a way of determining which areas have insufficient services (Wei, 2017; Xing et al., 2020). There are four main aspects in which UPGS accessibility can be improved: the distance-decay effect (Dai, 2011), service radius (Dony et al., 2015; Lin et al., 2021), competition between demand and supply (Zhang et al., 2021), and travel mode (Li et al., 2021). These improvements enhance the practicability and reliability of the 2SFCA model that is used to evaluate UPGS accessibility. However, scholars have paid more attention to improving demand and connection than to the impact of differences in UPGS regarding residents' demand (Xing et al., 2020).

Competition among heterogeneous forms of UPGS affects the visits of individuals, who tend to wish to enter a UPGS of high quality within an acceptable time threshold (Ekkel and de Vries, 2017). Parks can increase the number of visits by providing rich landscapes, healthy environments, diverse recreational places, and a complete infrastructure (Yu et al., 2018). For example, Schipperijn et al. found that residents' outdoor physical activity is positively related to the size of nearby UPGS, walking or riding paths, water body characteristics, lighting, pleasant scenery, and so forth (Cohen et al., 2010; Branas et al., 2011; Veitch et al., 2012; Schipperijn et al., 2013). However, Edwards et al. found that owing to the differences among parks, only 27% of teenagers use nearby UPGS (Edwards et al., 2015). Research has shown that a high greening level in UPGS can prolong users' outdoor activity time and improve visit frequency, encouraging residents to engage in physical activities and form a healthy lifestyle (Grigsby-Toussaint et al., 2011; Fong et al., 2018). When individuals are in a natural environment, their state is relaxed, which can unconsciously eliminate fatigue, reduce levels of directed attention, and facilitate the recovery of mental and physical strength (Chang et al., 2008). In addition, the natural environment directly or indirectly counteracts the acute and chronic negative health effects caused by air pollution, thereby promoting human health (Hirabayashi and Nowak, 2016). Influenced by the pandemic, urban residents preferred to visit UPGS with a high degree of greening, a quiet nature, and epidemic prevention and control interventions (Cheng et al., 2021; Marconi et al., 2022). Therefore, in the construction of UPGS, there needs to be a good match with public health needs. Assessments of the accessibility of urban parks should consider the impact of park heterogeneity on residents' needs.

To address this issue, we calculated the accessibility of UPGS by incorporating its public health-promoting environmental characteristics. First, we employed the entropy value method to construct a UPGS quality evaluation model based on questionnaire data, which evaluated park quality by aggregating variables that attract residents' visits. The quality evaluation results were then integrated with the improved Huff-2SFCA model for accessibility assessment. Finally, we determined the supply and demand for UPGS in the study area by overlaying the urban population and the accessibility index. The objectives of this study were to (1) quantify the spatial pattern of different quality levels of UPGS, (2) identify residential districts that are underserved in terms of UPGS, and (3) identify residential districts that are in dire need of improvement. In this study, the impact of scale and quality factors on supply capacity was taken into account to accurately evaluate accessibility, which guided the planning and construction of UPGSs and provided a basis for improving and optimizing the health-promotion benefits of UPGSs in the post-pandemic era.

Materials and methods

First, a quality evaluation system was constructed by analyzing the characteristics of UPGS that attract public visits and promote visitors' physical and mental health levels. Second, we used the entropy value method to construct a quality evaluation model based on the questionnaire data. Next, based on the traditional 2SFCA model, improvements were made to both the supply and demand aspects. On the supply side, supply capacity was first enhanced in combination with quality because supply is crucial to promoting residents' visits; on the demand side, we used the Huff model to capture the likelihood of individuals visiting UPGS to avoid overestimating the accessibility index. Finally, we incorporated the aforementioned parameters into the Huff-2SFCA model to calculate the accessibility index of UPGS in urban areas.

UPGS quality index

Visits are the main factor that improves the physical and mental health of UPGS visitors (Veitch et al., 2012). First, a UPGS's infrastructure and leisure facilities are the basic indicators that reflect their ability to attract residents. The infrastructure includes, for example, walking paths, streetlights, and public toilets; the leisure facilities include, for example, fitness facilities and sports fields (Biernacka et al., 2020). Outdoor thermal comfort (OTC) is another crucial attribute of UPGS that affects visits, increasing visits up to 2-fold (Cheung and Jim, 2018; Li et al., 2018). OTC is mainly affected by temperature, humidity, sunlight, and ventilation (Javadi and Nasrollahi, 2021). In addition, natural and human landscapes provide visitors with rich visual sensory experiences, such as mountain/water landscapes and historical sites, which can significantly enhance the attractiveness of UPGS (Francis et al., 2012; Ahn et al., 2020). Finally, management and safety significantly affect the frequency of residents' UPGS visits (Haque et al., 2013). During epidemics, setting up detection chokepoints, controlling the number of visitors, and implementing sanitation and disinfection practices can effectively guarantee the safety of a UPGS.

According to the aforementioned characteristics that attract public visits and promote visitors' health levels, we quantified a UPGS quality index (QI) based on 18 variables grouped under five key themes: thermal comfort, infrastructure, recreational facilities, visual sensory experience, and management and safety of parks. Second, we inputted the results of 1,520 questionnaires into SPSS 25 to obtain statistics; 20 random interviews were conducted for each UPGS, and invalid questionnaires were randomly re-interviewed by finding others who were not interviewed. Next, the QI was evaluated by employing the entropy evaluation method (EEM); its calculation formula was derived from the literature (Jiang et al., 2022). The EEM determines the variables' weights according to each variable's degree of dispersion. The variables, questionnaire assignments (Zhang et al., 2017; Chen et al., 2019; Ta et al., 2021), and weighting results are shown in Table 1.

Conventional 2SFCA model

The 2SFCA model was successively proposed and named by Radke and Luo et al. (Radke and Mu, 2000; Luo and Wang, 2003). To solve the distance-decay problems in accessibility evaluation,

TABLE 1 Variables and their weight by the QI.

Categories	Variables	Weight	Questionnaire assignments
Thermal comfort	Temperature	0.016	1 = very bad
	Humidity	0.032	2 = bad
	Sunlight	0.017	3 = general
	Ventilation	0.018	4 = good
Infrastructure	Green coverage rate	0.041	5 = very good
	Lighting	0.023	
	Signage system	0.044	
	Public restrooms	0.117	
	Trash cans	0.027	
Leisure facilities	Trail density	0.023	
	Fitness facilities	0.072	
	Playgrounds	0.217	
	Contact space	0.023	
Visual sensory factors	Green view index	0.034	
	Natural/humanistic landscapes	0.051	
Management and safety	Controllability of visitor numbers	0.029	
	Controllable distance of visitor activity	0.047	
	Health care	0.169	

Dai used a Gaussian function to modify the 2SFCA model (Dai, 2011); subsequently, it has been widely used in research. This method performs two searches based on supply and demand points, respectively. The first step is to search for the demand points i within the threshold d0 for each park j, and then calculate the supply–demand ratio R_j:

$$R_j = \frac{S_j^A}{\sum_{k\epsilon\{d_{kj}\le d_0\}} G(d_{ij},d_0)P_k} \quad (1)$$

where P_k is the population of residential area k within the spatial scope of park $j(d_{ij} \le d_0)$; d_{ij} is the space's distance from the center of residential area *k* to the center of park j; SA j is the capacity of park j, which generally includes the park area; and $G(d_{ij}, d_0)$ is the Gaussian function considering distance decay as follows:

$$G(d_{ij},d_0) = \begin{cases} \dfrac{e^{-\left(\frac{1}{2}\right)\times\left(\frac{d_{ij}}{d_0}\right)^2} - e^{-\left(\frac{1}{2}\right)}}{1-e^{-\left(\frac{1}{2}\right)}}, & \text{if } d_{kj} \le d_0 \\ 0, & \text{if } d_{kj} > d_0 \end{cases} \quad (2)$$

The second step is to use the demand point as the center, search for the supply points within the threshold d_0, and sum the supply–demand ratio R_j of all supply points to obtain the accessibility A_i.

$$A_i = \sum_{j\in\{d_{ij}\le d_0\}} G(d_{ij},d_0)R_j \quad (3)$$

where j is all parks within the catchment d_0. A_i represents the supply–demand ratio of a park in the catchment $(d_{ij} \le d_0)$ of demand point i.

Supply improvements

Size is sometimes used to express the service capacity of a UPGS. Size is essential because a large UPGS may provide more services than a small UPGS. However, having a large area does not guarantee improved service quality. Therefore, scholars have sought to quantify the service capacity of UPGS by improving the supply parameters. Zhang et al. assessed the attractiveness of peri-urban parks in terms of five aspects—infrastructure, activity facilities, leisure and entertainment facilities, landscape quality, and safety—and included them in a method for accessibility assessment of peri-urban parks (Zhang et al., 2021). Xing et al. improved the assessment of the service capacity of the park by taking into account sports facilities and the natural environment in terms of teenagers' willingness to engage in activity (Xing et al., 2020). These studies showed that to improve the supply quality of a UPGS, it is necessary to combine indicators of size and quality. Therefore, following these frameworks, we comprehensively describe supply capacity by combining size with UPGS QI. First, we calculate the relative quality index, that is, the ratio of each UPGS QI to the maximum index. Next, we obtain the comprehensive supply coefficient S′ j of the park based on the weighting of the relative QI. The formula is as follows:

$$S_j^{'} = S_j^A \frac{\boldsymbol{QI}}{(\max)\boldsymbol{QI}} \quad (4)$$

where S′ j is the comprehensive supply coefficient of comprehensive size and quality indicators, and SA j is the park supply capacity considering only the UPGS size; (Max) QI is the maximum QI score.

Demand improvements

The traditional 2SFCA model failed to account for competition between destinations and used the same visit probability for all residents in the threshold range, thus potentially leading to significant overestimation (Zhang et al., 2021). To solve this problem, Luo combined the Huff model and the 2SFCA model to quantify competition among destinations (Luo, 2014). Huff-2SFCA is more effective and reliable than the traditional 2SFCA model. The quality of UPGS significantly affects the probability of citizens choosing a specific UPGS because urban residents are more likely to enter a higher-quality UPGS than a lower-quality one. Therefore, the Huff model is integrated into the traditional 2SFCA model to enhance the calculation of population demand. The model calculates the population selection probability, taking into consideration residents' travel costs and the UPGS's supply capacity.

The Huff model is commonly used to quantify the probability of an individual choosing a service site over other nearby available sites (Ma et al., 2018). Its construction is influenced by two parameters: (Ifdil et al., 2020) the time or distance between supply and demand, and (Yang et al., 2015) the quality of all destinations in the threshold range. The Huff model is as follows:

$$Prob_i = \frac{S_j^{'} t_{ij} G(t_{ij},t_0^{'})}{\sum_{j=1}^{n} S_j^{'} t_{ij} G(t_{ij},t_0^{'})} \quad (5)$$

where $Prob_i$ is the selection probability of residents i visiting UPGS j based on the Huff model, t_{ij} is the travel time between i and j, $G(t_{ij},t'_0)$ is expressed as the distance time impedance coefficient based on the Gaussian function, S'_j is the supply capacity of the UPGS, and t'_0 is the travel time threshold.

We combine QI with traditional supply capacity. Population demand is obtained by weighting the selection probability based on the Huff model. The improved Huff-2SFCA model can be modified as follows:

$$A_i^{'} = \sum_{I\in\{t_{ij}\le t_0^{'}\}} Prob_i G\left(t_{ij}, t_0^{'}\right) \frac{S_j^{'}}{\sum_{k\in\{t_{ij}\le t_{ij}^{'}\}} Prob_i P_k G\left(t_{ij}, t_0^{'}\right)} \quad (6)$$

where A'_i is considered a comprehensive accessibility index to identify areas underserved by UPGS. The index takes time decay, size, and quality into consideration.

Case study

Study area

Mianyang is a prefecture-level city in Sichuan Province, China, located in the northwest of the Sichuan Basin and in the middle and upper reaches of the Fujiang River (30°42′–33°03′N and 103°45′–105°43′E). It holds the titles of National Civilized City, National Health City, National Forest City, and National Garden City. This study selected the central urban area, which is approximately 140 km^2 and includes 17 street areas, such as Chengxiang Street, Gongqu Street, and Chaoyang Street (Figure 1), as the study area. Its geographical location, with its "three mountains and two rivers," makes the area rich in natural resources, creating a clustered urban development model and an irregular urban form. Meanwhile, it has also led to the relatively backward development of transportation facilities between clusters and to poor sharing of UPGSs. Mianyang selected "Modern Park City" as the basic concept for guiding its urban planning and construction in 2021 and was chosen to form part of the national pilot list of urban convenient living circles in 2022.[1] For these reasons, Mianyang was selected as the study area.

1 http://www.my.gov.cn/

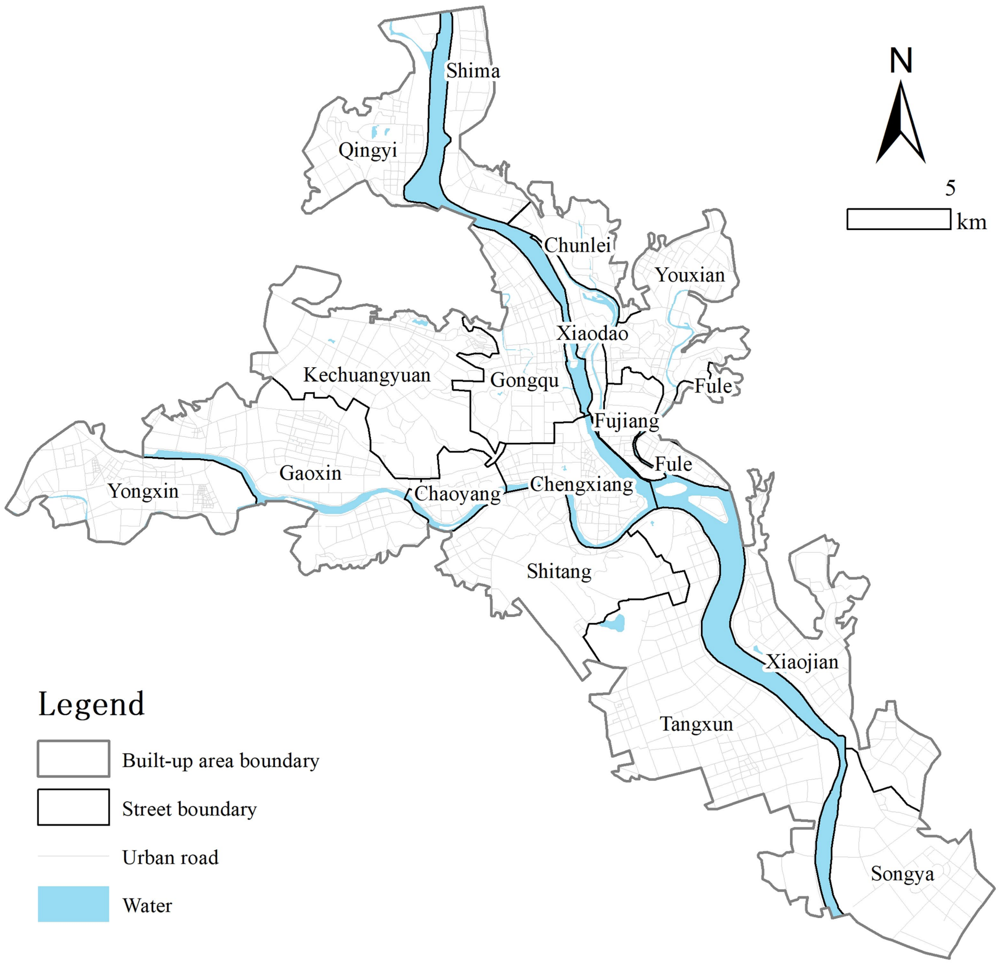

FIGURE 1
Overview of the study area.

Data source and pre-processing

Figure 2A shows the spatial distribution of the demand points and population sizes. We used points of interest in residential districts, obtained from Baidu electronic maps[2] in January 2022, to represent the demand points. The population size data were derived from 100 m × 100 m population grid data published on the WorldPop platform[3] in 2020. First, we corrected for population size using data from the seventh census. Second, a Voronoi diagram was constructed based on the demand points. Finally, we used a spatial linking tool to connect the population sizes of the demand points. There were 1,125 residential districts with a total population of approximately 916,300.

Figure 2B shows the spatial distribution of all UPGS levels and entrances, which represent the supply points. UPGS data were obtained from Mianyang Urban Green Space System Planning (MUGSSP; 2010–2020). Additionally, we referred to the MUGSSP and Standard for Urban Residential Area Planning and Design (GB50180-2018) to classify UPGS into four levels: municipal parks, district parks, community parks, and neighborhood parks. First, the location, scale, and entrances of the UPGSs were supplemented or deleted by reference to internet maps and by field research. Next, because of the importance of walking to health, we determined the walking time thresholds for the different levels of UPGS as 30, 15, 10, or 5 min by referring to the Standard for Urban Residential Area Planning and Design (GB50180-2018; Yang et al., 2021). Third, UPGSs not included in the plans were determined according to their scale and classified as neighborhood-level parks (area < 1 hm^2), community-level parks (1 hm^2 ≤ area < 5 hm^2), or municipal-level parks (area ≥ 5 hm^2). To make the accessibility calculation more accurate near the boundary areas, we included Yufucun Forest Park and Fuleshan Park near the boundary. Table 2 shows the number, area, and area ratio at all UPGS levels. Seventy-six instances of UPGS were observed, with an area of 698.91 hm^2 and 277 entrances.

The actual walking time was used to express the connection between the supply points and the demand points. The road network models provided by internet map service providers are more accurate than self-constructed models. First, we initiated the path-planning request with the coordinates of the supply points as the parameter through the path-planning interfaces of Baidu E-Map and Gaode E-Map. Next, the walking time data between each supply and demand point were obtained using a Python program. Finally, the shortest time between the demand and supply points was collected as the actual walking time.

2 https://map.baidu.com/
3 https://www.worldpop.org/

Results

UPGS quality index

In this study exploring variability in park quality, higher evaluation score values indicate higher quality in the UPGS quality model. Seventy-six urban parks were evaluated for their attractiveness and classified into four levels: low (0.178–0.693), second lowest (0.694–1.251), second highest (1.252–2.177), and high (2.178–3.344) quality by Natural Breaks (Figure 3), which is a statistical method for grading and classifying classes according

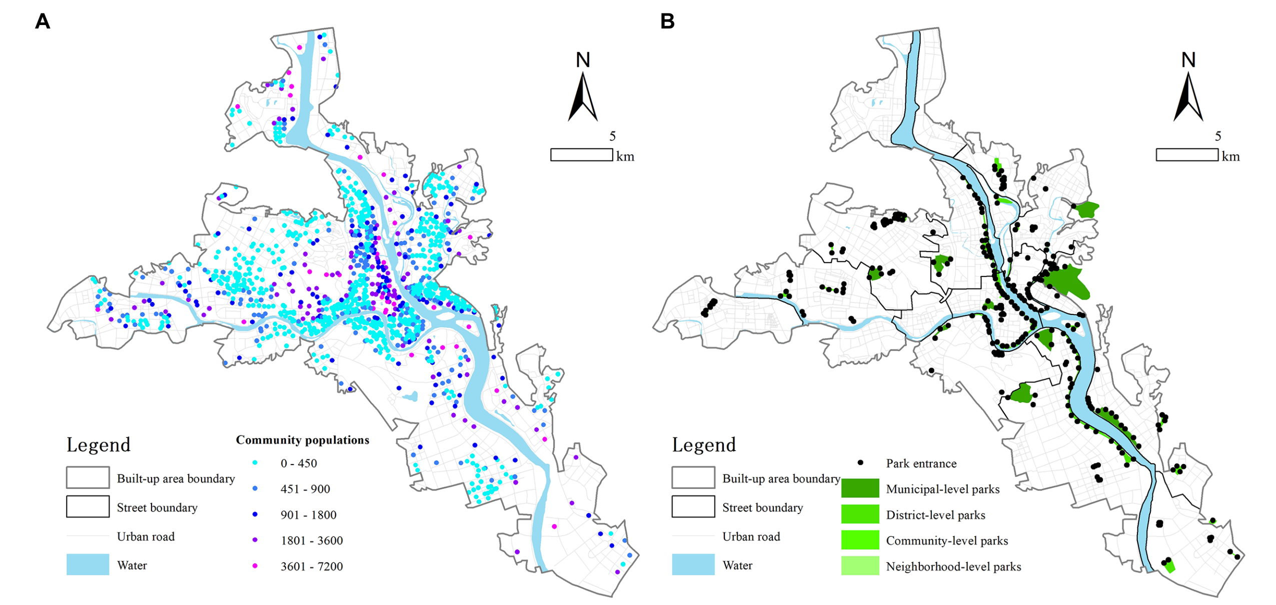

FIGURE 2
(A) Spatial distribution of residential district populations. **(B)** Locations of parks of various levels.

to the distribution of numerical statistics and can maximize the difference between classes.

Significant differences were observed in the spatial distribution of UPGS of different qualities: (1) Low-quality UPGS were mainly at the eastern edges of urban areas. Most of them were small in size and had infrastructure that provided places for the surrounding residents to interact with each other. However, insufficient leisure facilities, a poor activity environment and visual sensory experience, and insufficient safety controls decreased residents' attraction to these UPGSs. (2) The north of the Anchang River contained most of the second-lowest quality UPGSs. They had a better OTC and visual sensory experience than the low-quality UPGS. (3) Both sides of the Fujiang and Furong Rivers contained most of the high-quality UPGS. Compared with the less attractive parks, they can provide certain leisure and entertainment venues and facilities for residents. (4) Finally, the distribution of high-quality UPGS was more balanced than that of other UPGSs, with an overall "7" distribution matching the study areas' urban form. UPGSs of all qualities had an appropriate green space environment, complete infrastructure, good leisure and entertainment activities, good visual and sensory experiences, and effective safety controls.

TABLE 2 Overview of park statistics in the study area.

Service level	Number	Area (hm^2)	Area ratio (%)
Municipal-level parks	9	420.80	60.11
District-level parks	19	216.19	30.88
Community-level parks	23	49.36	7.05
Neighborhood-level parks	25	12.57	1.96

Next, we counted the quantity ratio of each level of UPGS in each street district. The results showed large differences in the quality of construction in each street area: (1) Gongqu Street, Tangxun Street, and the Xiaojian Area had the largest proportion (75.00%, 63.64%, and 75.00%, respectively) of second-highest-quality UPGSs and above, indicating that UPGS construction in these three locations is better than in other areas, followed by Gaoxin Street and Chunlei Street, both with 50.00%; and (2) the number ratio of the second-lowest-quality UPGSs and below in all other streets was larger, with an average value of 76.26%, indicating that UPGS quality is poor in most street districts.

Accessibility of the different UPGS levels

The current park area *per capita* is approximately 7.62 m^2 in the study area, and the MUGSSP determined that the park area *per capita* would be 9.02 m^2 at the end of the planning period and 11 m^2 in the long term. Referring to a related study (Zhao et al., 2022), the accessibility results were classified into six levels: extremely poor (= 0), poor (>0–3.8), slightly poor (≥3.8–7.62), average (≥7.62–9.0), good (≥9.0–11), and excellent (≥11).

We found that the accessibility of UPGS levels differs as follows: (1) the spatial distribution of accessibility at the neighborhood (Figure 4A), community (Figure 4B), and district levels (Figure 4C) is generally consistent with the spatial characteristics of UPGS, which indicates that accessibility is positively proportional to supply quality and inversely proportional to demand and travel time; (2) municipal-level UPGSs (Figure 4D) show a characteristic of "low in the west and high in the east," which is not significantly related to the UPGSs'

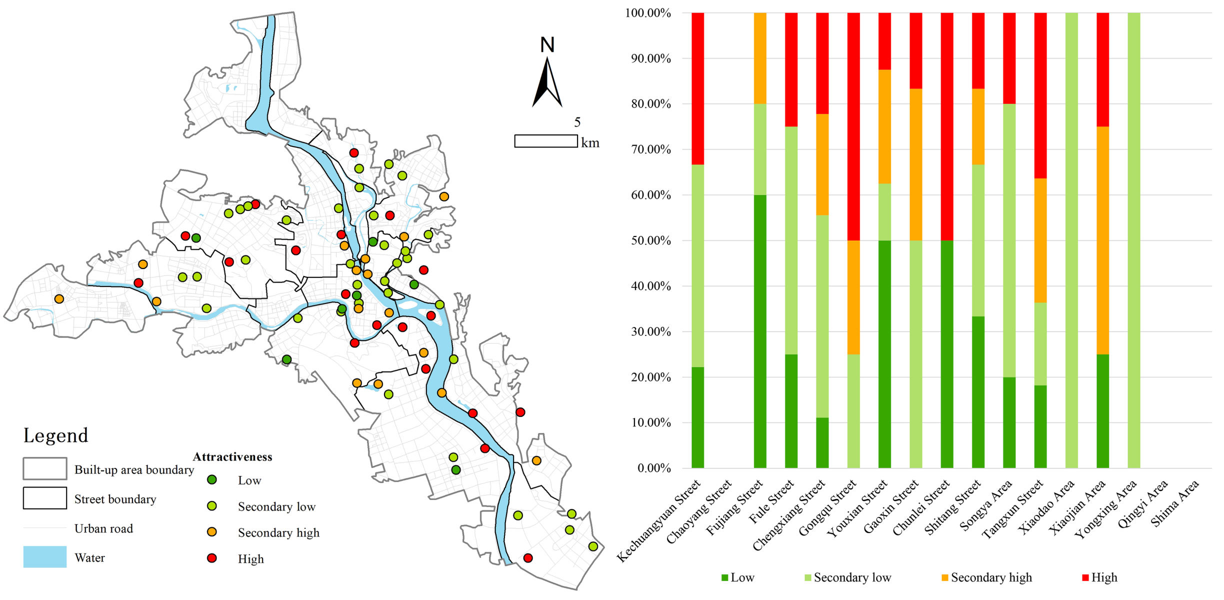

FIGURE 3
Spatial distribution of various parks with different levels of attractiveness.

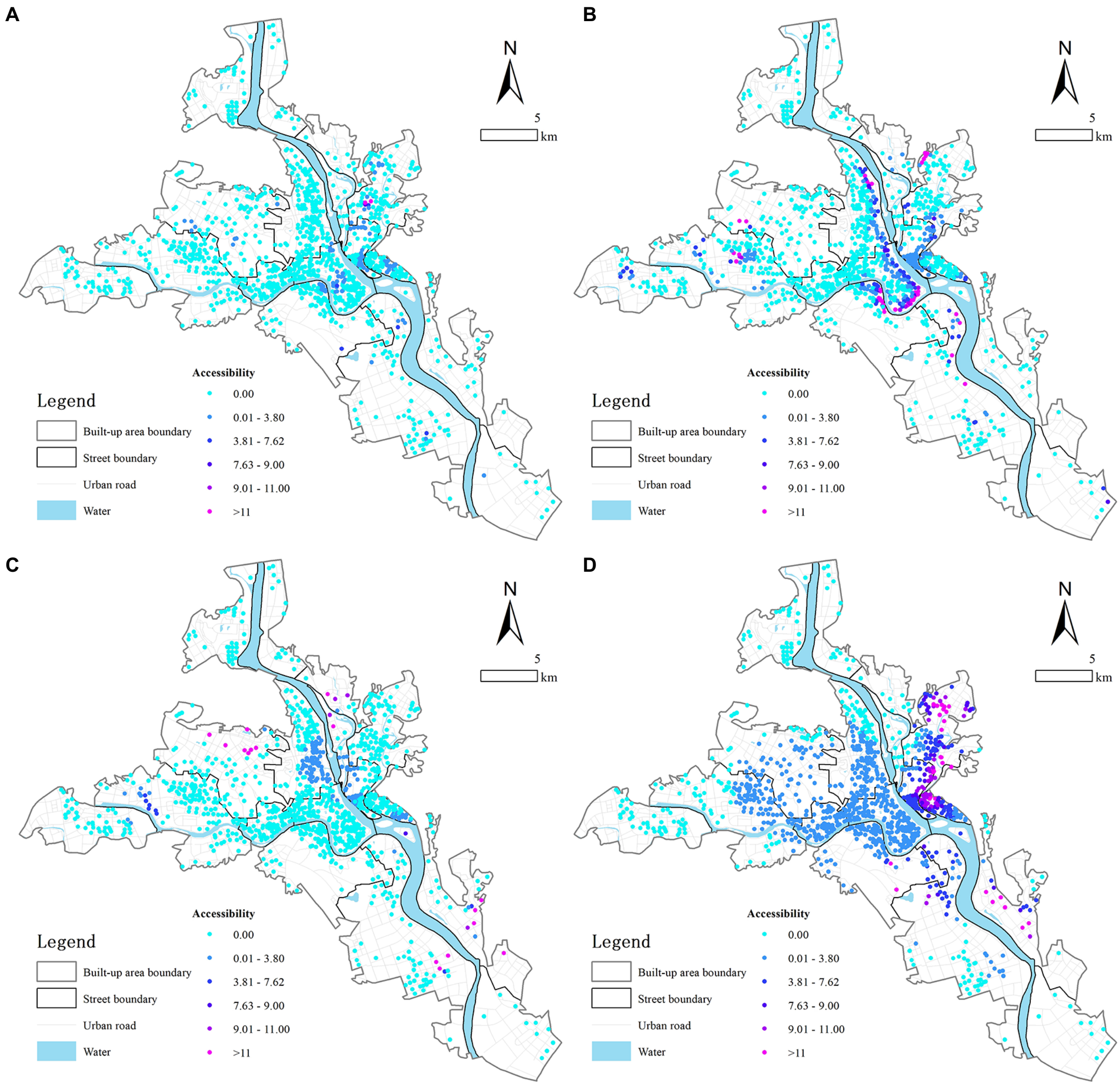

FIGURE 4
Spatial distribution of the accessibility of various level of parks. **(A)** Neighborhood-level parks. **(B)** Community-level parks. **(C)** District-level parks. **(D)** Municipal-level parks.

layout. The extremely poorly accessible residential districts are at the edge of the urban area and are far away in time terms, as residents cannot walk to a municipal park within 30 min; (3) poorly accessible residential districts are mainly located in the urban center, such as on Gongqu, Chengxiang, and Kechuangyuan Streets. Although some residents can walk to a municipal park within 30 min in these areas, many residents have poor access due to the inadequate road network and large population size; and (4) highly accessible residential districts are mainly located on the eastern edges of Youxian, Chunlei Street, and Xiaojian District. These areas have easy access and high-quality UPGS, which covers most of the neighborhoods in the area.

In addition, Table 3 shows the results for the accessibility of UPGS for different levels (i.e., the travel time threshold). Municipal-level UPGS was significantly better than UPGS at the district, community, and neighborhood levels: (1) municipal-level UPGS had a smaller standard deviation (3.864) and a more reasonable spatial layout than other types of UPGS; (2) 84.98%, 72.80%, and 91.11% of residential districts (accessibility index = 0) were unable to access a district, community, or neighborhood-level UPGS within the required walking time; and (3) 75.56% of residential districts had access to municipal-level UPGS, which was 5.03, 2.78, and 8.50 times more than that of the other types of UPGS.

Overall accessibility

We obtained overall accessibility by summing the accessibility index of the four levels of UPGS. Next, overall accessibility was graded using the method discussed in the section "Data Source and Pre-processing" (Figure 5). Accessibility distribution was generally characterized by a "decreasing trend along the riverbanks and inwards, with poor accessibility overall," and was similar to the spatial characteristics of UPGS that had a positive correlation between accessibility index and the size and number of UPGS areas.

Next, the number ratio of residential districts with different accessibility on each street district was counted: (1) the number ratios of residential districts with good and excellent accessibility were largest in Fuliang, Youxian, and Fule Streets (40.33%, 39.14%, and 38.08%, respectively), meaning that overall, accessibility in these three streets was relatively good; (2) the number ratios of residential districts with extremely poor accessibility were largest in Shima, Qingyi, and Yongxing districts (100%, 100%, and 79.55%, respectively); and (3) 93.27, 86.13, and 84.89% of the residential districts on Gongqu, Chengxiang, and Shitang Streets, respectively, had poor or slightly poor accessibility, indicating that accessibility is relatively poor in these three areas.

TABLE 3 Statistical description of UPGS accessibility values under different UPGS levels.

UPGS level	Mean	Standard deviation	Underserved residential districts
Neighborhood-level	0.118	0.721	1,025
Community-level	1.539	5.877	819
District-level	3.902	26.804	956
Municipal-level	2.224	3.864	275
Overall	6.527	17.230	195

The reasons for conducting this analysis were that (1) after years of building a landscape and ecological garden city, UPGSs in these areas have been effectively strung together to form a landscape corridor that benefits the surrounding residents; (2) district- and community-level UPGS had not been effectively implemented under the MUGSSP; and (3) the overall quantity, scale, and quality of UPGS are low and cannot fulfill residents' demand for a high-quality outdoor environment.

Accessibility differences

Based on the same dataset, we compared the overall accessibility index calculated using the traditional 2SFCA model and the Huff-2SFCA model. We obtained accessibility difference by using the results of conventional 2SFCA minus Huff-2SFCA. Larger difference values indicate larger model gaps and negative values indicate underestimated accessibility. Differences were calculated for the accessibility of 1,125 residential districts and graded into five classes: underestimated (−17.115–0.000), second smallest (0.001–13.494), small (13.495–27.082), second largest (27.083–53.777), and large (53.778–122.969) by Natural Breaks in 4.1 (Figure 6).

The accessibility difference distribution was generally characterized by a "decreasing trend along large UPGSs and outwards, with overestimated accessibility," and was similar to

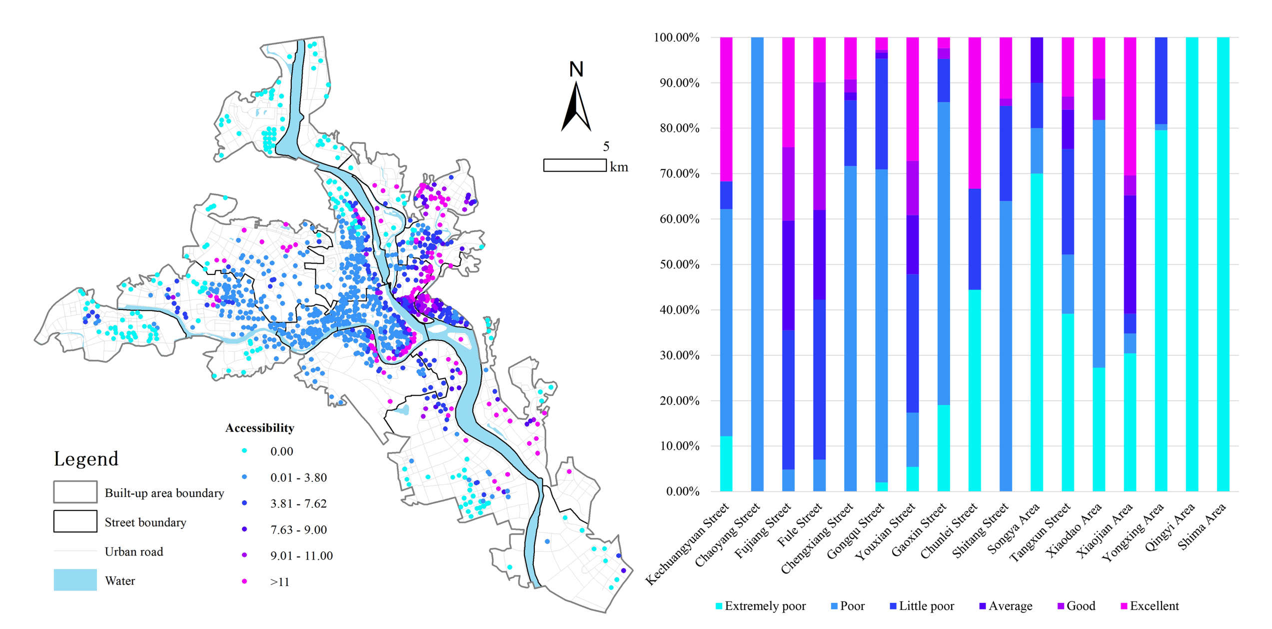

FIGURE 5
Spatial distribution of overall park accessibility in the study area.

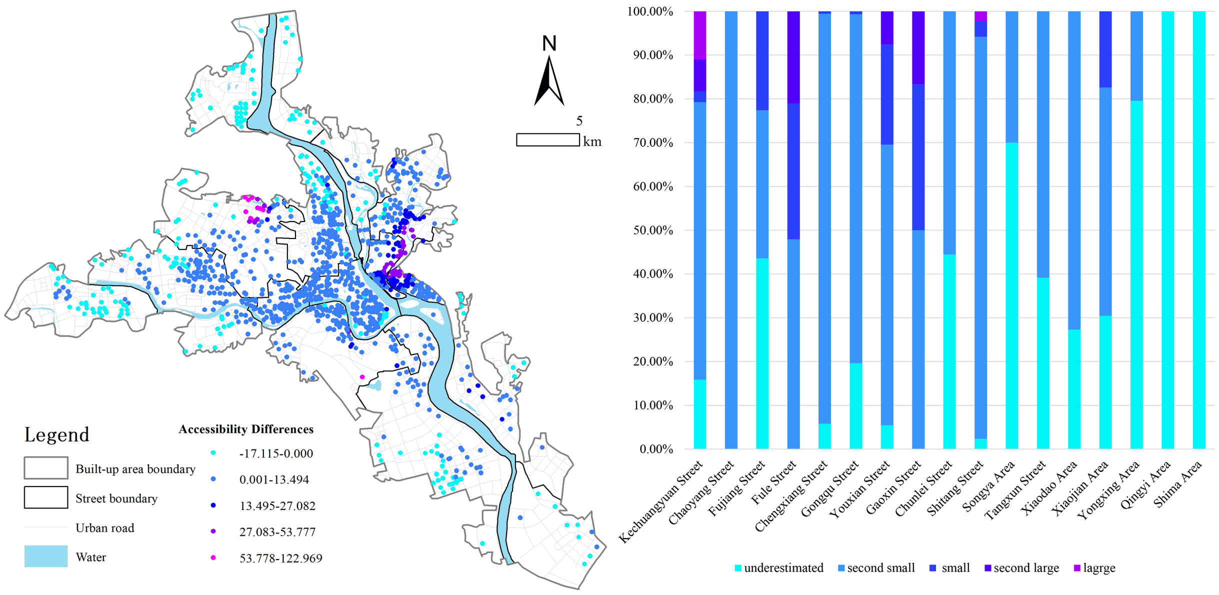

FIGURE 6
Spatial distribution of accessibility differences in the study area.

the spatial characteristics of the overall accessibility of UPGS. The findings are as follows: (1) the 221 underestimated residential districts were mainly located at the edge of the study area, with a quantity ratio of 19.64%, which is similar to the spatial characteristics of underserved areas; (2) 775 residential districts with small differences were mainly located in the central part, with a quantity ratio of 68.89%. Compared to other areas, they have more accessible parks of higher quality; (3) other residential districts mainly located near Fule Park and Kexuecheng Park. These areas are close to larger parks, but the QI difference between accessible UPGSs is large.

Next, we counted the quantity ratio of each level of difference value class in each street district. The results show that (1) except for Qingyi and Shima Areas, Songya and Yongxing Areas had the largest proportion (70.00 and 79.55%, respectively) of underestimated residential districts; (2) Chaoyang, Chengxiang and Shitang Streets had the largest proportion (100.00%, 94.22% and 95.35%, respectively) of small residential districts and below, indicating that the two models do not differ significantly in these areas; (3) Kechuangyuan, Fule, and Gaoxin Streets had the largest proportion (18.30%, 21.13% and 16.67%, respectively) of second-largest residential districts and above, indicating that the two models in these areas differ significantly.

Supply and demand relationship

To improve the allocation of green space resources, it is necessary to understand the relationship between UPGS supply and citizen demand. First, we performed a Z-score normalized calculation of population size. Next, we defined high-supply residential districts (accessibility index ≥7.62) and low-supply residential districts (accessibility index <7.62). Finally, accessibility and population sizes were superimposed. The results were divided into four categories: high demand–high supply; high demand–low supply; low demand–high supply; and low demand–low supply (Figure 7).

The findings are as follows: (1) the 64 high-demand–high-supply residential districts were mainly located close to the banks of the Fujiang and Furong Rivers, where there was higher demand than in other areas, with an average population of 1,760. These residential districts were closer in time than the other districts to the landscape corridor; thus, the residential plots mostly showed high-demand–high-supply characteristics; (2) the 243 high-demand–low-supply residential districts were scattered across various street districts, indicating that the high-demand residential districts had poor UPGS accessibility; and (3) there were 193 low-demand–high-supply residential districts with a quantity ratio of 17.16%. The distribution characteristics were similar to the distribution of high UPGS accessibility, indicating a certain "population–green space mismatch"; and (4) the 625 low-demand–low-supply residential districts, the largest in number, were mainly located on the streets on both sides of the Anchang River and relatively far from the Fujiang and Furong Rivers.

Our statistics showed the number ratio of the different types of residential districts in each street area: (1) Xiaojian district had the largest proportion of high-demand–high-supply residential districts (43.48%), indicating the best

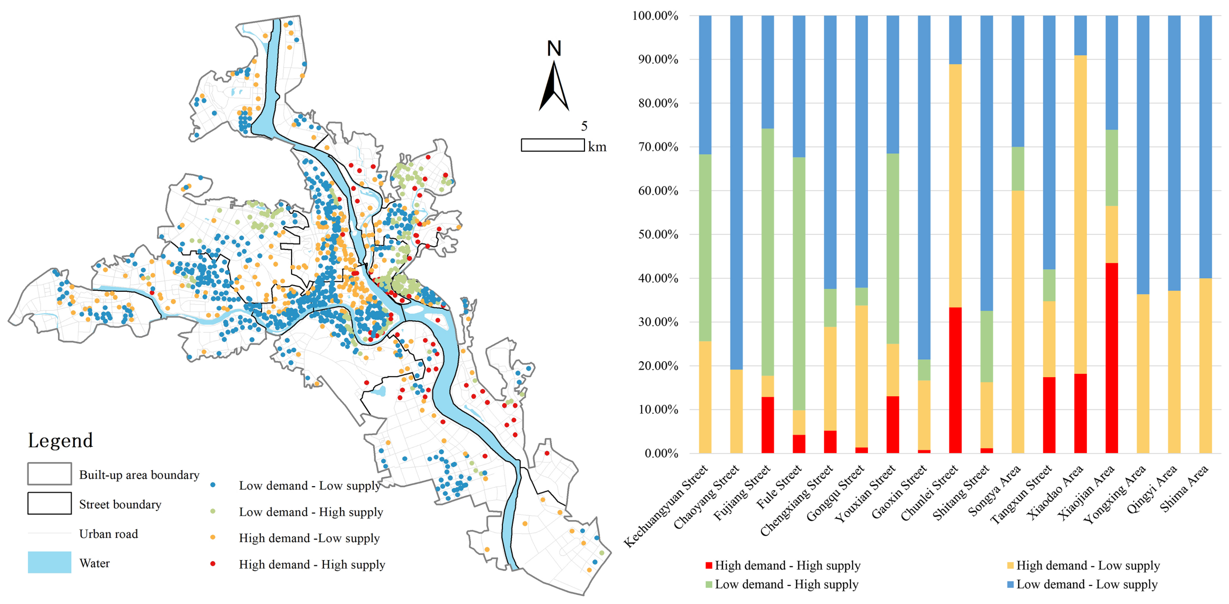

FIGURE 7
Spatial distribution of supply and demand relationships in the study area.

supply–demand match; (2) Chunlei street, Songya district, and Xiaodao district had the largest proportion of high-demand–low-supply plots, at 55.56%, 60.00%, and 72.73%, respectively; (3) the number of low-demand–high-supply residential districts was largest on Kechuangyuan Street, Fujiang River Street, Fule Street, and Youxian Street, at 42.68%, 56.45%, 57.75%, and 43.48% respectively, indicating a "population–green space mismatch" problem in these seven streets and districts; and (4) other street areas all had a larger number ratio of low-demand–low-supply communities than others, with an average of 66.22%, indicating that these areas have development potential. Thus, plans for and construction of UPGS should consider residents' needs.

Discussion

Walking time, supply quality, and public demand are the main factors that affect the accessibility and health-promotion benefits of UPGS. Walking time significantly affects public participation in park activities. The literature has seldom considered the impact of scale and quality factors on supply capacity, resulting in differences in accessibility assessment. Due to the lack of sufficient land in urban areas to provide a natural environment, upgrading the quality of existing UPGS is an effective measure for fulfilling the public's physical and mental health needs in the post-pandemic era. In addition, as discussed above, high-quality parks enable the public to push the limits of minimum travel times in destination selection. Therefore, when determining whether and where individuals will be able to avail of activities in UPGSs, a comprehensive consideration of these three factors is necessary. In this study, the three parameters of time, supply, and demand were integrated into the 2SFCA model. First, quality indicators including OTC, infrastructure, leisure facilities, visual sensory factors, management, and safety were integrated to improve the supply parameters with the health-promotion characteristics of UPGS as the quality evaluation component. Second, a variable service range threshold was adopted for the pedestrian mode to ensure that high-level UPGS corresponded to a larger service range. Third, the competitive effect between heterogeneous UPGSs avoids overestimating accessibility. These improvements ensure that the accessibility assessment method proposed in this paper is more accurate than the existing methods in the literature in identifying underserved areas.

The empirical research in this paper has policy implications for the planning, conservation, and management of parks in urban areas. First, this study proposes an index of relative park quality based on OTC, infrastructure, recreational facilities, visual sensory factors, and management and safety. Thus, urban planners and policymakers can use the evaluation framework to identify low-quality UPGS around cities and determine how to improve their quality. Second, this accessibility assessment allows for the accurate monitoring of vulnerable residential districts without access to nature. In terms of access to park health services, residents of underserved residential districts are unable to enjoy services or access UPGS within acceptable walking times. Residents of high-demand–low-supply residential districts can access UPGS within acceptable walking times, but they are less likely to visit those UPGSs, which may be due to long walking times, small size, or poor quality. For underserved residential districts, UPGSs within acceptable walking times should be built to improve services. For high-demand–low-supply residential districts, urban planners should consider optimizing the pedestrian transportation network and enhancing the quality of UPGS. In the post-pandemic era, urban residents are experiencing a public health crisis, and improving the accessibility of UPGS can help promote the recovery of urban residents' physical and mental health and maintain sustainable urban development. These improvements are important for fulfilling public needs and promoting a quality, healthy urban development.

However, the weights of park quality characteristics in this study were determined based on the questionnaire data by constructing an entropy method model, which is somewhat subjective. In further research, more accurate results may be obtained based on using objective data combined with an analytic hierarchy process. Because population size data is difficult to obtain, in this study, we used a reprocessing of the population distribution raster, which has some errors when compared with the real population size. In the future, more accurate data can be obtained through collection from property websites, remote sensing inverse calculation, cell phone signaling data derivation, and government consultation. In addition, accessibility studies could be conducted for specific groups because of differences in park activity preferences. Fourth, we only studied park accessibility with respect to walking mode. In the future, accessibility can be calculated based on residents' different travel patterns. Fifth, we considered only the environmental characteristics of UPGS, and certain external environmental characteristics can also seriously affect UPGS quality. Further research should integrate key external environmental features and further revise the Huff-2SFCA model (Guo et al., 2022; Zhao et al., 2022).

Conclusion

In cities, the only provision of natural or semi-natural environments for urban residents is UPGS. We highlighted the fact that urban park green space (UPGS) fulfills the physical and mental health needs of the public and that its accessibility affects its health-promotion benefits. However, studies have not considered the impact of heterogeneous UPGS on residents' needs. In this study, we introduced the characteristics of UPGSs' health-promotion benefits into the quality evaluation and used an improved Huff-2SFCA model to calculate accessibility. The model takes into consideration not only the time factor but also the size and quality of the UPGS. This study successfully identified 195 residential districts that are underserved by UPGS and 243 high-demand–low-supply residential districts that are in urgent need of improvement, possibly because of the long walking time between UPGSs and residential districts, poor UPGS quality, and small size.

Data availability statement

The original contributions presented in the study are included in the article/Supplementary material, further inquiries can be directed to the corresponding author.

Ethics statement

Ethical review and approval was not required for the study on human participants in accordance with the local legislation and institutional requirements. The patients/participants provided their written informed consent to participate in this study.

Author contributions

XW and CZ: conceptualization, funding acquisition, investigation, methodology, software, validation, visualization, and writing—original draft. LY and JF: data curation, funding acquisition, methodology, supervision, and writing—review and editing. YB and XL: conceptualization, methodology, resources, funding acquisition, and writing—review and editing. All authors contributed to the article and approved the submitted version.

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Conflict of interest

During the study, YB and XL were employed by the Architectural Design & Research Institute Co., Ltd.

The remaining authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

The reviewer YO declared a shared affiliation with the author XL (The University of Hong Kong—different departments).

Publisher's note

Supplementary material

The Supplementary material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/fevo.2022.1083563/full#supplementary-material

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Emotional wellbeing in intercity travel: Factors affecting passengers' long-distance travel moods

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The travel mood perception can significantly affect passengers' mental health and their overall emotional wellbeing when taking transport services, especially in long-distance intercity travels. To explore the key factors influencing intercity travel moods, a field survey was conducted in Xi'an to collect passengers' individual habits, travel characteristics, moods, and weather conditions. Travel mood was defined using the 5-Likert scale, based on degrees of happiness, panic, anxiety, and tiredness. A support vector machine (SVM) and ordered logit model were used in tandem for determinant identification and exploring their respective influences on travel moods. The results showed that gender, age, occupation, personal monthly income, car ownership, external temperature, precipitation, relative humidity, air quality index, visibility, travel purposes, intercity travel mode, and intercity travel time were all salient influential variables. Specifically, intercity travel mode ranked the first in affecting panic and anxiety (38 and 39% importance, respectively); whereas occupation was the most important factor affecting happiness (23% importance). Moreover, temperature appeared as the most important influencing factor of tiredness (22% importance). These findings help better understand the emotional health of passengers in long-distance travel in China.

KEYWORDS

travel mood, emotional wellbeing, intercity travel, ordered logit model, SVM model

Introduction

To meet the needs of passengers' growing travel demands, the national transportation infrastructure in China has been developing rapidly, encompassing 5,198,100; 230,000; 127,700; and 146,000 km of total highways, air routes, waterways, and railways by December 2020, respectively (including 30,000 km of the high-speed railway—HSR). Concurrently, the annual passenger flow volume reached 4 billion travelers, with passengers' intercity traffic accounting for 71.3% of road transport, 22.8% of railway transport, 4.3% of civil aviation, and 1.6% of water transport (1).

Corresponding with the increasing demand for intercity travel, passengers have higher requirements for travel service quality, turning greater focus to their own emotional wellbeing during travel. Accordingly, travel mood is an expression of passenger satisfaction regarding their emotional state, and an improved understanding of passenger moods during trips, as well as the factors affecting emotional perception during intercity long-distance travel, is critical for improving nationwide transportation services in a manner consistent with improved traveler mental health.

Namely, *mood* refers to "the emotional interpretation of perception, information, or knowledge" (2). Indeed, many studies related to travel behavior have highlighted the important role of mood on trips (3), as investigating travel moods is a popular topic in the literature. For example, Bel and Jordan (4) argued that passenger preferences were shifting from a focus on basic functional services, to travel mood and pleasure-seeking moments; whereas Jonas (5) argued that the contemporary enjoyable car experience was related to the travel mood and visual stimuli. Alternatively, Stradling et al. (6) noted that bus ride experiences included a variety of non-instrumental travel mood factors, such as scenery, stress, and entertainment. Further, Rui et al. (7) studied passengers' travel mood responses to bus services, Rajesh and Daruri (8) assessed the effect of social cues on passengers' travel moods using comfort, relaxation, and joy, and Meenar et al. (9) studied the relationship between passengers' travel moods and the transport environment, linking various travel mood experiences related to fear, anger, sadness, joy, and anticipation.

Passengers with different individual attributes would undergo various moods when traveling between cities. Therefore, the individual attributes of passengers may be hypothesized to affect the passengers' subjective feelings during intercity travel. In addition, passengers often choose different modes of transportation at different intercity travel distances. The differentiated service quality provided by different modes of transportation facilities may lead to obvious changes in the travel mood of passengers. Thus, the travel attributes, such as travel mode choice and travel distance, may also influence the travel mood of passengers. What's more, weather conditions can also affect the mood of travelers. It's straightforward to realize that good weather can make people feel better when they travel long distance between cities. From what has been discussed above, it could be inferred intuitively that the travel mood of passengers may be affected by the individual attributes of passengers, travel attributes and weather conditions.

With the excellent prior knowledge explored by many previous studies (4–7, 10–12) on people's emotional perception during traveling, it is relatively clear on this topic in urban transportation field. However, little has been known and explored toward a comprehensive investigation investigating the factors influencing passengers' emotional perception over long-distance intercity travels. Moreover, existing studies have discussed the impacts of individual and travel attributes on corresponding moods; nonetheless, the potential impact of transportation mode choices on travel mood has been largely overlooked, especially with respect to the nationwide integrated comprehensive transportation network, including airplanes, high-speed railways (HSRs), conventional railways, and express busses throughout China. Due to the differential service qualities, travel mode choices may potentially impact passenger mood during intercity travel as well. Although some previous studies have explored the influence of weather on passenger mood during intra-city travel (10, 11, 13), it is not known if these same factors are at play during intercity travel as well. Additionally, the vast majority of the cities used as cases are located in developed countries such as the United States and Europe, while few cases exist in developing countries, including China, which has the longest high-speed railway in the world.

Accordingly, to strengthen and fill the aforementioned links and gaps in present understanding, this research used a random sampling survey method to obtain data on passengers' intercity travel activities from Xi'an and matched it with the weather characteristics at the moment of passenger departure. Both an ordered logit model (OLM) and SVM (14–20) were applied in tandem to explore the critical factors affecting passengers' intercity travel emotional perception, and a confusion matrix was used to assess model accuracies for validating the results and implications. The primary contributions of this study can be summarized as follows:

(1) This study explores the relationship between individual passenger's intercity travel moods, personal characteristics, weather conditions, travel mode choices, and intercity travel time, and helps better understand the complexity of emotional wellbeing, and its various determinants during long-distance human mobility.
(2) The SVM and OLM were used to reveal the effect of passenger's personal characteristics, weather conditions, travel mode choices, and intercity travel time on passenger's intercity travel moods, which effectively help to better understand the importance of these factors and their positive or negative effects.
(3) Taking a representative tourist city in China as the case study, this study provides an interdisciplinary lens for better managing mobility travel and tourism, offering insights into different travel emotional perceptions with respect to travel mode (including HSR), purpose (including tourism or leisure), and socio-economic attributes.

The remainder of this paper is organized as follows: Section Literature review presents a literature review; Section Data and material introduces the sources and methods for data collection; Section Methods discusses the developed models and the corresponding model evaluation methods; Section Results provides the results and the main findings of this study, and Section Discussion offers the conclusions.

Literature review

To date, previous studies have explored the weather (21), travel time (11), travel cost (22), and modes of transport (23) on passengers' travel emotion. Yazdanpanah and Hosseinlon (24) conducted a passenger questionnaire survey at IKIA and adopted a mixed discrete potential class model to explore the factors affecting intercity travel emotions, revealing that both weather and intercity travel cost had a significant influence. Notably, the results showed that passengers were more likely to have experienced negative emotions when traveling in a poor weather condition. Moreover, Alberto et al. (25) applied a binomial logistic model to study the impacts of extreme intercity travel weather conditions on passenger travel emotions between London and Glasgow, UK, which revealed that traffic interruption was most associated with negative passenger emotions. Wu and Liao (26) explored intercity passenger travel in Beijing from 2014 to 2018, concluding that extreme weather greatly affected passengers' travel emotions and reduced their travel demand.

Furthermore, it is found that intercity travel time can also affect passenger travel emotions. For instance, Masson and Petiot (27) explored the HSR in Southern Europe between Perpignan, France, and Barcelona, and used the New Economic Geography model to explore the impacts of intercity travel distance, time, weather, education level, personal monthly income, gender, and built environment on passenger emotion, revealing that intercity travel time had the most significant impact, where the two were strongly negatively correlated. However, the detailed influential effects of those factors remained underdeveloped. Beam et al. (11) examined southwest Atlanta to explore the impacts of intercity travel time, extreme weather, and travel distance on passenger emotions, concluding that passengers with uncertain travel times experienced psychological pressure, and thus suffered from greater irritability.

Travel costs may also impact intercity passenger emotions as well. Delaplace and Dobruszkes (22) interviewed tourists near the Eiffel Tower, Lyon Central Railway Station, and Notre Dame Cathedral in Paris, using a logit model to analyze the influencing factors of passenger travel emotion. Their results showed that ticket price, convenience, and speed were the strongest determining factors. In addition, Harvey et al. (28) investigated British passengers' travel emotions toward intercity travel, similarly revealing that travel cost, reputation, and comfort had the most significant impacts.

Lastly, the importance of transportation mode choice on intercity passenger emotions has also been explored. For example, St-Louis et al. (29) used commuter travel survey data at McGill University in Montreal and adopted ordinary least squares regression to compare the different travel emotions of passengers across six travel modes (walking, cycling, car, bus, subway, and commuter train). The authors found that individual attributes, transportation modes were all the most significant determinants. Specifically, the results showed that slower modes of transportation (walking and cycling) seemed to generate more positive emotions than others, as pedestrians, train commuters, and cyclists reported significantly higher positive emotions than drivers or subway and bus users. Later, Morris and Guerra (23) investigated the emotions of more than 13,000 interviewees engaged in randomly selected intercity travel activities across the United States, using an ordinary least square method and fixed effects panel regression model to explore the impacts of transportation modes on passenger emotions. The results showed that passengers had a better emotional experience when traveling by car than by trains, as individuals experienced feelings of power, mastery, control, prestige, or self-esteem, which showing an interesting findings for the passengers in intercity travel in the US.

In terms of the approach of modeling and analytics, traditional discrete choice models, including the ordered logit model, are often used to explore the influencing factors of intercity passenger travel emotion (30–32). In recent years, machine learning is increasingly used in traffic behavior research (33–38). One such example, SVM, is often used to solve classification and regression problems (39), due to its strong capability to process data classification. In particular, SVMs are often widely applied for the detection (40) and severity level predictions of traffic accidents (41), as well as travel behavior analyses (43). For example, Wang et al. (44) used SVM to predict the short-term traffic flow of expressways, citing that this technique could overcome problems related to over-fitting of data and local minima solutions, in addition to its superior prediction capability than multi-layer feedforward neural network models. Yao et al. (45) applied an SVM to traffic accident detection on expressways and urban main roads, similarly explaining a higher correlated improved accident detection capability in SVMs than multilayer feedforward and probabilistic neural network models. Li et al. (41) examined data points of motorcycle traffic accidents along rural Texas Highway 88, revealing that the average absolute deviation and mean square prediction error measures verified that the SVM outperformed the traditional negative binomial regression model prediction accuracy on accident severity level. Luo et al. (42) discussed the applicability of SVM for assessing the choice of travel mode based on a 1990 travel survey of San Francisco Bay Area residents, concluding that this method can offer improved predictive ability compared to multi-logit or multi-layer feedforward neural network models under different training sample sets. Yang et al. (46) also compared the prediction accuracy of SVM, nested logit, and multi-layer feedforward neural network models based on a 1-day 2005

TABLE 1 Previous intercity travel passenger emotion research.

References	Dataset	Dependent variable	Independent variable	Method	Results
Yazdanpanah and Hosseinlou (24)	Survey conducted in January–February, 2015 at Imam Khomeini International Airport (IKIA)	Travel emotion	The five personality factors	Hybrid discrete latent class model	Passengers were more likely to experience negative emotions during bad weather; Conscientious individuals considered travel cost more likely than other attributes
Alberto et al. (25)	Internet-based travel behavior survey with >2,000 respondents in London and Glasgow	Travel emotion; travel behavior	Extreme weather; long-distance travel;	Binomial logit	Respondents were generally cautious about traveling during extreme weather events
Beam et al. (11)	Survey data collected at the six-mile buffer zone of the Atlanta Belt Line Eastside Trail; Three-mile transit access zone around three transit stations in southwest Atlanta	Travel emotion	Travel time; extreme weather; long-distance travel	LTS	Uncertain travel times produced psychological pressure, resulting in agitated moods among passengers
Masson and Petiot (27)	Forthcoming South European HSR lines between Perpignan and Barcelona	Tourism attractiveness	Travel distance, education level; car; income; gender; weather; built and natural environment	New economic geography (NEG) models	Under the same time limit, passengers tended to choose the fastest mode of transportation or travel directly to a nearby location, prioritizing short time journey times, and remaining at the destination for long time
Delaplace and Dobruszkes (22)	The Eiffel Tower and Lyon visitors near the central station and the Notre Dame cathedral in Paris	Travel emotion	Ticket price; convenience degree; rail speeds	Logistic regression model	Higher ticket prices negatively affected travel mood
Harvey et al. (28)	Attitudes and perceptions of long-distance travel in the UK	Long-distance travel emotion	Travel security; prestige of HSR; comfort; negative HSR aspects; travel time	Varimax rotation and alphas	Travel costs, as well as the reputation and comfort of high-speed trains significantly impacted passengers' travel mood
St-Louis et al. (29)	Commuter survey carried out at McGill University in Montreal, Canada	Travel emotion; travel satisfaction.	Trip and travel characteristics; personal characteristics; travel and mode preferences	Ordinary least square regression analysis	Slower modes of travel (walking and cycling) appeared to generate more positive emotions than cars and public transport, with pedestrians, train commuters and cyclists reporting significantly higher positive feelings than drivers or subway and bus users

travel survey of residents in China, showing that the SVM maintained a faster convergence speed and higher predictive accuracy. Lastly, Allahviranloo and Recker (43) used SVM to explore the data from a 2001 California residents' travel survey regarding their daily activity-travel pattern recognition and found it advantageous and outperforms a multinomial logit model in terms of its predictive accuracy.

From the aforementioned literature (readers can also refer to the summary of the representitative studies from above in Table 1), however, we found an obvious research gap regarding passenger emotions in intercity transportation modes (airplanes, HSR, conventional trains, and express buses), especially for HSR—it is more underdeveloped comparing to other tranditional modes. Moreover, while most scholars have discussed the impacts of individual and travel attributes on travel mood, the potential impacts of intercity transportation mode choice and weather on travel mood, however, have largely been in deficiency. In addition, the vast majority of assessed cities are located in developed countries within the United States and Europe, while few cases exist from developing countries, including China, which maintains the world's longest HSR infrastructure and operation system. Lastly, traditional discrete choice models, such as the OLM, have been widely used; however, the feature importance of significant influential factors cannot be extracted and visualized by suchlike tranditional modeling techniques—a more interpreatable machine-learning-combined approach is needed.

Data and material

Field survey

In this paper, we select the Xi'an city as the study area and the destination of our field survey investigation. Xi'an is the capital city of Shaanxi Province in China, the starting point of the famous Silk Road, the core city in the "Belt and Road" strategy, and an important national center for tourism, education, and industry. Xi'an is one of the top tourist destinations in China, and six sites have been listed on the World Heritage Lis.

The questionnaire consists of three parts: First, the individual's socioeconomic characteristics and weather conditions, including gender, age, occupation, personal monthly income, car ownership, temperature, rainfall, relative humidity, wind speed, air quality index, and visibility, Second, passenger travel characteristics, including travel purpose, intercity modes of transport, and travel time. Third, passenger travel mood was defined by happiness, panic, anxiety, and tiredness (10), and classified according to the Likert scale (e.g., five levels of happiness: very unhappy, unhappy, general, happy, and very happy). The detailed design and marking of variables are shown in Table 2; whereas the definitions of travel mood are shown in Table 3.

TABLE 2 Variable definitions and markings.

Variables	Marking or calculation of variables
Gender	"Male" = 1, "Female" = 0
Age	"0–29" = 1, "30–59" = 2, "≥60" = 3; Unit: Year
Occupation	"Enterprise personnel" = 1, "Institution personnel" = 2, "Students" = 3, "Farmers" = 4, "Self-employed" = 5, "Others" = 6.
Personal monthly income	"<3" = 1, "3–4" = 2, "4–5" = 3, "5–6" = 4, ">6" = 5; Unit: Thousand yuan
Car ownership	"No" = 1, "Yes" = 0
Travel purposes	"Mandatory travel "(e.g., business, returning from holidays) = 0, "Leisure travel" (e.g., tourism, visiting relatives) = 1
Intercity mode of transportation	"Airplane" = 1, "HSR" = 2, "Bullet train" = 3, "Train" = 4, "Express bus" = 5
Temperature	">25" = 1, "15–25" = 2, "10–15" = 3, "5–10" = 4, "<0" = 5; Unit: °C
Happiness degree	"Very unhappy" = 1, "Unhappy" = 2, "General" = 3, "Happy" = 4, "Very happy" = 5
Panic degree	"Very unpanicked" = 1, "Unpanicked" = 2, "General" = 3, "Panicked" = 4, "Very panicked" = 5
Anxiety	"Very un-anxious" = 1, "Un-anxious" = 2, "General" = 3, "Anxious" = 4, "Very anxious" = 5
Tiredness degree	"Very unfatigued " = 1, "unfatigued" = 2, "General" = 3, "Tired" = 4, "Very tired" = 5

Data acquisition

Field survey data was obtained through questionnaires. Investigators conducted field surveys at Xi'an Xianyang International Airport, Xi'an North Passenger Station, Xi'an Railway Station, and Xi'an Bus Station from April 10 to 17, 2020. A random sampling technique was used in all field surveys to ensure uniform distribution across the survey population at different levels. Investigators first explained the purpose of the survey to respondents, then invited them to participate the questionnaire survey. All respondents were assured that the survey was completely voluntary and their data were recorded anonymously. It took ∼2 min to fill out the questionnaire and the investigator can respond immediately to any questions the respondents may have.

A total of 2,400 questionnaires were distributed in the survey and 2028 valid questionnaires were obtained (84.5% effective recovery rate) after excluding 372 invalid questionnaires that contain missing answers or non-compliant answers based on the situation and guidelines. *Baidu Map* was used to measure intercity travel distance and travel time according to the operation schedule, origin, destination, and identification number of the selected mode of transportation. Weather information at the time of passenger departure was also obtained. Wind and air quality indices were based on weather forecasts recordings, while temperature, humidity, rainfall, and visibility data were derived from the National Meteorological Data Sharing Platform (47). Description of the category variables and continuous variables are shown in Tables 4, 5, respectively.

Methods

The data mining tool Python *pycaret* was used to perform the SVM model, and STATA (*v*.16.0) was used to carry out the ordered logit regression and confusion matrix calculations.

Ordered logistic regression

To date, the discrete choice model based on the logit model has been widely used in traffic travel-related research, primarily including the logit, probit, and their many variations. As the

TABLE 3 Definitions of travel moods.

Variable degree	Observation variables
Happiness	Indicates reasonable traffic policies during travel, that passengers can easily rest and communicate during travel, and the travel environment is comfortable.
Panic	Represents feelings that under the pressure of large passenger flow (i.e., the carrying capacity of the specific transportation mode is in a supersaturated state), may lead to the occurrence of large-scale disorderly crowding, trampling, and other dangerous situations. If an emergency occurs, the passenger believes that they or the people around them will be in danger, resulting in uncooperative and unreasonable psychological and behavioral responses in the face of real or imagined threats.
Anxiety	Depicts that during the process of intercity travel, trains or planes are delayed due to traffic congestion, or some other intercity travel time delay, disrupting passengers schedule due to the tension.
Tiredness	Represents congestion in the process of taking a vehicle or the travel time is too long causing passengers to feel tired.

dependent variables in this study were ordered categorical variables, an ordered logistic regression was selected. Ordered logistic regression is obtained by defining an unobserved variable $\boldsymbol{Z}$, which can be used as the basis of ordered data modeling. Here, the mood of intercity travelers is an ordinal variable, in which happiness, panic, anxiety, and tiredness were divided into five levels. Each involved variable could thus be expressed by Equation (1):

$$\boldsymbol{Z} = \boldsymbol{\beta X} + \varepsilon_i \tag{1}$$

where X is the vector of the independent variable determining the discrete ordering i for each observation, $\boldsymbol{\beta}$ is the vector of the regression coefficient, and ε_i is the random error term (48).

Accordingly, travelers' moods could be expressed by Equation (2):

$$y = \begin{cases} 1 \ when\ \boldsymbol{Z} \le \mu_1 \ (Particularly\ dissatisfied) \\ 2 \ when\ \mu_1 < \boldsymbol{Z} \le \mu_2 \ (Dissatisfied) \\ 3 \ when\ \mu_2 < \boldsymbol{Z} \le \mu_3 \ (Generally) \\ 4 \ when\ \mu_3 < when\ \mu_3 < \boldsymbol{Z} \le \mu_4 \ (Satisfied) \\ 5 \ when \\ 5 \ when\ \boldsymbol{Z} > \mu_4 \ (Particularly\ satisfied) \end{cases} \tag{2}$$

where μ_i is the unknown estimated parameter of the traveler's mood, and y (i.e., the threshold) corresponds to the integer order.

To estimate regression coefficient $\boldsymbol{\beta}$ and estimated parameters μ_i, the random error term ε_i was assumed to be an independent and identically distributed logistic distribution. Through this hypothetical result, an ordered logistic model was obtained and the probability that passengers' travel moods belong to any one of the five levels was defined by Equation (3):

$$P_i = \boldsymbol{\Omega}(\mu_i - \boldsymbol{\beta} X) - \boldsymbol{\Omega}(\mu_{i-1} - \boldsymbol{\beta} X) \tag{3}$$

where $i = 1, 2, 3, 4, 5$, respectively, and Ω is the upper and lower limits of the standard logistic cumulative distribution function, while μ_i and μ_{i-1} rendered the outcomes of i. Further parameters could be estimated by maximum likelihood. For a population of N observations, the log-likelihood function of the ordered logistic model was defined by Equation (4):

$$LL = \sum_{n-1}^{N} \sum_{i-1}^{I} \delta_{in} \ln \left[\Omega(\mu_i - \boldsymbol{\beta} X_n) - \Omega(\mu_{i-1} - \boldsymbol{\beta} X_n) \right] \tag{4}$$

where δ_{in} is equal to 1 if the observed discrete outcome point n is i, otherwise it is zero.

An odds ratio (OR) was used to quantify the impacts of the explanatory variables on the outcome. Specifically, the OR was calculated for variables of interest in the ordered logit regressions, where OR results represent the increase in the odds of the outcome if the value of the variable increased by one unit (49, 50). The OR for the j^{th} variable x_j can be calculated by Equation (5):

$$OR = \frac{odds(\boldsymbol{X}, x_{j+1})}{odds(\boldsymbol{X}, x_j)} = \frac{\exp(\boldsymbol{X\beta}) \times \exp(\beta_j)}{\exp(\boldsymbol{X\beta})} = \exp(\beta_j) \tag{5}$$

Support vector machine

SVM is a supervised learning method developed from statistical learning theory used for data analysis and pattern recognition and can be used for data classification and regression (51). The present study used SVM as the regression technology, with the basic principle based on non-linear mapping of the data to high-dimensional feature space, and then constructing a regression estimation function within the feature space, before mapping it back to the original space. The non-linear transformation is carried out by defining an appropriate kernel function (52, 53). In addition, considering that some samples

TABLE 4 Description of the category variables.

Categorical variables	Categories	Unit	Marking	Frequency	Proportion
Dependent variable					
Happiness degree	Very unhappy	/	1	240	11.83%
	Unhappy	/	2	604	29.78%
	General	/	3	839	41.37%
	Happy	/	4	319	15.73%
	Very happy	/	5	26	1.28%
Panic degree	Very unpanic	/	1	147	7.25%
	Unpanic	/	2	278	23.71%
	General	/	3	500	24.65%
	Panic	/	4	829	40.88%
	Very panic	/	5	274	13.51%
Anxiety	Very unanxious	/	1	137	6.76%
	Unanxious	/	2	305	15.04%
	General	/	3	519	25.59%
	Anxious	/	4	832	41.03%
	Very anxious	/	5	235	11.59%
Fatigue degree	Very indefatigable	/	1	168	8.28%
	Indefatigable	/	2	409	20.17%
	General	/	3	650	32.05%
	Fatigued	/	4	644	31.76%
	Very fatigued	/	5	157	7.74%
Independent variables					
Gender	Male	/	1	1,002	49.40%
	Female	/	0	1,026	50.60%
Age	0–30	Year	1	1,112	54.80%
	31–60	Year	2	898	44.30%
	60 and above	Year	3	18	0.89%
Career	Enterprise units	/	1	592	29.20%
	The personnel of institutions	/	2	276	13.60%
	Students	/	3	624	30.80%
	Farmers	/	4	148	7.30%
	Self-employed households	/	5	167	8.23%
	Others	/	6	221	10.90%
Personal monthly income	0–3,000	Yuan	1	741	36.60%
	3,000–4,000	Yuan	2	565	27.90%
	4,000–5,000	Yuan	3	260	12.80%
	5,000–6,000	Yuan	4	207	10.20%
	6,000 and above	Yuan	5	253	12.50%
Car ownerships	No	/	0	977	48.20%
	Yes	/	1	1,051	51.80%
Travel purposes	Mandatory travel	/	0	1,032	50.89%
	Leisure travel	/	1	996	49.11%
Intercity mode of transportation	Airplane	/	1	460	22.68%
	HSR	/	2	648	31.95%
	Bullet train	/	3	126	6.21%

(Continued)

TABLE 4 (Continued)

Categorical variables	Categories	Unit	Marking	Frequency	Proportion
	Train	/	4	496	24.46%
	Express bus	/	5	298	14.69%
Temperature	>25	°C	1	96	4.73%
	15–25	°C	2	1,127	55.60%
	10–15	°C	3	547	27.00%
	5–10	°C	4	211	10.40%
	<0	°C	5	47	2.32%

TABLE 5 Description of the continuous variables.

Continuous variables	Unit	Minimum value	Maximum value	Mean value	Standard deviation
Relative humidity	%	0	90	40.17	21.976
Rainfall	mm	0	54	0.525	2.346
Windpower	Wind level	0	8	2.313	1.01
Air quality index	µg/sqr meter	5	387	101.324	54.6
Visibility	km	216	8,200	5,528.418	858.161
Intercity travel time	h	0	680	6.169	16.554
Intercity travel cost	Yuan	0	5,400	354.056	364.795
Intercity travel distance	km	0	8,748	894.041	646.304

cannot be correctly classified by the separation of hyperplanes, relaxation variables were used to resolve this problem (54). Here, it was assumed that the data set had N sample spaces, the training set was $D = \{(x_n, y_n)|n = 1, 2, 3, , N\}$, and the regression function was $y = w^T\Phi(x) + b$, where $\Phi(x)$ is the non-linear mapping function. Accordingly, the original space was mapped to a high-dimensional space, and the optimization of the support vector regression model equation was defined by Equation (6):

$$\min \frac{1}{2}||w||^2 + Z\sum_{n=1}^{N}(\xi_n + \xi_n^*)$$

$$s.t., \begin{cases} y_n - w^T \bullet \Phi(x_n) - b \leq \varepsilon + \xi_n^* \\ w^T \bullet \Phi(x_n) + b - y_n \leq \varepsilon + \xi_n \\ \xi_n \geq 0, \xi_n^* \geq 0 \end{cases} \tag{6}$$

where w and b are the weight vector and offset, respectively; Z is the penalty parameter; ξ_n and ξ_n^* are the relaxation variables, and ε is the loss function parameter. The loss of the model was then calculated only when the absolute value of the difference between the predicted and actual values was greater than ε. Notably, the basic form of the above problem is a constrained convex quadratic program. A Lagrange multiplier buffer was introduced, and the constraints were integrated into the objective function using a Lagrange function to solve the dual problems (Equation 7) (55):

$$\max\left[-\frac{1}{2}\sum_{n=1}^{N}\sum_{r=1}^{N}(\alpha_n - \alpha_n^*)(\alpha_r - \alpha_r^*)\Phi(x_n)\bullet\Phi(x_r) + \sum_{n=1}^{N}(\alpha_n - \alpha_r^*)y_k - \sum_{n=1}^{N}(\alpha_n + \alpha_k^*)\varepsilon\right]$$

$$s.t., \sum_{n=1}^{N}(\alpha_n - \alpha_n^*) = 0, 0 \leq \alpha_n \leq Z, 0 \leq \alpha_n^* \leq Z \tag{7}$$

Here, the kernel function determines the mapping relationship between the training samples from the original space to the high-dimensional feature space. In this paper, the RBF radial basis kernel function was used (56) and can be expressed as Equation (8):

$$f(x, y) = \exp(-\eta||x - y||^2) \tag{8}$$

where η is the parameter set of the radial basis kernel function.

SHAP is a novel model interpretation method that utilizes the Shapley value from game theory to combine optimal credit allocation with local explanations (57), and was applied here

TABLE 6 Multi-classification confusion matrix.

	Mode *i*	Predictive class					Recall
		1	2	3	...	*I*	
Actual class	1	h_{11}	h_{12}	h_{13}	...	h_{1I}	$Recall_1$
	2	h_{21}	h_{22}	h_{23}	...	h_{2I}	$Recall_2$
	3	h_{31}	h_{32}	h_{33}	...	h_{3I}	$Recall_3$
	...	...	...	...	...	...	
	I	h_{I1}	h_{I2}	h_{I3}		h_{II}	$Recall_S$
	Precision	$Precision_1$	$Precision_2$	$Precision_3$		$Precision_S$	Accuracy

to measure variable feature importance. It can be used in conjunction with different machine learning models for model interpretation. For a factor subset $S \in F$ (where F stands for the set of all factors), two models are trained to extract the effects of factor j. The first model $f_{S\cup\{j\}}\left(X_{S\cup\{j\}}\right)$ is trained with factor j, while the second $f_S\left(X_S\right)$ is trained without it. Here, $X_{S\cup\{j\}}$ and X_S are the values of input feature factors. The differences in model output $f_{S\cup\{j\}}\left(X_{S\cup\{j\}}\right) - f_S\left(X_S\right)$ are computed for each possible subset $S \in F\backslash\left\{j\right\}$, and the Shapley value of a factor j is calculated *via* Equation (9) (57, 58):

$$\varnothing_j = \sum_{S\in F\backslash\{j\}} \frac{|S|!\left(|F|-|S|-1\right)!}{|F|!}\left(f_{S\cup\{j\}}\left(X_{S\cup\{j\}}\right) - f_S\left(X_S\right)\right) \tag{9}$$

Confusion matrix

The collected data were randomly divided into calculation and verification sets according to an 8:2 ratio. Assuming that there were S travel modes in a data set, different prediction models based on the data will produce different estimated values. Accordingly, to test the accuracy of the prediction models, the calculation and verification datasets can be used, and the prediction results of each model can be summarized in a confusion matrix (Table 6) (59), where $Recall_i$ is the recall rate, $Precision_i$ is the accuracy rate, $Accuracy$ is the correct rate, and N is the total number of samples (Equations 10–12):

$$Recall_i = \frac{h_{ii}}{\sum_{t=1}^{I} h_{it}}, \tag{10}$$

$$Precision_i = \frac{h_{ii}}{\sum_{t=1}^{I} h_{ti}}, \tag{11}$$

$$Accuracy = \frac{\sum_{i=1}^{I} h_{ii}}{N}. \tag{12}$$

TABLE 7 Multicollinearity test results.

Variables	VIF	1/VIF
Intercity travel cost	2.31	0.43365
Intercity travel distance	1.93	0.517114
Intercity mode of transportation	1.78	0.562454
Relative humidity	1.44	0.694347
Personal monthly income	1.25	0.801631
Rainfall	1.22	0.82139
Temperature	1.21	0.829228
Visibility	1.19	0.837374
Air quality index	1.17	0.851836
Age	1.13	0.881774
Occupation	1.12	0.896377
Car ownership	1.1	0.906249
Wind power	1.09	0.919628
Intercity travel time	1.07	0.932903
Travel purposes	1.05	0.949109
Gender	1.05	0.956899
Mean VIF	1.32	

Results

Determination of variables

Before data analysis, a multicollinearity test was conducted on the relevant independent variables, and no obvious collinearity relationships were revealed (Table 7).

Parameter estimation and feature importance

The ordered logit model (OLM) parameter estimation results are shown in Table 8, where the coefficient reflects the influence degree of the specific explanatory variable on the dependent variable. Furthermore, a positive (negative) regression coefficient indicates that the occurrence ratio will increase (decrease) when the explanatory variable increases by one unit.

In addition, the significant influencing factors in the OLM were taken as the input features, and an SVM was used to build a model for each of the four dependent variables. After the model construction and calibration, a 4-fold cross-validation and hyperparameter tuning were applied to produce the optimal training model, and the conclusions of the models evaluation are shown in Table 9; whereas the feature importance of the four SVM models is shown in Figure 1.

Model interpretation

Factors from individual's socioeconomic background

According to the OR values and importance of factors (Table 8; Figure 1), the impact of each significant variable on passenger mood during intercity travel was analyzed. Firstly, gender (male vs. female) was found to have a significant impact on the degrees of happiness and panic of passengers, both ranking the 6th place in importance according to the results of the SVM; whereas the OR values of happiness and panic degrees were 0.849 and 1.219, respectively, indicating that the odds of male passengers' happiness toward intercity travel would decrease 15.1% compared with females, while an additional level of passengers' panic for males would increase 21.9%. One possible reason is that males assume more social responsibilities in Chinese society, and feel greater pressure from both work and home life (60); thus, in general, they might suffer from more likelihood to be less happy than women, and even more anxious when traveling between cities.

Age (>60 vs. 30–60) was also found to have a significant impact on passenger happiness and tiredness during intercity travel according to the OLM. The SVM model showed that the importance of age ranked the 16th and 19th for happiness and tiredness, respectively. The OR value of the variable for happiness showed that the odds of an additional level of happiness for passengers over 60 would decrease by 25.2% in contrast to passengers aged 30–60 years-old; whereas, the odds of an additional level of tiredness for passengers > 60 years-old would increase by 37.7%. This is intuitive as more elderly passengers typically have less energy than their middle-aged counterparts, both physically and mentally; thus, they are more likely to feel tired during long-distance travel.

Occupation (institution personnel vs. enterprise personnel) showed a significant negative correlation with travel happiness and panic in the OLM results, with the SVM model revealing the 13th place in terms of importance for both mood factors. In addition, the OR values of occupation were 0.56 and 0.763 for institution personnel and enterprise units, respectively, suggesting that the odds of an additional degree of happiness perceived by institution personnel would reduce by 34%, and the odds of an additional degree of panic would decrease by 23.7%. This might be related to the travel system of the public institutions maintaining strict regulations, with limited choices of travel mode; thus, these employees would likely experience a corresponding reduction in happiness during travel.

Similarly, occupation (students vs. enterprise personnel) had a significantly negative effect on passengers' intercity travel happiness, while that of farmers vs. enterprise units and self-employed vs. enterprise units retained a significantly negative effect on passenger's panic feelings. Here, the OR value for occupation (students vs. enterprise units) was 0.809, suggesting that the odds of an additional degree of happiness perceived by the students would reduce by 19.1%; whereas the OR values for panic were 0.519 and 0.708, respectively, indicating that the odds of an additional degree of passenger panic toward intercity travel for farmers would decrease by 48.1% compared with enterprise units, while that for self-employed passengers would decrease by 29.2%. This could be a result that hinges on the very limited choices for students due to their financial constraints. For example, for those college and university students from a low-income household, they are more willing to trade a lower travel cost with sacrifice of comfortness in long-distance travel (this is quite typical in China), thus, leading to a relatively lower degree of happiness during travel.

Personal monthly income also had a negative correlation with traveler panic according to the ordered logistic regression, with the SVM model indicating it ranked the 3rd in importance. Further, the OR value of 0.95 indicated that the odds of an additional degree of passenger panic would decrease by 5% for every 1,000¥ increase in personal monthly income. This may derive from passengers with higher incomes often choosing safer and more efficient modes of travel (e.g., airplanes and HSRs), reducing their panic degree during intercity travel.

Car ownership was also identified to have a significant impact on the happiness, panic, anxiety, and tiredness of passengers during intercity travel according to the regression results. The OR values of car ownership for these four factors were 0.757, 1.354, 1.447, and 1.242, respectively, indicating that the odds of an additional degree of happiness for passengers with cars would decrease by 24.3% compared to those without cars, while additional degrees of panic, anxiety and tiredness would increase by 35.4, 44.7, and 24.2%, respectively. This might be related to the fact that passengers with cars often go to airports or stations by driving their own private cars, and thus, facing the additional mental pressures of finding parking lots and paying for a longer parking period, which might lead to an increasing level of anxiety, panic, and exhaustion.

Factors relate to weather conditions

The external temperature was the most critical factor influencing passenger mood during intercity travel, ranking the

TABLE 8 Parameter estimation from OLM.

Variables	Happiness degree			Panic degree			Anxiety			Tiredness degree		
	Coefficient	*P* > *Z*	OR	Coefficient	*P* > *Z*	OR	Coefficient	*P* > *Z*	OR	Coefficient	*P* > *Z*	OR
Gender												
Male vs. female	−0.164	0.05	0.849	0.198	0.018	1.219	/	/	/	/	/	/
Age												
Over 60 years old vs. 30–60	−0.29	0.036	0.748	/	/	/	/	/	/	0.32	0.018	1.377
Occupation												
Institution personnel vs. Enterprise units	−0.579	0	0.56	−0.27	0.032	0.763	/	/	/	/	/	/
Students vs. Enterprise units	−0.211	0.03	0.809	/	/	/	/	/	/	/	/	/
Farmers vs. Enterprise units	/	/	/	−0.656	0	0.519	/	/	/	/	/	/
Self-employed vs. Enterprise units	/	/	/	−0.345	0.029	0.708	/	/	/	0.431	0.007	1.539
Other vs. Enterprise units	/	/	/	−0.321	0.019	0.726	−0.319	0.017	0.727	/	/	/
Personal monthly income	/	/	/	−0.051	0.036	0.95	/	/	/	/	/	/
Car ownership												
Yes vs. No	−0.279	0.001	0.757	0.303	0	1.354	0.37	0	1.447	0.217	0.011	1.242
Temperature												
≥25°C vs. 15–25°C	−0.717	0	0.488	1.286	0	3.619	0.964	0	2.621	0.089	0.649	1.093
10–15°C vs. 15–25°C	−0.343	0.001	0.71	0.58	0	1.785	0.64	0	1.896	0.814	0	2.256
5–10°C vs. 15–25°C	−0.254	0.086	0.776	0.507	0.001	1.661	0.654	0	1.924	0.947	0	2.577
≤0°C vs. 15–25°C	−1.462	0	0.232	1.034	0	2.813	1.086	0	2.963	1.143	0	3.136
Rainfall	/	/	/	0.034	0.045	1.035	0.045	0.018	1.046	0.057	0.011	1.058
Relative humidity	0.01	0	1.01	/	/	/	/	/	/	−0.004	0.048	0.996
Wind power	−0.146	0.001	0.864	0.161	0	1.174	0.201	0	1.223	0.175	0	1.191
Air quality index	−0.006	0	0.994	0.009	0	1.009	0.006	0	1.006	0.002	0.024	1.002
Visibility	0.003	0.041	1.003	−0.001	0.053	0.999	/	/	/	−0.002	0	0.998
Travel purposes												
Leisure travel vs. Mandatory travel	0.46	0	1.585	−0.245	0.004	0.783	−0.232	0.005	0.793	−0.214	0.01	0.808
Intercity travel mode												
Airplane vs. HSR	/	/	/	−0.764	0	0.466	−0.649	0	0.523	−0.438	0	0.645
Bullet train vs. HSR	−0.683	0	0.505	/	/	/	/	/	/	/	/	/
Train vs. HSR	0.635	0	1.888	−1.029	0	0.357	0.415	0	1.515	−0.309	0.008	0.734
Express bus vs. HSR	/	/	/	/	/	/	−0.768	0	0.464	−0.365	0.007	0.695
/cut1	−2.624			−1.210			−1.612			−0.644		
/cut2	−0.778			0.153			−0.144			0.879		
/cut3	1.400			1.531			1.214			2.340		
/cut4	4.257			3.866			3.573			4.549		

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TABLE 9 Confusion matrix.

Model			Mode	Calculation set						Validation set					
				Predictive class						Predictive class					
				1	**2**	**3**	**4**	**5**	**Recall**	**1**	**2**	**3**	**4**	**5**	**Recall**
Ordered logistic model	Happiness	Actual class	1	3	85	98	0	0	1.61%	4	35	15	0	0	7.41%
			2	6	144	318	0	0	30.77%	4	76	55	1	0	55.88%
			3	2	120	561	1	0	82.02%	1	42	108	4	0	2.58%
			4	2	19	232	3	0	1.17%	0	9	53	1	0	1.59%
			5	0	6	14	0	0	0.00%	0	4	2	0	0	0.00%
			Precision	23.08%	38.50%	45.87%	75.00%	0.00%	**44.05%** (Accuracy)	44.44%	45.78%	46.35%	16.67%	0.00%	**45.65%** (Accuracy)
	Panic	Actual class	1	0	11	74	37	1	0.00%	0	7	13	4	0	0.00%
			2	0	37	89	94	3	16.59%	2	14	23	15	1	25.45%
			3	0	13	109	268	5	27.59%	0	7	43	51	4	40.95%
			4	1	7	79	556	17	84.24%	0	3	17	140	9	82.84%
			5	0	0	22	181	10	4.69%	0	0	4	52	5	8.20%
			Precision	0.00%	54.41%	29.22%	48.94%	27.78%	**44.11%** (Accuracy)	0.00%	45.16%	43.00%	53.44%	26.32%	**48.79%** (Accuracy)
	Anxiety	Actual class	1	0	9	67	38	1	0.00%	0	7	12	3	0	0.00%
			2	0	27	94	121	0	11.16%	0	21	30	11	1	33.33%
			3	0	19	121	273	1	29.23%	0	6	29	68	2	27.62%
			4	0	9	80	574	3	86.19%	0	7	24	132	3	79.52%
			5	0	1	17	158	1	0.56%	0	0	7	48	3	5.17%
			Precision	0.00%	41.54%	31.93%	49.31%	16.67%	**44.80%** (Accuracy)	0.00%	51.22%	28.43%	50.38%	33.33%	**44.69%** (Accuracy)
	Tiredness	Actual class	1	0	3	120	17	0	0.00%	0	6	16	5	0	0.00%
			2	0	21	207	76	0	6.91%	0	17	48	29	0	18.09%
			3	1	17	331	167	0	64.15%	0	17	59	48	0	47.58%
			4	0	3	231	279	0	54.39%	0	6	40	82	0	64.06%
			5	0	1	43	78	0	0.00%	0	3	11	18	0	0.00%
			Precision	0.00%	46.67%	35.52%	45.22%	0.00%	**39.56%** (Accuracy)	0.00%	34.69%	33.91%	45.05%	0.00%	**39.01%** (Accuracy)
SVM	Happiness	Actual class	1	100	43	37	6	0	53.76%	17	20	17	0	0	31.48%
			2	15	321	103	29	0	68.59%	17	64	38	17	0	47.06%
			3	11	79	546	47	1	6.87%	8	38	80	28	1	51.61%
			4	5	24	75	152	0	55.00%	0	12	20	31	0	49.21%
			5	1	1	5	2	11	55.00%	1	3	2	0	0	0.00%
			Precision	75.76%	68.59%	71.28%	64.41%	91.67%	**70.01%** (Accuracy)	39.53%	46.72%	50.96%	40.79%	0.00%	**46.38%** (Accuracy)

(Continued)

TABLE 9 (Continued)

Model			Mode	Calculation set						Validation set					
				Predictive class						Predictive class					
				1	2	3	4	5	Recall	1	2	3	4	5	Recall
	Panic	Actual class	1	70	13	18	21	1	56.91%	5	5	9	4	1	20.83%
			2	20	123	29	43	8	55.16%	4	24	10	17	0	43.64%
			3	14	27	231	107	16	58.48%	7	8	27	44	19	25.71%
			4	18	16	46	557	23	84.39%	7	9	22	110	21	65.09%
			5	3	6	22	60	122	57.28%	0	3	15	24	19	31.15%
			Precision	56.00%	66.49%	66.76%	70.69%	71.76%	**68.34%** (Accuracy)	21.74%	48.98%	32.53%	55.28%	31.67%	**44.69%** (Accuracy)
	Anxiety	Actual class	1	35	5	47	27	1	30.43%	3	5	9	5	0	13.64%
			2	8	78	75	75	6	3.31%	3	22	22	14	2	34.92%
			3	12	30	173	193	6	41.79%	4	8	23	63	7	21.90%
			4	16	11	77	554	8	83.18%	4	4	26	124	8	74.70%
			5	2	6	30	90	49	27.68%	1	1	5	42	9	15.52%
			Precision	47.95%	60.00%	43.03%	59.00%	70.00%	**55.08%** (Accuracy)	20.00%	55.00%	27.06%	50.00%	34.62%	**43.72%** (Accuracy)
	Tiredness	Actual class	1	54	24	33	26	3	38.57%	3	8	8	8	0	11.11%
			2	7	151	104	39	3	49.67%	4	27	38	19	6	28.72%
			3	14	41	377	74	10	73.06%	10	18	60	29	7	48.39%
			4	16	33	99	357	8	69.59%	4	13	46	62	3	48.44%
			5	0	12	41	15	54	44.26%	2	3	17	5	5	15.63%
			Precision	59.34%	57.85%	57.65%	69.86%	69.23%	**62.26%** (Accuracy)	13.04%	39.13%	35.50%	50.41%	23.81%	**38.77%** (Accuracy)

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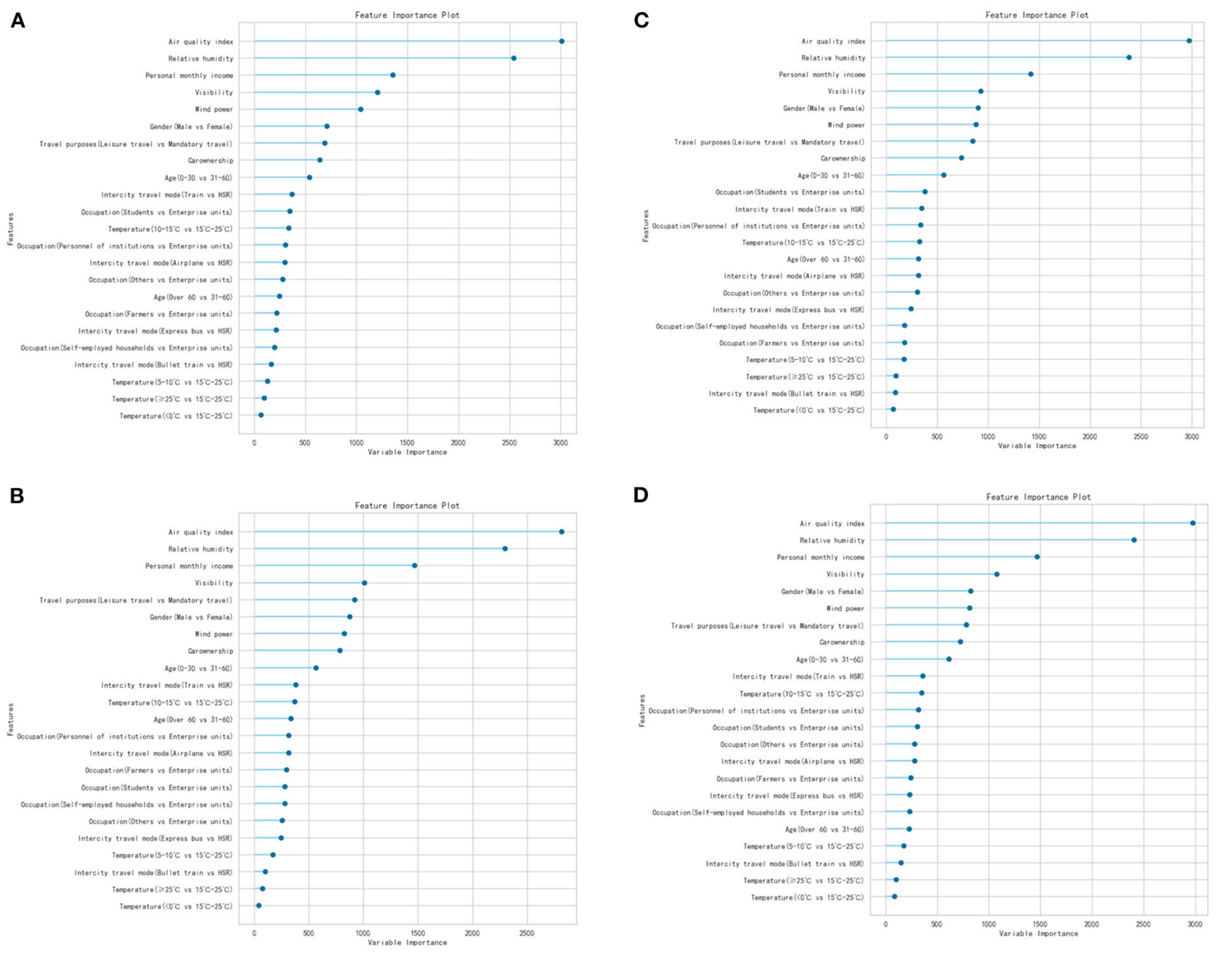

FIGURE 1
Importance analysis of support vector machine (SVM). **(A)** Happiness degree. **(B)** Panic degree, **(C)** Anxiety degree, **(D)** Tiredness degree.

12th, 11th, 13th, and 11th in the importance for happiness, panic, anxiety, and tiredness, respectively. The OR value for temperatures: ≥25°C vs. 15–25°C, 10–15°C vs. 15–25°C, 5–10°C vs. 15–25°C), and ≤0°C vs. 15–25°C) were 0.488, 0.71, 0.776, 0.232, respectively, showing that compared with the passengers traveling in temperature of 15–25°C, the odds of additional degrees of happiness perceived by passengers traveling at temperatures 25°C, 10–15°C, 5–10°C, and ≤0°C would decrease by 51.2, 29.0, 22.4, and 76.8%, respectively. In addition, temperature showed a significant effect on passenger panic, and the OR values of this indicated that the odds of an additional degree of panic perceived by passengers traveling in temperatures >25°C, 10–15°C, 5–10°C, and ≤0°C would increase by 261.9, 78.5, 66.1, and 181.3%, respectively. Similarly, the odds of an additional degree of anxiety perceived by passengers traveling in temperatures >25°C, 10–15°C, 5–10°C, and ≤0°C would increase by 162.1, 89.6, 92.4, and 196.3%, respectively.

Moreover, the odds of additional degrees of tiredness being perceived by passengers traveling in temperatures >25°C, 10–15°C, 5–10°C, and ≤0°C would increase by 9.3, 125.6, 157.7, and 213.6%, respectively. This indicates that the external temperatures between 15 and 25°C showed a significantly positive effect on passenger emotion, which may be derived from the additional comfort provided by environments between 15 and 25°C.

Rainfall is another generally important characteristic variable impacting travel mood, resulting in a series of OR values of 1.035, 1.046, and 1.058, indicating that the odds of additional degrees of panic, anxiety, and tiredness would increase by 3.5, 4.6, and 5.8%, respectively. This is likely because rainfall would directly affect the operation of intercity traffic modes, as well as passengers' moods. Specifically, an increase in rainfall could likely lead to a large-scale delays, while extreme rainfall may even lead to disruptions and cancellations. This will inevitably increase passengers' anxiety, mental tension, and exhaustion to a higher extent. Such findings are supported by Wu and Liao (26), who showed that extreme rainfall can significantly impact passengers' travel moods and reduce travel demand.

Relative humidity also displayed significant positive and negative impacts on happiness and tiredness, respectively, with corresponding OR values of 1.01 and 0.996, indicating that the odds of the additional degrees of happiness would increase by 1.0%, while that of additional tiredness would decrease by 0.4%. The ranking results of the importance degree, however, showed that relative humidity had little influence on passengers' happiness and tiredness degrees in intercity travel.

Furthermore, wind speed ranks the 5th, 7th, 6th, and 6th, respectively, while the OR values of wind speed for happiness, panic, anxiety, and tiredness are 0.864, 1.174, 1.223, and 1.191 respectively, indicating that the odds of an additional degree of passengers' happiness would be decreased by 13.6% with every unit of increment in wind speed. In addition, the increase of one unit of wind speed will increase the odds of the additional level of passengers' panic, anxiety, and tiredness degree by 17.4, 22.3, and 19.1%, respectively. Intuitively, a windy weather would lead to higher anxiety, panic, and even fatigue in long-distance travel, thereby reducing their happiness. This can be supported by the findings from Yazdanpanah and Hosseinlon (24) and Alberto et al. (25). Similarly, the air quality was also found to be an important variable impacting passengers' emotions during intercity travel. The OR value for happiness on this factor was 0.994, showing that each additional unit of the air quality index decreased the odds of additional degrees of happiness by 0.6%. The odds of additional degrees of panic, anxiety, and tiredness increased by 9, 6, and 2%, respectively. The higher the air quality index, the worse the air quality is, which is very intuitive to realize its effects on the travel mood.

Visibility was similarly revealed to have a measurable impact on intercity passenger happiness, panic, and tiredness, all ranking the 4th according to the SVM models. An OR value for happiness degree of 0.994 showed that an increase of each additional unit of visibility increased the odds of additional degrees of happiness by 3%. Additionally, the odds level of passengers' panic and tiredness decreased by 1 and 2%, respectively. In general, what we can see from the above is that a good weather condition, with clean air, moderate temperature and wind, and clear vision, would significantly produce good emotional feelings in long-distance travel.

Factors of travel characteristics

Travel purpose was similarly discovered to have a significant effect on happiness, panic, anxiety, and tiredness, ranking the 7th, 5th, 7th, and 7th, respectively. Specifically, the OR values of travel purpose were 1.585, 0.783, 0.793, and 0.808, respectively, indicating that compared with mandatory travel, the odds of the additional degrees of happiness perceived by passengers engaging in leisure travel can increase by 58.5%, while those of for panic, anxiety, and tiredness would decrease by 21.7, 20.7, and 19.2%, respectively. This also seems relatively intuitive, as passengers involved in leisure travel are more prone to feel happy, and less likely to suffer from panic, anxiety, and tiredness.

Lastly, intercity mode of transportation (airplane vs. HSR) was an essential characteristic variable in travel mood, ranking the 10th, 10th, 11th, and 10th in happiness, panic, anxiety, and tiredness according to the SVM. The OR values for intercity travel mode (airplane vs. HSR) were 0.466, 0.523, and 0.645, respectively, indicating that compared with HSR, the odds of an additional degree of panic, anxiety, and tiredness would decrease by 53.4, 47.7, and 35.5%. This is likely related to the greater travel speed, and efficiency of air travel, as has been shown by Masson and Petiot (27), where under the same time conditions, passengers tended to choose the mode of transportation with a faster speed to reduce travel time.

Alternatively, the OR values of intercity transportation mode (train vs. HSR) were 1.888, 0.357, 1.515, and 0.734, respectively, indicating that compared with HSR, the odds of additional degrees of happiness and anxiety perceived by passengers would increase by 88.8 and 51.5%; whereas those of panic and tiredness would decrease by 64.3 and 26.6%, respectively. In particular, we found that HSR was associated with negative emotions compared with other modes of transportation. One possible reason could lie in the poor inter-connections among various functional areas at the HSR stations in most of the major Chinese cities (such as arrival area, ticketing area, security check points, transfer area, waiting zones, and other basic facilities). China's major cities have now all equipped with new HSR stations that built with overhead suspension truss-like structures with massive open space and long overarching internal span distance, and various functional areas are often arranged on different floors, which leads to long walking time for passengers. This can easily lead to negative emotions among passengers traveling by HSRs, especially those with heavy carried luggages. Interestingly, we found that this finding is actually inconsistent with St-Louis et al. (29), who found that the positive mood of pedestrians, train commuters, and cyclists was significantly higher than that of drivers or subway and bus users, which could be due to the significant differences between HSR and traditional trains in China.

Discussion

From the results, several practical implications for the development of intercity transportation and environmental protection can be inferred. First of all, the result shows that weather have a crucial impact on the mood of passengers during inter-city travel. A lower PM2.5 concentration (i.e., a better air quality) and wind speed, suitable temperature (20–25°C) and higher visibility are closely related to the positive travel mood of passengers. Given the current circumstances in China, it suggests that the protection of the urban environment is still an important work in the process of China's rapid urbanization and strategic development, which aims to effectively improve the social wellbeing and health of the citizens in a long run.

In addition, we found that the travel mode can also affect the travel mood of the passengers. Surprisingly, passengers traveling by HSR are more likely to be associated with negative travel moods than those passengers traveling by other transportation modes. One of the implications could be that the design of the functional divisions at HSR stations in China should be further improved with better inter-connections and smoother internal transitions. This deficiency might lead to some negative experience, such as a long walking distance for passengers, especially with heavy luggages during inter-city trips. This shows, to a large extent, that the efficient inter-connection of various functional areas of high-speed railway stations, such as the entrance and exit of HSR stations, ticket counters, waiting areas, car-parking facilities and taxi parking areas, could be a managerial focus for station management in the future.

The findings on the car ownership reveals that the travel emotion of passengers with cars is surprisingly lower in intercity travel. Given the possible reason that this might be due to the difficulties and burdens from parking issues at the stations, optimizing the design of parking lots seems to be a fairly reasonable measure. By providing more parking spaces connecting with intercity transportation hubs, it could be an effective and efficient measure to improve the travel emotion of those particular passengers. For example, a better sign design in the parking lobby and signal indicators of available parking lots could be considered here for this particular issue, and we have witnessed that suchlike design has been widely implemented at many transportation hubs in recent years in China. Finally, given the prominent phenomenon of rapid aging populations in China, the elderly over 60 are more likely to suffer from unhappiness and tiredness, which suggests that developing more effective measures to provide extra care for the elderly travelers in the intercity long-distance mobility could be a good managerial policy and should be considered by the local authorities, the government, and transportation service providers.

Conclusions

The present study analyzes the factors affecting passengers' moods in intercity travel in Xi'an city, including individual socioeconomic characteristics, transportation modes, weather conditions, and passengers' moods. Four dimensions—happiness, panic, anxiety, and tiredness—are divided into five levels to represent an objective evaluation system for assessing passenger mood conditions during intercity travel. Using the OLM and SVM models in tandem to establish the regression relationship between the four different dimensions of passenger moods and independent variables, the major determinants, and importance of these influential factors are explored and several policy and managerial implications are put forward. The main conclusions of this study can be summarized as follows.

(1) By applying the ordered logit regression model to analyze and identify the influential factors affecting passengers' moods during intercity travel, it was revealed that gender, age, occupation, personal monthly income, car ownership, temperature, rainfall, relative humidity, wind speed, air quality index, visibility, travel purpose, intercity mode of transportation, and intercity travel time all have significant effects on the different dimensions of passengers' moods, including happiness, panic, anxiety, and tiredness.

(2) Compared with females, males were more prone to feel panic, and less likely to feel happiness during intercity travel. Compared to passengers of age 30–60, individuals with an age of over 60 were less happy when traveling and more likely to experience tiredness. Compared with enterprise units, institution personnel and students maintained a lower sense of happiness during travel, while self-employed households were more prone to tiredness. Furthermore, for every ¥1,000, increase in monthly income, the probability of passenger panic can be reduced by 5%. For weather conditions, temperatures between 15 and 25°C, lower wind speeds, greater relative humidity, lower air quality index (i.e., better air quality), higher visibility, and lower precipitation all bettered the moods of intercity passengers (i.e., increasing their sense of happiness). Compared to mandatory travel, passengers engaged in leisure travel were more likely to feel happy, and less likely to feel panic, anxiety, and tiredness.

(3) To explore the different effects of independent variables on passengers' moods during intercity travel, SVMs were used to calculate the contribution of independent variables (i.e., the relative importance of features), where the higher the relative importance value, the greater the contribution to estimating the dependent variable. These results showed that the most important variable affecting happiness was occupation (23% importance); whereas those for panic and anxiety were intercity transportation mode (38 and 39%,

respectively), while the most important variable affecting tiredness was the weather temperature (22%).

Finally, we also acknowledge three limitations of this study: (1) only one city in China was investigated as the case study, yet factors affecting passengers' emotional perceptions and wellbeing could be affected by different cultural backgrounds and urban environments. Hence, additional data from other cities with various geographical contexts should be further investigated in the future to verify the sensitivity of the findings. (2) Even though it would not alter the main findings and conclusions, it should still be noted that the survey data on multi-classes could be slightly imbalanced due to random sampling, therefore, the prediction accuracy of models was only at moderate and acceptable levels. Statistically, this issue can be addressed in future studies by adopting over- or under-sampling methods to re-balance the classes. (3) It is also noteworthy that passengers traveling to one city as the destination and those passengers leaving this city as the origin might have slightly different moods when carrying out their long-distance intercity travels, which might cause some potential estimation bias. Likewise, other unpredictable coincidences and various trivial, yet dynamic, influencing factors, such as instantaneous perceptions, could also affect the overall travel moods, which can hardly be observed through questionnaire surveys. The future work could explore more on these issues and interesting findings might be further revealed.

Data availability statement

The datasets presented in this article are not readily available because the authors do not have permission to share the data. However, metadata might be available to share upon request. Requests to access the datasets should be directed to lixiaowei@xauat.edu.cn.

Author contributions

Conceptualization, methodology, data curation, validation, and software: XL, YW, and JT. Writing original draft, investigation, and writing review and editing: XL, YW, JT, LS, and TZ. Funding acquisition and supervision: XL, JT, and JC. All authors contributed to the article and approved the submitted version.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Publisher's note

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Modeling the resumption of work and production of enterprises during COVID-19: An SIR-based quantitative framework

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The ongoing COVID-19 pandemic has evolved beyond being a public health crisis as it has exerted worldwide severe economic impacts, triggering cascading failures in the global industrial network. Although certain powerful enterprises can remain its normal operation during this global shock, what's more likely to happen for the majority, especially those small- and medium-sized firms, is that they are experiencing temporary suspension out of epidemic control requirement, or even permanent closure due to chronic business losses. For those enterprises that sustain the pandemic and only suspend for a relatively short period, they could resume work and production when epidemic control and prevention conditions are satisfied and production and operation are adjusted correspondingly. In this paper, we develop a novel quantitative framework which is based on the classic susceptible-infectious-recovered (SIR) epidemiological model (i.e., the SIR model), containing a set of differential equations to capture such enterprises' reactions in response to COVID-19 over time. We fit our model from the resumption of work and production (RWP) data on industrial enterprises above the designated size (IEDS). By modeling the dynamics of enterprises' reactions, it is feasible to investigate the ratio of enterprises' state of operation at given time. Since enterprises are major economic entities and take responsibility for most output, this study could potentially help policy makers better understand the economic impact caused by the pandemic and could be heuristic for future prevention and resilience-building strategies against suchlike outbreaks of public health crises.

KEYWORDS

COVID-19 pandemic, economic loss, industrial enterprises, SIR model, simulation

1. Introduction

1.1. Background information

On 30 January 2020, WHO declared the COVID-19 outbreak a Public Health Emergency of International Concern. Governments worldwide have taken various control and mitigation measures to limit the spread of the virus, which comes at a cost of suspension of work and production nationwide. The COVID-19 pandemic turns out to be not only a public health crisis but also an economic one (i.e., in 2020, a recent investigation carried out by The World Bank showed that the world GDP fell by 3.29% because of COVID-19 impacts). Thus, exploring the economic impact of COVID-19 and related mechanism have become an important research subject. One perspective to study the adverse impact of the pandemic is to investigate what enterprises of various sizes have experienced during and after COVID-19.

By March 2020, China has quickly taken the COVID-19 outbreak under control by implementing stringent measures, such as lockdown, restrictions of human mobility, and public gathering (1, 2). The number of new daily confirmed cases in China peaked on 14 February, 2020 (WHO). By the end of March, most provinces, except Hubei, the epicenter of the first round outbreak, have already lessened restrictions on movement and shifted their focus to reviving the economy. However, effective virus containment measures were carried out at the cost of substantial economic losses. In the first quarter of 2020, China's GDP contracted by 6.8% from the same quarter a year ago; the utilization rate of national industrial capacity was 8.6% lower than the same period of 2019; the total value added of the industrial enterprises above the designated size (IEDS)[1] went down by 8.4% year on year (3).

There is a high level of interdependency and connectedness among the closure of enterprises, especially for those within one supply chain network. How the state of one enterprise will influence another is, however, not clear. Furthermore, an enterprise can experience several possible operation states during an outbreak, from normal operation, operation suspension to full recovery. To understand how these possible states evolve over time and how fast the evolution are important in that supportive intervention strategies (e.g., those preventing an enterprise from closure) can be designed accordingly. Nevertheless, existing studies have not yet proposed proper method to model the evolving state of an enterprise over time and thus are incapable of providing insights toward the interdependency of enterprise closures. This paper proposes a novel analytical framework to simulate the operation states of enterprises during COVID-19, with the goal to understand how enterprises respond to public health crisis and supportive intervention policy making, concerning post-pandemic resilient recovery of work, and production during COVID-19. Our framework is based on the classic susceptible-infectious-recovered (SIR) epidemiological model, which is wildly used in infectious disease study. The basic logic of SIR model is to classified the population by their infectious status, and use a system of ODEs to simulate the spread of the disease. Based on the SIR model, we classify the business state of each enterprise into four compartments and develop a compartment-based framework to quantify the evolving state of an enterprise over time. Specifically, at each time period, an enterprise will be in one of the following four states: (1) it may remain in operation throughout the epidemic without any suspension or even shut down; (2) it may also be in the state of temporary suspension due to various reasons, such as financial pressure, epidemic control, supply chain disruptions, and more; (3) it can be permanently shut down; and another possible state is that (4) it is currently operating normally but the difference from the first state is that it first experience a suspension and then recover to normal state. For easy exposition, we term these four states as in normal operation, temporary suspension, permanent shutdown, and in recovered operation. Four coupled differential equations, which involve four time-dependent functions, are used to describe the dynamics of the number of enterprises in each class.

We collect data on enterprises resuming production from China's four provinces (Anhui, Hebei, Heilongjiang, and Shandong) to fit the model and calibrate the model by the least square method. Specifically, we collect data about the province-daily-level ratio of IEDS that have resumed production from news announcement and government website. In 2020, Chinese government extended Chinese New Year Holiday, which was supposed to end on January 30, to February 2 due to the epidemic. Most provinces, including Anhui, Hebei, Heilongjiang, and Shandong, officially extended the resumption of work and production (RWP) to February 10[2]. Before official RWP, the ratio of IEDS that have resumed production is only 21.8% in Shandong, and less than 14% in Anhui and Hebei (As for Heilongjiang, the RWP ratio we collect starts from February 17). By mid March, that ratio has increased to over 90% in all four provinces. Although we do not have data on the ratio from a daily basis, we do manage to collect the data on most of the observation days. In terms of data, the relation between COVID-19 and its adverse impact on small and medium-sized enterprises (SME) has been amply investigated in the literature [see (4–6)], while the impact of the epidemic on the IEDS is still an open field

1 According to National Bureau of Statistics of China, industrial enterprises consist of enterprises in the following sectors: mining and quarrying, manufacturing, and production and distribution of electricity, heat, gas, and water. Industrial enterprises above designated size are enterprise with annual revenue from principal business over 20 million yuan.

2 According to their government announcements, the resumption of work and production should start no earlier than 24:00 on February 9.

of research. This article utilized real data on IEDS to investigate the rate of resumption of work and production during and after a wave of COVID-19 in China.

1.2. Literature review

It is widely accepted that there are trade-offs between economic and health outcomes under COVID-19. Abandoning the containment policy too early would avoid a sharp drop in output and employment in the short term, but it would greatly increase mortality and ultimately lead to a decline in social welfare (7).

Since the outbreak of COVID-19 pandemic, there has been a large number of emerging studies devoted to evaluating the consequent economic loss using real data or by simulation. Their focuses range from macroeconomic consequences, such as inflation, unemployment, and exchange rates (8–10), supply chain disruptions (11–14), to influence on financial market (15–17), labor market (18–20), and firms (21–25). During the pandemic, people cut back on consumption and work to reduce the chances of being infected (26).

Studies on China's economic loss under COVID-19 paid special attention to the economic impact of lockdown. Chen et al. (27) found that a 1-month full-scale lockdown causally reduces the truck flows connected to the locked down city and the city's real income in the month by 54%. Cities in lockdown experienced a 34% reduction in the year-on-year growth rate of exports (28). Hubei province, which experienced the most drastic lockdown in China, lost 37% in GDP compared to the counterfactual situation without lockdown; the losses in value added of agriculture, secondary, and service industry are 17%, 46%, and 31%, respectively (29).

The main purpose of our work is to develop a mathematical model to study the evolution of enterprises' operation states, such as suspension and production resumption, under the pandemic outbreak. It is found that, in China, the manufacture sector was scheduled to resume work the earliest (5), and experienced a quick V-shape recovery (30). In February 2020, China's manufacturing Purchasing Manager Index (PMI) was 35.7%. In March, the index has increased by 16.3 percentage points to 52%, 2 percentage points higher than that in January. Labor shortages and the increased operating costs were the main obstacles hindering the manufacturing industry from resuming full production (5). According to Dai et al. (6), 47.6% of employees were unable to return to work in manufacturing enterprises, the highest among all sectors in February 2020. Higher prices of raw material, logistics, and labor were all adding to increases operation costs (27). Besides, enterprises had to pour resources and efforts into disinfection and protective measures, which further led to higher costs and lower efficiency. Using online surveys on small and medium-sized enterprises from Sichuan province, China, Lu et al. (5) found that the manufacturing industry is more likely to face product delivery and supply chain pressures, and less likely to face financial pressures. Gu et al. (4) examined the impact of COVID-19 on firms' activities using daily electricity usage data for 34,040 micro-enterprises in Suzhou city, China in the period from December 31, 2019 to March 31, 2020, via difference-in-differences method. They found that the manufacturing industry incurred the greatest negative impact at the early stage of the pandemic.

In general, our work is also widely related to the literature on the impact of disasters on enterprises. The effects of disasters differ across types of disasters and economic sectors (31). An important research question concerns enterprises' recovery from natural disasters (32–37). The key point is that more efficient firms are less likely to go bankrupt after an earthquake both inside and outside of the affected areas (38), as also found in Cole et al. (39) which explored the birth, life, and death of manufacturing plants after the 1995 Kobe earthquake and shows that the continuing plants experience a temporary increase in productivity, while those most likely to exit are the least productive ones. Apart from productivity, how enterprises perform during disasters will also depend on their position in a supply chain (40), and how well they are prepared and how they respond to the risk (41).

To sum up, it is an important research topic to learn the economic impact of COVID-19. To understand how enterprises are affected, existing studies have mainly focused on conducting surveys or providing empirical evidence. Apart from these methods, mathematical model is a useful but currently rarely used tool. On this basis, our work propose an SIR-based modeling framework to analyze the RWP of enterprises during COVID-19 to enrich our understanding of the impact of the pandemic on enterprises.

1.3. Contribution statement

The contributions of this work can be summarized as follows. First, this study borrows ideas from the infectious disease community and novelly applies the SIR model to characterize the evolving state of enterprises affected by the COVID-19 pandemic. The compartments of enterprises are realistically modeled as those remain in operation, temporary suspension, permanent shutdown, and those finally recover to normal state. Second, we conduct a case study of four provinces in China to mimic the actual RWP process during the first wave of COVID-19 outbreak. We find that the resumption rate is the largest in Shandong province, and the smallest in Heilongjiang. Besides, the differences in parameter value among these provinces are reflected in governments' policy intensity to support RWP. Third, we conduct numerical simulations to examine the sensitivity of the model output to changes in parameter value, and provide policy implications on this basis. The simulations results indicate that governments' supportive policies toward enterprises under an epidemic should be primarily focused on limiting bankruptcy and accelerating resumption rate. Policies aimed at depressing suspension rate would have little impact on reducing economic loss to an outbreak.

2. The proposed SIR-based quantitative framework

In this section, we propose an SIR-based modeling framework to characterize the evolving states of enterprises' operation under COVID-19. This framework is neat, yet representative, for modeling the real-world situations without complex parameter settings.

The SIR model, proposed by Kermack and McKendrick (42), is widely used to describe the spread of an epidemic virus [e.g., (43–47)]. The basic logic is to divide the population into three compartments: *susceptible* (individuals who are healthy but can contract the disease), *infected* (individuals who have contracted the disease and are infectious), and *recovered* (individuals who have recovered and cannot contract the disease again). An individual is classed in the *susceptible* compartment before contracting the disease. When a susceptible individual enters into contact with an infectious individual and contracts the disease, the susceptible individual moves from the *susceptible* compartment into the *infected* compartment and becomes infectious. Those individuals who recover from the disease gain immunity and will not contract the disease again. At the same time, they leave the *infected* compartment for the *recovered* compartment. Two parameters are used to denote the rate at which individuals move from one compartment to another. The value of epidemiological parameters reflects characteristics of the virus studied, such as infectiousness, recovery time, fatality, and so on. They are also influenced by some aspects of the affected community, such as demographic characteristics, measures taken to mitigate local transmission and so on.

In our framework, the study object is enterprise instead of people. Enterprises are divided into four classes (Figure 1): enterprises that are in normal operation (denoted by compartment Q), enterprises that suspend operation (denoted by compartment A), enterprises that resume operation after suspension (denoted by compartment B), and enterprises that are permanently shut down (denoted by compartment C). Before an outbreak occurs, all enterprises are in normal operation (Q). Since the onset of the outbreak, they could either suspend operation (A) out of epidemic prevention requirements or operation difficulties, or close permanently (C). Enterprises move from normal operation to suspension at a rate of β, and to permanent closure at a rate of γ. Then, enterprises in suspension (A) would gradually resume operation (B) at a rate of α, or move from temporary closure to a permanent one (C) if they cannot survive. δ is the rate at which enterprises move from suspension to closure. Specifically, we put all enterprises that have resumed operation into compartment B, no matter if they operate at full or partial capacity after work resumption. The transformation from one compartment to another is indicated by a link arrow in Figure 1. It is important to note that, we assume during one wave of an epidemic, enterprises that have resumed operation will not go into suspension again or bankrupt, that is, no link arrow exists from compartment B to compartment A or C. And there is no new enterprises established during the time.

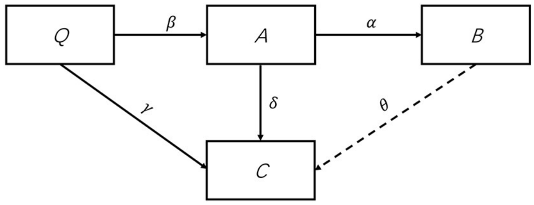

FIGURE 1
Flowchart of enterprises in a pandemic.

To highlight the time-varying change of these compartments, we formally represent Q, A, B, C as $Q(t)$, $A(t)$, $B(t)$, and $C(t)$, which are functions of time t. The total number of enterprises are denoted by N, which is assumed constant over the study. The sum of the sizes of these four compartments at each time period t satisfies:

$$N = Q(t) + A(t) + B(t) + C(t) \quad (1)$$

To ease exposition, we normalize the constant $N = 1$. And the model is represented by a system of ordinary differential equations (ODEs) as follows:

$$\frac{dQ(t)}{dt} = -\beta Q - \gamma Q \quad (2)$$

$$\frac{dA(t)}{dt} = \beta Q - \alpha AB - \delta A \quad (3)$$

$$\frac{dB(t)}{dt} = \alpha AB \quad (4)$$

$$\frac{dC(t)}{dt} = \gamma Q + \delta A \quad (5)$$

Equations (2), (3), (4), and (5) describe the change of compartments Q, A, B, and C, respectively. Notice that the number of enterprises moving from suspension to resumption per unit of time is non-linear. It is not only positively correlated to the number of enterprises in compartment A, but also positively correlated to the number of enterprises in compartment B. The latter positive correlation is derived based on the observation that, for enterprises to resume operation, they need to make sure the epidemic control and prevention conditions are satisfied and production are correspondingly adjusted. Enterprises that have resumed operation could provide not only knowledge and experience on epidemic control and prevention, but also confidence in operation resumption. Thus, we propose that more enterprises in compartment B lead to faster movement of enterprises from compartment A to B. At the onset of an epidemic, all enterprises are in the class of normal operation, i.e., $Q(0) = 1, A(0) = B(0) = C(0) = 0$. As time proceeds, these enterprises could move to different classes and constitute values of $A(t), B(t), C(t)$ at time t.

We next present two special cases of the abovementioned model, which can mimic the realistic situation as well. The main difference of these two special models from the general one is that analytical solutions can be directly derived and thus commercial solver is not required to solve these two models. In the first case, we assume that all enterprises suspend operation at the onset of an epidemic. This could happen if lockdown is imposed immediately. In this case, the model can be reduced to having only three compartments, A, B, and C. It can be simply represented as follows:

$$\frac{dA(t)}{dt} = -\alpha AB - \delta A \quad (6)$$

$$\frac{dB(t)}{dt} = \alpha AB \quad (7)$$

$$\frac{dC(t)}{dt} = \delta A \quad (8)$$

By making assumptions that $A(T_{end}) = 0, B(T_{end}) + C(T_{end}) = 1$, dividing Equation (7) by Equation (8) we get $\frac{dB}{dC} = \frac{\alpha}{\delta}B$, and thus compartment B can be approximately written as an exponential function $B = e^{\frac{\alpha}{\delta}C} - 1$. Moreover, since $A(t) + B(t) + C(t) = 1$, we have $A = 1 - B - C = 2 - e^{\frac{\alpha}{\delta}C} - C$. We can also have the function expression of $B(t)$ and $C(t)$ by making some assumptions on the function expression of $C(t)$. In the second case, we assume that there are no enterprises going into permanent closure. That is, the model consists of only two compartments, A and B. This could happen if the community recover quickly from the epidemic, or enterprises in the study are equipped with abundant supportive policies and well prepared to weather the negative shock. In this case, the model takes the form:

$$A'(t) = -\alpha AB \quad (9)$$

$$B'(t) = \alpha AB \quad (10)$$

We could derive the analytical representation of compartment A as $A = \frac{A(T_k)e^{\alpha(T_k - t)}}{A(T_k)e^{\alpha(T_k - t)} + 1 - A(T_k)}$, where $A(T_k)$ is the value of A at time T_k. By letting $B(t) = 1 - A(t)$, we end up with the analytical expression of $B(t)$.

3. Data description

The data we use is the province-daily-level ratio of IEDS that have resumed production from four provinces in China, which are Anhui, Hebei, Heilongjiang, and Shandong. In 2020, Chinese New Year Holiday and post-holiday work resumption were both officially extended due to COVID-19. February 10 marked the start of formal RWP in most provinces where the epidemic had been under control. Since then, the RWP ratio among IEDS was often released to make public the progress in RWP. We manually collect the raw data from local governments' press conference and official website[3] and use it for model calibration purpose.

The population of enterprises here is all IEDS in each province. According to National Bureau of Statistics of China, Anhui had 17,616 units of enterprises above the designated size at the end of February, 2020. Those numbers in Hebei, Heilongjiang and Shandong are 13,020, 3,501, and 26,174, respectively. Table 1 lists all available RWP ratio and the corresponding date of each province. We focus on Anhui, Hebei, Heilongjiang, and Shandong provinces because we can collect data on at least 10 dates in these provinces. The RWP ratios of Anhui, Hebei, and Shandong provinces at the beginning of formal RWP are available. For Heilongjiang province, the data starts from one week later, which is February 17. Notice that the numerator used to calculate the RWP ratio actually refers to all enterprises that were in operation at the time, regardless whether they had experienced suspension or not. That is, the RWP ratio represents the sum of compartment Q and B corresponding to our model. Before official RWP, the ratio is less than 14% in Anhui and Hebei, and 21.8% in Shandong. On one hand, livelihood-enterprises keep their operation throughout the epidemic to provide essential supplies of electricity, gas, and water for residents. On the other hand, a large part of enterprises making medical material and daily necessities had already resumed work during the holiday to support epidemic control supplies and services. By mid March, the RWP ratio are nearly 100% in all provinces except for Heilongjiang, where the ratio is 92.4%.

As mentioned above, the RWP ratio in our data is an aggregated count of compartment Q and B. To facilitate modeling, we assume that the size of Q stays constant (i.e., after formal RWP, no enterprises in normal operation at the time would go to suspension or permanent closure during our data period). To approximate the size of Q, we use the ratio of livelihood-enterprises among IEDS in each province in 2020[4], which is 2.81%, 4.83%, 13.39%, and 4.83%, respectively, in Anhui, Hebei, Heilongjiang, and Shandong province. The assumption is reasonable since daily reported new cases

3 The main sources of data include official website of provincial government, Economic and Information Department, and Development and Reform Commission, and so on.

TABLE 1 Data on resumption of work and production (RWP) of IEDS.

Anhui		Hebei		Heilongjiang		Shandong	
Date	RWP ratio	Date	RWP ratio	Date	RWP ratio	Date	RWP ratio
10/2/2020	0.138	10/2/2020	0.131	17/2/2020	0.369	9/2/2020	0.218
13/2/2020	0.277	16/2/2020	0.375	18/2/2020	0.39	10/2/2020	0.41
14/2/2020	0.319	19/2/2020	0.616	21/2/2020	43.1	11/2/2020	0.486
15/2/2020	0.367	20/2/2020	0.667	28/2/2020	0.64	12/2/2020	0.551
16/2/2020	0.404	21/2/2020	0.719	4/3/2020	0.73	14/2/2020	0.677
17/2/2020	0.461	24/2/2020	0.841	7/3/2020	0.808	15/2/2020	0.715
18/2/2020	0.515	25/2/2020	0.86	10/3/2020	0.868	17/2/2020	0.774
23/2/2020	0.827	26/2/2020	0.874	11/3/2020	0.885	18/2/2020	0.794
25/2/2020	0.92	29/2/2020	0.917	12/3/2020	0.91	19/2/2020	0.82
26/2/2020	0.948	1/3/2020	0.925	13/3/2020	0.917	20/2/2020	0.841
28/2/2020	0.974	3/3/2020	0.961	14/3/2020	0.924	21/2/2020	0.86
29/2/2020	0.981	8/3/2020	0.961			27/2/2020	0.98
		9/3/2020	0.979			1/3/2020	0.995
						10/3/2020	0.997

TABLE 2 Ratio of IEDS that closed in 2020.

Province	Number of new establishment	Number of change	Number of closure	Ratio of closure
Anhui	2,174	987	1,187	$\frac{1,187}{17,616} = 6.74\%$
Hebei	2,531	1,123	1,408	$\frac{1,408}{13,020} = 10.81\%$
Heilongjiang	591	307	284	$\frac{284}{3,501} = 8.11\%$
Shandong	6,679	4,086	2,593	$\frac{2,593}{26,174} = 9.91\%$

have peaked in all four provinces before formal RWP, and government has pledged to spare no efforts to help companies resume production after Chinese New Year Holiday. Then, we subtract the ratio of livelihood-enterprises from RWP ratio to derive data on compartment B.

Due to data availability constraints, we do not possess data on the size of compartment C, which is the ratio of IEDS that close permanently during data period. To address this, we firstly collect record on newly established IEDS in 2020 for each province. Then, we calculate changes in the number of IEDS in 2020 using data of enterprise numbers at the end of 2019 and 2020. Changes in enterprise number also equal the result of using newly established enterprises number minus the number of enterprises that went down, which is the target information we need. Finally, we calculate the ratio of IEDS that closed in 2020 (Table 2). Since the data observation period is about 1 month, we divide the ratio of closure in a whole year by 12 as the approximate ratio of closure in 1 month.

4 As for Hebei, we do not get the ratio of livelihood-enterprises among industrial enterprises above designated size in 2020, and use the data in 2019 instead.

TABLE 3 Initial inputs of Q, A, B, and C.

Province	$Q(T_0)$	$A(T_0)$	$B(T_0)$	$C(T_0)$
Anhui	0.028	0.862	0.110	0
Hebei	0.048	0.869	0.083	0
Heilongjiang	0.134	0.631	0.235	0
Shandong	0.048	0.782	0.170	0

4. Results

In this section, we firstly use data from the aforementioned four provinces (recall Anhui, Hebei, Heilongjiang, and Shandong) to calibrate the model's parameters. Then, we show several numerical simulations of "what-if" scenarios by varying the key parameters of the model and demonstrate the

TABLE 4 Optimized parameter values and growth rate of industrial value-added.

Province	β	γ	α	δ	Growth rate of industrial value-added year on year	
					January and February 2020	March 2020
Anhui	0.001	0	0.328	0.002	−12.1%	6.2%
Hebei	0	0	0.341	0.002	−9.4%	3%
Heilongjiang	0	0	0.151	0.001	−10.9%	−5.5%
Shandong	0	0	0.467	0.004	−10.6%	1.7%

strength of this analytical framework by discussing several policy implications based on the tests.

4.1. Calibration of the model

We solve the ODE model in Python and calibrate the parameters $\beta, \gamma, \alpha, \delta$ using the least square method. Matching the first day of data, February 9 is set as T_0 for Shandong province. T_0 of Anhui and Hebei is set to be February 10, and that of Heilongjiang is February 17. As mentioned earlier, $Q(T_0)$ is 2.81%, 4.83%, 13.39%, and 4.83% for Anhui, Hebei, Heilongjiang, and Shandong province, respectively. $B(T_0)$ equals RWP ratio on T_0 minus $Q(T_0)$. We assume there was no permanent closure before formal RWP. That is, $C(T_0)$ is set to be zero. The assumption is reasonable since larger enterprises are better prepared to weather the negative shock from COVID-19. And we know from data that the number of IEDS that closed in 2020 is rather small. We also input the value of C at the end of our data period, which is the approximate ratio of closure in 1 month. Finally, $A(T_0)$ is $1 - Q(T_0) - B(T_0) - C(T_0)$. Table 3 shows the initial inputs of Q, A, B, and C.

Table 4 presents the optimized parameters $\beta, \gamma, \alpha, \delta$ for each province. These parameters are derived from minimizing the least square loss function which consists of three parts: the squared sum of $Q+B$ minus the RWP data value, the last-period value of C minus the approximated monthly closure ratio, and the last-period value of Q minus the livelihood-enterprises' ratio. The latter two parts of the loss function are further weighed by hyperparameters setting as 10.

The optimized value of parameters β (suspension rate) and γ (operation-to-closure rate) are zero in all four provinces, except that $\beta = 0.001$ in Anhui. Although the optimized suspension rate of Anhui is not zero, it is very small. These are in line with our assumption that no enterprises moved from normal operation to suspension or closure after formal RWP.

The optimized value of parameter α, which represents the rate at which enterprises move from suspension (A) to operation resumption (B), is 0.467 in Shandong, the largest among four provinces. It implies that IEDS resume operation faster in Shandong than the other three provinces. On February 4, 2020, Shandong was one of the first provinces in China to release a plan of resuming full production by the end of the month (48). According to data from the Department of Industry and Information Technology of Shandong province, as of February 6, 2020, 32 mask makers in the province have been running at full capacity. As a reference, the optimized value of parameter α is 0.341 in Hebei, 0.328 in Anhui, and 0.151 in Heilongjiang, the smallest among four provinces. Differences in resumption rates could also be partially explained by the differences in governments' policy responses to support the resumption of work and production. To connect with policies, we collect government policy documents in support of resumption of work and production from AMiner website. For each province, we calculate the number of policy documents issued by mid March, 2020 (see Table 5), and classified them into provincial and municipal levels. The government supportive policies mainly consist of operation support, tax relief, and deferral, liquidity measures, social security support, rent reduction, and so on. The Shandong government has issued 67 policy documents during February 1 and March 15, 2020, to support enterprises (see Table 5). By comparison, there were only 23 policies introduced during the same period in Heilongjiang, nearly one-third of the number of Shandong. The policies can be divided into provincial policies and municipal policies, which are launched

TABLE 5 Number of government policy documents to support resumption of work and production by mid March, 2020.

Province	Anhui	Hebei	Heilongjiang	Shandong
Number of policy documents	61	40	23	67
Provincial level	17	32	21	26
Municipal level	44	8	2	41
Operation support	34	19	12	22
Tax	12	15	7	19
Finance	35	15	6	30
Social security	27	8	3	17
Rent reduction	13	8	2	13
Others	9	5	5	11

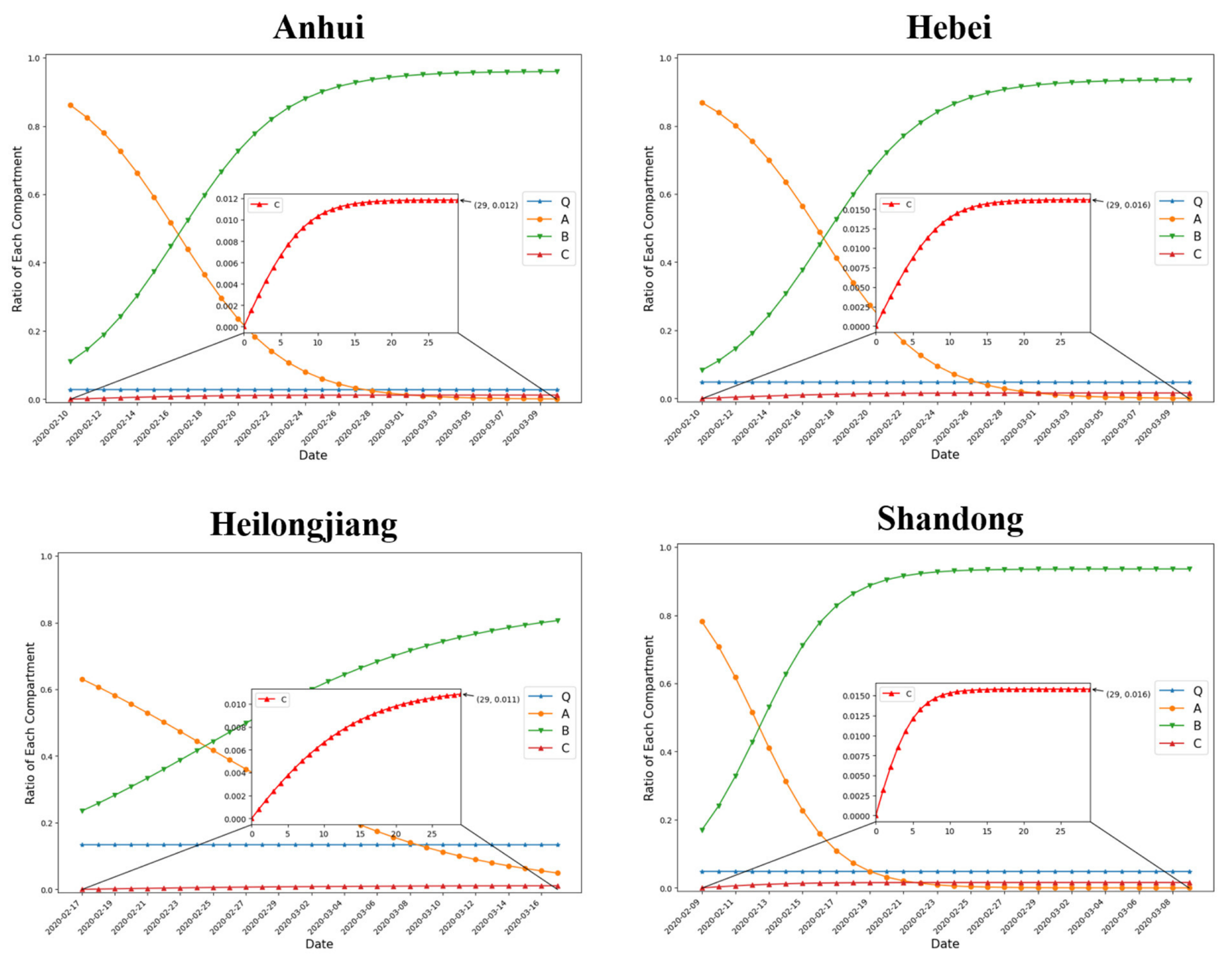

FIGURE 2
Dynamics of $Q(t)$, $A(t)$, $B(t)$, $C(t)$ over time.

by municipal governments and implemented only within a city. In Anhui, although the number of municipal policies is comparable with that of Shandong, there were deficiencies in provincial ones. Hebei has introduced 32 provincial policies, six more than the number in Shandong. However, municipal policies were scarce in Hebei during that time. We note that the estimated value of α is close between Anhui and Hebei. Anhui has launched more policy documents than Hebei, but the number of provincial policies in Hebei is almost twice that of Anhui.

Finally, the optimized value of parameter δ is 0.02 in Anhui and Hebei, 0.01 in Heilongjiang, and 0.04 in Shandong. The optimized suspension-to-closure rates are small in all four provinces, which is in line with the fact that IEDS that closed during the outbreak accounted for only a small proportion.

To better understand the economic implications of the model parameters, we further look into industrial output data. Table 4 presents the growth rate of industrial value-added in the first three months of 2020. Put it together with the optimized parameter values, we can find that a larger suspension-to-closure rate is associated with a significant negative impact on industrial output. Intuitively, we would suppose that a larger resumption rate means enterprises experience a shorter disruption before quick recovery, which leads to a smaller economic loss. However, the cumulative added value of industries above designated size of January and February, 2020, decreased by about 11% year on year both in Shandong and Heilongjiang, although the optimized resumption rate of the former province is nearly three times faster than the latter. Another difference between these two provinces is that, the optimized suspension-to-closure rate of Heilongjiang is four times that of Shandong. In other words, the losses from a larger suspension-to-closure rate in Shandong is big enough to offset the benefits from a quicker resumption. Besides, while a large suspension-to-closure rate means an instant significant shock to industrial output, the negative effect of a slow resumption rate tends to persist longer. In March, the added value of industries above designated size increased by 1.7% on a year-on-year basis in Shandong. However, it continued to decrease in Heilongjiang.

Given $Q(T_0), A(T_0), B(T_0), C(T_0)$, and the optimized value of parameters $\beta, \gamma, \alpha, \delta$, we graphically show the dynamics of $Q(t), A(t), B(t), C(t)$ in Figure 2. At T_0, the size of compartment A has passed its peak and is already in decline in all four provinces. It decreased fastest in Shandong, and slowest in Heilongjiang. The ratio of IEDS in suspension declined to below 1% at $t = 14$ in Shandong, and $t = 22$ in Anhui and Hebei. However, even at $t = 29$, there were 4.9% IEDS suspending operation in Heilongjiang. Then, we focus on changes in the size of compartment B, which monotonically increases with time. From the abovementioned, the size of B increased fastest in Shandong, and slowest in Heilongjiang. The ratio of IEDS that have resumed operation after suspension has risen to above 90% at $t = 11$ in Shandong, $t = 15$ in Anhui, and $t = 18$ in Hebei. However, there were only 80.6% IEDS that had resumed operation from suspension at $t = 29$ in Heilongjiang. The size of compartment C experiences a small increase in all provinces. These are enterprises that go down after a period of suspension.

Although we use China's RWP data to fit the model, two caveats should be well-noted here: Firstly, the COVID-19 outbreak in China overlapped with Chinese New Year, China's most popular nationwide holiday. On one hand, a great number of industrial enterprises would have suspended production during the holiday no matter of the epidemic. On the other hand, operation resumption were mostly arranged to start after the holiday, which was extended in 2020 due to COVID-19. Thus, in China, suspending production and resuming production did not happen simultaneously as our model suggested. Since we only have data on RWP, the process of enterprises moving from normal operation to suspension or closure can not be observed. Secondly, we do not have sufficient data to implement a precise fitting given the inclusion of four compartments in our model. To this end, we further conduct several numerical simulations to demonstrate the strength of the analytical models after the calibration.

4.2. "What-if" scenario simulation and policy implications

Table 6 presents our baseline setting. We use $Q(T_0) = 0.98$, $A(T_0) = B(T_0) = 0.01$, and $C(T_0) = 0$ as initial value of compartment Q, A, B, and C. That is, most enterprises are in normal operation at T_0. Parameters β, γ, α, and δ are set to be 0.5, 0.01, 0.5, and 0.01, respectively. Figure 3 graphically shows the dynamics of the size of four compartments within 43 days in baseline setting. The size of compartment A peaks at about Day 6, which means that the number of enterprises suspending operation starts to decline after that. In the end, 11% of enterprises close permanently and 89% resume operation after a period of suspension. We point out that the area size under curve A, which is the integral of the function of the curve, could be used to compare the loss from operation suspension under different scenarios. Similarly, the area size under curve C can be employed to analyze the differences in the loss from enterprise closure of each scenario.

TABLE 6 Baseline setting for simulation.

$Q(T_0)$	$A(T_0)$	$B(T_0)$	$C(T_0)$	β	γ	α	δ
0.98	0.01	0.01	0	0.5	0.01	0.5	0.01

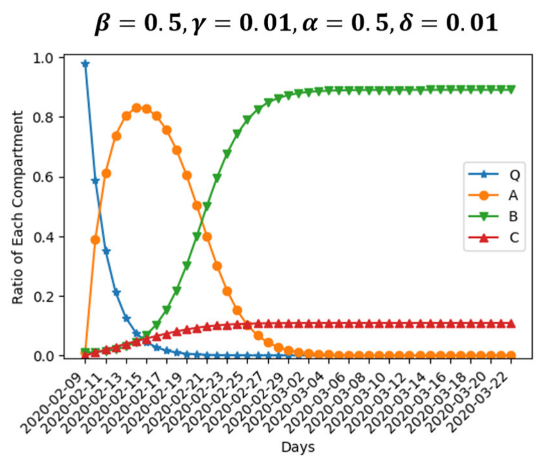

FIGURE 3
Baseline simulation.

We are interested in the evolution of the model when the value of parameters varies. Figure 4 presents two scenarios where β is set to be 1 and 0.25, respectively, while the rest of inputs are the same as our baseline setting. β is the rate at which enterprises move from normal operation to suspension. Large value of parameter β means operation suspension proceeds fast. The number of enterprises suspending operation peaks at about Day 5 if $\beta = 1$, while the peak arrives at about Day 9 if $\beta = 0.25$. Besides, the size of compartment A differs at the peak. The ratio of enterprises suspending operation at the peak is 90.2% in the former scenario, and 72.2% in the latter. This particular finding indicates that, changing the suspension rate from 1 to 0.25 could lead to fewer enterprises on average suffering from suspension. However, the enterprises that suspend operation would have to live with longer suspension. In the end, 10% of enterprises close permanently and 89% resume operation after a period of suspension if $\beta = 1$. The ratio of permanent closure and operation resumption in the end is 0.13 and 0.87, respectively, if $\beta = 0.25$, not much different from the scenario of $\beta = 1$. That is, policies aimed at depressing the suspension rate would barely reduce the negative effect of an outbreak.

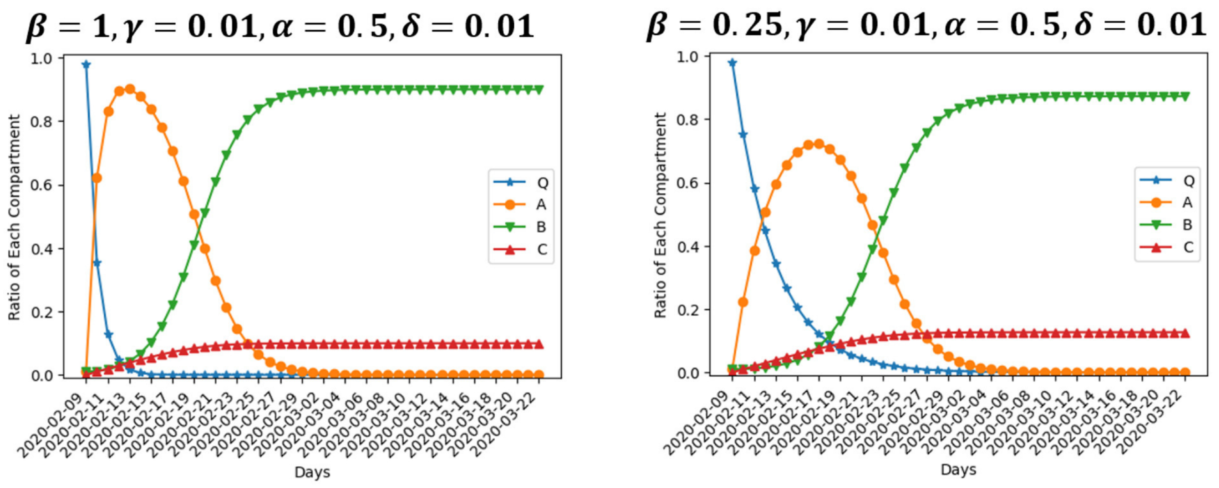

FIGURE 4
Simulation using different values of β.

Figure 5 presents two scenarios where γ is set to be 0.1 and 0.001, respectively, while the rest of inputs are the same as our baseline setting. γ is the rate at which enterprises move from normal operation to permanent closure. Larger value of parameter γ means enterprises close at a faster rate. In the end, 25% of enterprises close permanently if $\gamma = 0.1$, while the ratio is 9% if $\gamma = 0.001$, nearly one-third of the former ratio. Enterprises experiencing suspension will recover and resume production, while enterprise closure leads to permanent loss of output. Changing the operation-to-closure rate from 0.1 to 0.001 reduces bankruptcy by nearly two-thirds, which could make a significant difference. Correspondingly, the ratio of enterprises resuming operation after a period of suspension is 75% in the former scenario, and 91% in the latter. The number of enterprises suspending operation peaks at about Day 6 in both scenarios. However, the number of suspended enterprises differs at the peak since more enterprises in closure means less in suspension. The ratio of enterprises suspending operation at the peak is 72.9% if $\gamma = 0.1$, and 84.2% if $\gamma = 0.001$. To conclude, the effect of a smaller γ is that more enterprises on average will experience suspension and fewer ones will end up with bankruptcy. Since the output loss to enterprise closure is larger than that to operation suspension, policies aimed at depressing the operation-to-closure rate could narrow the negative effect of an outbreak.

Figure 6 presents two scenarios where α is set to be 1 and 0.25, respectively, while the rest of inputs are the same as our baseline setting. α is the rate at which enterprises move from suspension to operation resumption. Large value of α means enterprises experience a short suspension and resume operation quickly, while a small α means enterprises on average go through a long period of suspension. The size of compartment A declines slowly after it peaks at the value of 0.87 at about Day 8 if $\alpha = 0.25$. If $\alpha = 1$, it peaks at the value of 0.75 at about Day 5. This finding demonstrates that, changing the resumption rate from 0.25 to 1 would result in not only shorter suspension duration, but also fewer enterprises experiencing suspension on average. Besides, longer suspension leads to more closure. In this scenario, 19% of enterprises close permanently, 80% resume operation, and about 1% is still in suspension at Day 43, the end of our simulation period. However, the ratio of enterprises close permanently and resume operation in the end is 6% and 94%, respectively, if $\alpha = 1$. Therefore, policies aimed at accelerating the resumption rate bring about significant benefits. Those policies could decrease the average number of enterprises experiencing suspension and shorten the suspension duration for those that do, as well as reducing the ultimate number of bankruptcies.

Figure 7 presents two scenarios where δ is set to be 0.1 and 0.001, respectively, while the rest of inputs are the same as our baseline setting. δ is the rate at which enterprises move from suspension to permanent closure. Larger value of parameter δ means enterprises close at a faster rate after a period of suspension, which also leads to a larger ratio of enterprises end up in permanent closure. If $\delta = 0.1$, 70% of enterprises close permanently in the end, while only 30% survive the suspension. The ultimate ratio of permanent closure in this scenario is even much bigger than the one in the scenario of $\gamma = 0.1$ (Figure 5, left). If $\delta = 0.001$, 3% of enterprises end up in permanent closure and 97% resume operation after a period of suspension, showing that, changing γ from 0.001 to 0.1 would result in almost 23 times more bankruptcies. It is important to for the government to depress the suspension-to-closure rate, and prevent enterprises in suspension from quick bankruptcy.

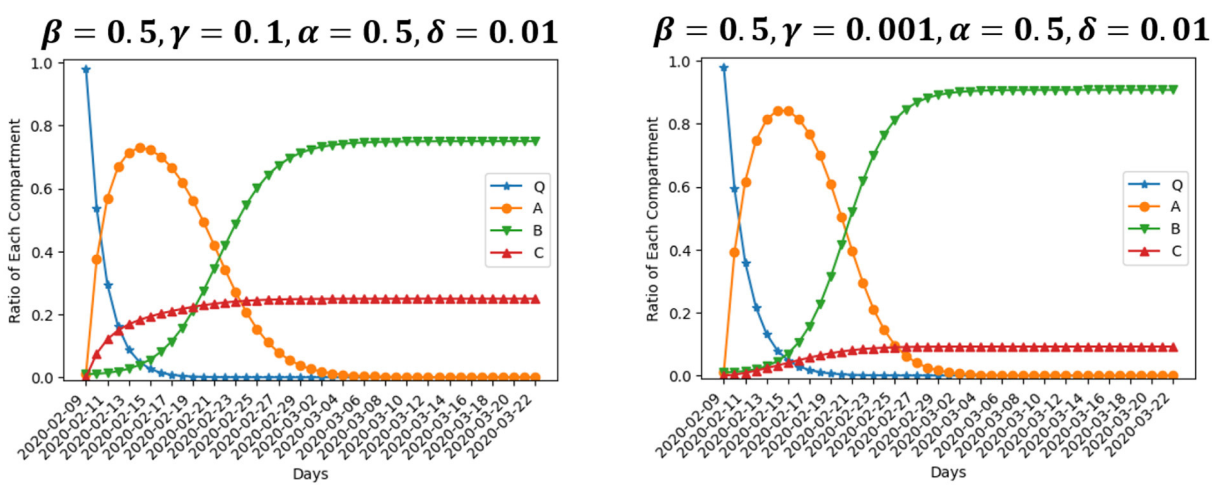

FIGURE 5
Simulation using different values of γ.

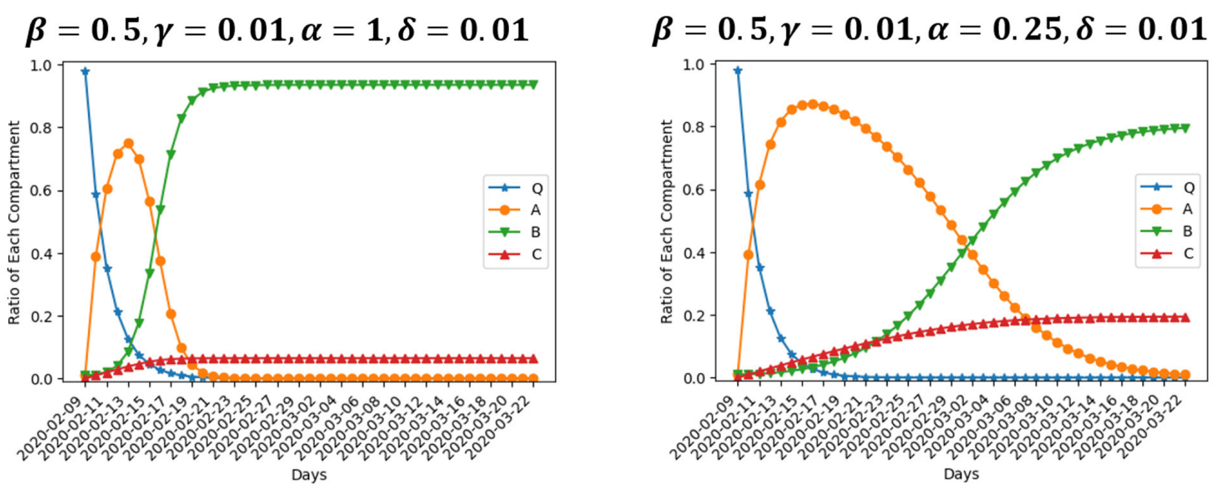

FIGURE 6
Simulation using different values of α.

5. Conclusion

The COVID-19 pandemic has evolved beyond a public health crisis and caused severe economic consequences globally. During COVID-19, an enterprise may remain its normal operation throughout, though at a low chance. What's more likely is that it will experience temporary suspension out of epidemic control requirement, or even permanent closure for failure to tolerate chronic business loss. For those enterprises that sustain the pandemic and only suspend for a certain period, they will resume work and production when epidemic control and prevention conditions are satisfied and production and operation are adjusted correspondingly. In this paper, we develop a neat, yet representative, quantitative framework which contains a set of differential equations to capture such enterprises reactions against external pandemic shock over time, inspired by the susceptible-infectious-recovered (SIR) model. We collect data on IEDS resuming production from China's four provinces (Anhui, Hebei, Heilongjiang, and Shandong) spanning from February 9 2020 to mid-March 2020 to fit the model and calibrate the model by the least square method.

We found that the estimated value of parameter α, which represents the rate at which enterprises move from suspension to operation resumption, indicates that IEDS resume operation fastest in Shandong province, and slowest in Heilongjiang.

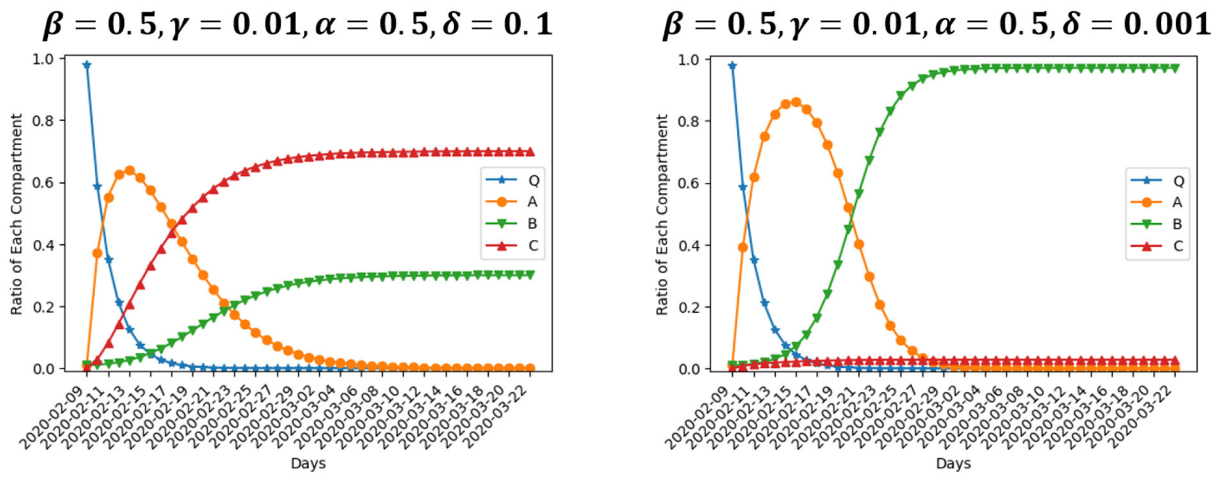

FIGURE 7
Simulation using different values of δ.

This is consistent with the supportive policy intensity in four provinces. Shandong had issued 67 government documents introducing policies to support RWP by mid March, 2020. The number is the highest among four provinces, and nearly three times that of Heilongjiang. The estimated value of δ, which denotes the rate at which enterprises move from suspension to permanent closure is 0.004 in Shandong, 0.01 in Heilongjiang, and 0.02 in the rest two provinces. This reflects the fact that only a small proportion of IEDS close permanently under COVID-19, and a small increase in suspension-to-closure rate is associated with significant loss to industrial output, as in Shandong. We further perform theoretical simulations to verify the strength of the model. The results indicate that policies aimed at depressing the operation-to-closure rate narrow the negative effect of an outbreak. In contrast, policies aimed at accelerating the resumption rate bring significant benefits, whereas policies aimed at depressing the suspension rate would have little impact on the amount of economic loss to an outbreak. In addition, it is paramount for the government to depress the suspension-to-closure rate, and prevent enterprises in suspension from fast bankruptcy to save the economic meltdown.

Based on these findings, we suggest that governments' supportive policies toward enterprises under an epidemic should be primarily aimed at limiting bankruptcy. One important policy package to achieve the goal is providing access to finance, including measures such as credit payment deferral, interest payment suspension, debt rollover, access to new credit, and so on (49). Governments could also reduce taxes, defer tax payment or provide wage subsidies to ease the cost pressure of enterprises. Secondly, to accelerate production resumption, it is important for governments to assist enterprises to meet epidemic control and prevention requirements. Specifically, they could supply anti-epidemic materials, provide epidemic prevention instructions and support, ensure online government services, and so on.

The main contributions of this work are as follows. First, this study borrows ideas from the infectious disease community and novelly applies the SIR model to characterize the evolving state of enterprises affected by the COVID-19 pandemic. Second, we conduct a case study of four provinces in China to mimic the actual RWP process during the first wave of COVID-19 outbreak. Third, we conduct numerical simulations to examine the sensitivity of the model output to changes in parameter value, and provide policy implications on this basis.

Finally, we also acknowledge two limitations of this study. First, due to data availability issue, we cannot collect more detailed data to refine the simulation scenarios, which might have potential missing cases from our investigation and discussion. Second, the scope of this study was designed at a macroscopic scale in which four provinces in China were targeted. The idea of applying the proposed SIR-based analytical framework to enterprises' reaction toward COVID-19 can be plausibly extended to model individual agent's reaction to ubiquitous adverse events involving similar status at different phases (for instance, a detailed modeling of infrastructure components in response to natural disasters such as urban floods with incremental phases). Thus, to further test the applicability of the proposed framework the future work could focus on engaging more case studies and further develop extensions for the framework.

Data availability statement

Publicly available datasets were analyzed in this study. This data can be found here: National Bureau of Statistics of China, http://www.stats.gov.cn/english/.

Author contributions

HZ, ZH, and LX: conceptualization, methodology, data curation, validation, and software. HZ, ZH, LX, and JT: writing original draft, investigation, and writing review and editing. YC: funding and writing revision and editing. All authors contributed to the article and approved the submitted version.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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Spatio-temporal evolution of the resilience of Chinese border cities

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In China, border cities are developing in the direction of trade, investment, tourism, and regional diversification and becoming crucial for the national opening-up strategy and inter-regional exchange. In this study, we construct a comprehensive system for measuring and evaluating the resilience of border cities in China that also reveals the spatial and temporal characteristics of resilience. Three representative sample zones (Northeast, Northwest, and Southwest) are selected within the three major regions of China to analyze the regional differences in border city resilience and propose targeted coping strategies. The findings of this study are as follows. First, the spatial distribution of resilience in Chinese border cities varies significantly, with the overall resilience decreasing in the following order: Northeast China > Southwest China > Northwest China > North China > Tibetan China. Higher resilience of border cities is predominantly related to better economic foundations and advantages in border trade. Second, the resilience of China's border cities has increased significantly over the past decade, with highly resilient border cities concentrated in the northeastern part of China, the northern part of Xinjiang, and Guangxi Province. Moreover, high resilience generally spreads to surrounding low-resilience cities over time. Third, the spatial distribution and development trends of resilience levels differ among the three sample zones. Therefore, it is crucial to improve urban resilience according to the regional characteristics of each border city and its specific developmental stage.

KEYWORDS

border cities, spatio-temporal pattern, urban resilience, regional differences, Chinese prefecture-level cities, China border region

1. Introduction

With further globalization of the Chinese economy, urbanization, industrialization, and informatization are increasingly spreading to the country's border areas. Thus, frontiers that served as barriers in earlier times no longer exist. Cities that have evolved from settlements based on their unique locations, typically considered border cities, now take on the dual functions of national security barriers and economic and cultural links (1). Since the introduction of the Belt and Road Initiative, China's border cities have strengthened their roles in economic exchange, trade activities, and population movements in the process of opening the country to the outside world (2). In this context, the State Council and the Ministry of Commerce have issued a series of policies to support economic development and urban construction in border areas. However, because of their natural resources and location, border cities are more fragmented and weaker than mainland and coastal cities in terms of the transport of goods, information transfer, and cultural exchange. Border cities that develop in a frontier environment are exposed to a greater variety of uncertainties and unknown risks, as well as more significant potential negative impacts and consequences (3, 4). Therefore, optimizing the development of China's border cities involves two main aspects: (1) increasing the resilience of border cities in response to unpredictable shocks and (2) mitigating the negative impacts of external and internal disruptions to the greatest possible extent.

Research on border cities has long been a key issue in political geography (5–7). Most studies focus on cross-border trade and investment in developed countries (8), the "twin cities" model of symbiotic development (9), community management in small border cities (10), ethnicity and refugees (11), terrorism, and drug trafficking under non-traditional security (12); therefore, relatively little attention has been paid to developing countries. Within China, research has focused on economic development, trade activities, population movements, urbanization levels, ethnic culture, and tourism development at the border (13–17). Advances in border city research have also been mutually absorbing and complementary, despite vast differences in terms of research perspectives, scales, focus, and methodologies. Notably, regarding non-traditional security and global cooperation across regions and borders, countries have paid more attention to the development of border cities, as well as the origins of urbanization and its special development process in typical regions, including border cities (18, 19). Currently, qualitative analysis such as policy interpretation and historical evolution is often used to analyze the commonalities of Chinese border cities or the specificities of a particular city (20, 21). Conversely, quantitative studies construct evaluation index systems for border cities to measure their development status and driving forces, which compensates for the lack of research on the development issues of domestic border cities from the perspective of border location conditions (16, 22). Owing to historical development differences and geographical constraints, the development of China's border cities shows clear spatial imbalances. Coupled with crises in recent years, such as terrorist activities in neighboring countries, refugee problems caused by war, and the risk of importing infectious diseases, the issue of border city governance has become increasingly urgent. Therefore, applying the concept of resilience to the study of Chinese border cities has profound theoretical and practical value.

Collectively, little research has been conducted on the development quality and status of China's border cities, with most studies on urban resilience focusing on national or regional scales, such as cities in the central-eastern and coastal regions of China; thus, border cities have long been neglected (23). Moreover, the influence of economic and policy factors has led to strong regional differences in the development level of Chinese border cities. As a composite dynamic system, the level of urban resilience varies significantly with regional development under various disturbance factors. Therefore, in this study, we use the TOPSIS method to construct a systematic analysis framework for determining the resilience of border cities. Spatial analysis is then used to analyze the spatio-temporal patterns of resilience development for 45 border cities in China from 2010 to 2020. Three representative sample zones are selected to further analyze the spatial differences in border city resilience. The purpose is to explore macro-regional differences in the resilience of Chinese border cities, hoping to provide guidance for the healthy development of China's border cities in the future and provide theoretical reference for government management.

2. Concept of border city resilience

Originally conceived in the field of physics as the ability of an object to return to its initial state, the concept of resilience was introduced to ecology by Holling in the 1970s and has since been cited in psychology, engineering, and socioeconomic research (24). After ICLEI-Local Governments for Sustainability formally introduced the concept of resilience to urban issues in 2002, research on urban resilience and the concept of resilient cities have spread worldwide (25). With the increasing complexity of urban development disturbance factors, urban resilience research has gradually become a hot topic in society and academia (26). Currently, the study of urban resilience has become an important way of exploring and addressing sustainable urban development issues in regional economics and geography by closely integrating the "human–land" territorial relationship and the "economic–social–ecological" coupled system. Existing urban resilience research shows multi-disciplinary and multi-disciplinary cross-fertilization, with research methodologies shifting from traditional mathematical and physical characterization to spatial analysis (27). The research area has also become more comprehensive, covering all levels from national to provincial, regional, local municipalities, and villages and towns (28).

The concept of border city resilience encompasses the state and degree of adaptation of the border city territorial system in overcoming the adverse disturbances caused by the interaction between changes in the natural environment and human activities, based on the advantages of its own structural characteristics and functional attributes. As location conditions carry all the elements necessary for the creation and development of a city, dynamic changes in location conditions inevitably affect the economic, social, and planning development of a city in multiple ways (29). The border is one of the country's most important locational environments, and border cities, as a special type of city, carry the important function of the country's external links, with mutual feedback between the locational conditions of the border and the development of the city. As a result, therefore, the relationship between urban development and location in national border areas is often stronger than that in central cities. Border cities, when viewed as independent systems, also have the systemic property of resilience. Moreover, material transport, information transfer, and energy exchange between the country's inland hinterland and border crossings and between villages and cities in border areas are more frequent and intense than general cities. As an important branch of human–territory relations, the spatial system of border cities must co-ordinate various elements to strengthen development of the urban system and cope with pressures while also linking the internal and external aspects under the border system, absorbing policies, and overcoming disturbances from neighboring countries. In summary, the resilience of border cities can be strengthened or weakened by changes in the ability of the border city system to recover, adapt, and renew itself. At a deeper level, this is reflected in complex interactions between the geographic space of the border, with the border at its core, and the productive space of human settlements, with the city at its core (Figure 1).

3. Methodology

3.1. Overview of the study area

China has the longest land border (~22,800 km) and the largest number of neighboring countries in the world. The geopolitical development of China's border areas is complex, with widely varying locational conditions. China has 14 land neighbors and 45 prefecture-level border cities in nine border provinces and regions, including Liaoning, Jilin, Heilongjiang, Inner Mongolia, Gansu, Xinjiang, Tibet, Yunnan and Guangxi (Table 1).

3.2. Data sources

Forty-one prefecture-level cities in the border areas of China were selected as the study objects, of which Daxinganling, Tacheng, Ali, and Shannan were excluded from the study owing to serious data deficiencies. The three time points chosen for the study were 2010, the first year of the 12th Five-Year Plan; 2015, the closing year of the 12th Five-Year Plan; and 2020, the end of the 13th Five-Year Plan. The data were mainly obtained for the period 2010–2020 from the China Urban Statistical Yearbook 2010–2020, the Urban Construction Statistical Yearbook of the Ministry of Housing and Construction (http://www.mohurd.gov.cn/xytj/tjzljsxytjgb/jstjnj/), statistical yearbooks of the border provinces and regions, and statistical bulletins of the cities (http://www.tjcn.org/tjgb/) for data supplementation. Data on government-issued policies were obtained from the Ministry of Commerce of the People's Republic of China, the Office of Port Management of the General Administration of Customs, and a list of key border areas in the Opinions on Several Policy Measures to Support the Development and Opening of Key Areas along the Border issued by the State Council. The Country Vulnerability Index was obtained from the *Fund for Peace* website. The UN Human Development Index is based on the United Nations Development Program. Geographical distances were measured using the Baidu map pickup co-ordinate system and ArcGIS10.2 software. Missing data were interpolated to complete the dataset.

3.3. Composite evaluation system and model construction

3.3.1. Evaluation indicator system

According to border city-related research and the concept of urban resilience in different fields, we constructed a composite system for evaluating the resilience level of Chinese border cities from two aspects: the city system and the border system. Specifically, we included 21 and 8 indicators at the city and border system levels, respectively, giving a total of 29 indicators (Table 2). The border city resilience index (BCR) was used to characterize the resilience level of each border city in China. A positive or negative BCR indicates whether each indicator increases or decreases the resilience of the border cities. The specific indicators are described below.

(1) Urban system layer

According to the urban resilience measurement method, we consider the harmonious symbiosis between production, life, and ecology for three urban spaces. The economic base, resource allocation, and production structure are the basic conditions for the resilience of urban systems. The effectiveness of living space is a fundamental function of a city and a measure of the resilience of the "people" in the city. As a key physical element, the city infrastructure is a direct and real factor influencing the quality of life of its inhabitants. Ecology builds the green barrier of a city, and the creation of a livable ecological city is crucial for preventing flooding and mitigating pollution. Indicators referring to each of these three spatial layers were used to measure the role that each element of the urban system layer in the border city has on its level of resilience.

(2) Border system layer

From its birth to its development, a border city cannot be separated from the geography of the border area, which is connected to the interior and exterior of the city, forming

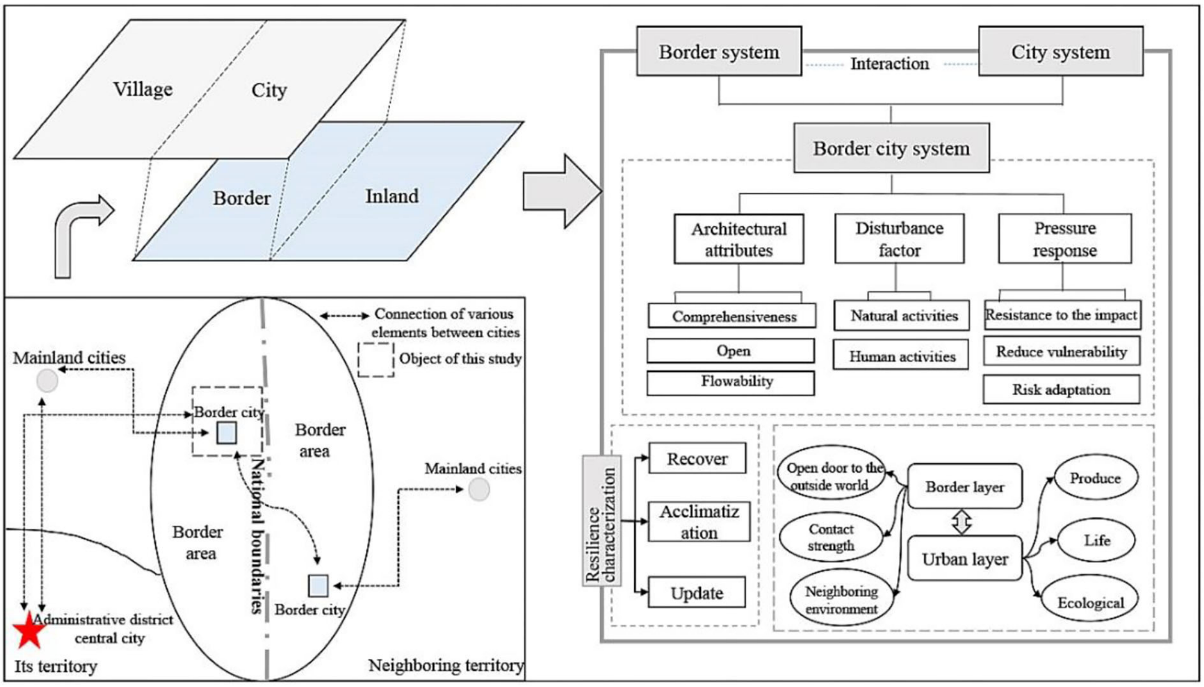

FIGURE 1
Conceptual representation of border city resilience.

the basis on which cross-border trade is conducted, with the economic prosperity of the city as the carrier. The degree of openness to the outside world in a border economy oriented toward trade at ports has always been a key concern for the state. According to the law of distance decay in geography, the distance between a border city and its neighboring important cities affects the ease of transmitting its resources. In addition, border areas are bordered by neighbors in a complex and volatile environment, where political and social conflicts and the economic level of other countries can become factors of vulnerability that threaten the country according to the openness of its borders. Therefore, we used a three-layer sub-system of openness, strength of ties, and neighboring environment to measure the role that each element of the border system layer in border cities has on the level of resilience.

3.3.2. Comprehensive measure of border city resilience

As each evaluation index has different levels and orders of magnitude, we adopted the z-score standardization method to process the data in a dimensionless way and eliminate the influence of data with different levels of magnitude on the resilience evaluation. The TOPSIS evaluation model, which is based on entropy weights, was used to measure the resilience of Chinese border cities. Specifically, the standardized data were normalized, the weights of each indicator were determined by the entropy weighting method, and the TOPSIS model was applied to calculate the positive and negative ideal solution distances of the target vector for each year by defining a measure in the target space, where the closeness of the evaluation target to the ideal value was calculated for ranking. Finally, we calculated the resilience evaluation value of each border city. The advantage of the entropy-TOPSIS model is that it is operational and the results are reasonable (30). The level of resilience was quantitatively and objectively evaluated for each border city; see the work of (30) for the specific steps.

3.4. ArcGIS spatial analysis and resilience grading of border cities

The BCR was calculated using the above evaluation model. Then, ArcGIS10.2 was used to spatially link the BCR values to the study area in vector format and visualize the spatio-temporal geographic information. The natural breakpoint method takes into account the range and number of elements in each group, as close as possible, and can be used to divide subjects into groups with similar attributes. Based on Jenks' natural breakpoint method, the BCR was divided into five categories based on its magnitude, i.e., lowest, lower, medium, higher, and highest

TABLE 1 Geographical divisions of border provinces and cities in China.

Geographical area	Border provinces	Border city
Northeast border	Heilongjiang province	Daxing'anling, Heihe, Yichun, Hegang, Jiamusi, Shuangyashan, Jixi, Mudanjiang
	Jilin province	Yanbian Korean Autonomous Prefecture, Baishan, Tonghua
	Liaoning province	Dandong
The northern frontier	Inner Mongolia autonomous region	Hulunbuir, Xing'an League, Xilin Gol League, Ulaan Chab, Baotou, Bayannur, Alashan League
Northwest frontier	Gansu province	Jiuquan
	Xinjiang Uygur autonomous region	Hami, Changji Hui Autonomous Prefecture, Altay Prefecture, Tacheng Prefecture, Bortala Mongolian Autonomous Prefecture, Ili Kazak Autonomous Prefecture, Aksu Prefecture, Kizilsu Kirgiz Autonomous Prefecture, Kashgar Prefecture, and Hotan Prefecture
Tibet border	Tibet autonomous region	Ngari Region, Shigatse, Shannan, Nyingchi
Southwest border	Yunnan province	Nujiang Lisu Autonomous Prefecture, Baoshan, Dehong Dai Jingpo Autonomous Prefecture, Lincang, Pu 'er City, Xishuangbanna Dai Autonomous Prefecture, Honghe Hani and Yi Autonomous Prefecture, Wenshan Zhuang and Miao Autonomous Prefecture
	Guangxi Zhuang autonomous region	Baise, Chongzuo, Fangchenggang

resilience (31). The value range and classification standard of BCR are shown in Table 3.

3.5. Sample zones and geostatistical trendline methods

The sample zone is a collection of continuous linear study sites that represent a series of sites that vary regularly or show significant differences in geographical gradients owing to dominant factor drivers (32). To reveal differences in the spatial patterns of resilience for border cities in typical regions, we selected three sample zones in this study: the northeast region bordering Mongolia, Russia, and North Korea; the Xinjiang region bordering Central Asia; and Guangxi and Yunnan provinces bordering Southeast Asian countries. These sample zones were used to characterize differences in the resilience of border cities in Northeast, Northwest, and Southwest China, respectively. Trendline analysis, which is an analytical method that uses ArcGIS as the analysis platform to plot research data in three-dimensions (X, Y, and Z directions) by projection, is the projection of values into a scatter plot on the X and Z planes and a scatter plot on the Y and Z planes. Think of it as a horizontal view formed from 3D data, and then fit the scatter plot with polynomials on the projection plane, was employed to further reveal the spatial development trend of urban resilience in typical border areas in China.

4. Results

4.1. Spatio-temporal characteristics of resilience in Chinese border cities

The BCR of the 45 prefecture-level cities, states, or regions in China's border areas was measured for the three study years (2010, 2015, and 2020) according to the model described in Section 3.3.2. The average BCR of border cities was 0.3174, 0.3323, and 0.3397 in 2010, 2015, and 2020, respectively, showing a gradual increase in resilience over time, the average resilience of China's border cities in 2015 was 4.694% higher than that in 2010, and in 2020, it was 2.227% higher than that in 2015. When comparing individual BCR values across the 3 years, Xinjiang Changji Prefecture had the highest BCR of 0.5048 in 2015, whereas Kashgar, Xinjiang, had the lowest BCR of 0.2449 in 2010 (Supplementary Table 1). Figure 2 shows the spatial distribution of the five BCR levels for border cities in China.

In 2010, the resilience levels of most border cities in China were generally low, with minimal regional differences. According to the five major regions (Northeast China, Southwest China, Northwest China, North China (Inner Mongolia Autonomous Region and Gansu Province), and Tibetan China), the average resilience level of border cities in 2010 decreased in the following order: North China (0.3222), Northeast China (0.3128), Southwest China (0.3053), Northwest China (0.3043), and Tibetan China (0.2604) (Supplementary Table 2). In terms

TABLE 2 Evaluation index system of border city resilience.

System	Sub-systems	Elemental indicators	Weighting	Properties
Urban system	Production sub-system	Total GDP/billion RMB (X_1)	0.0338	+
		GDP per capita/(RMB/person) (X_2)	0.0323	+
		Year-end urban and rural savings deposit balance/billion RMB (X_3)	0.0331	+
		Share of tertiary sector in GDP/%(X_4)	0.0298	+
		Annual tourism revenue/billion RMB (X_5)	0.0355	+
		Share of science and technology expenditure in fiscal expenditure/% (X_6)	0.0339	+
		Share of education expenditure in fiscal expenditure/% (X_7)	0.0389	+
		Volume of goods transported by road/million tons (X_8)	0.0305	+
	Living sub-system	Total urban resident population/person (X_9)	0.0380	+
		Number of undergraduates enrolled/person (X_{10})	0.0302	+
		Natural population growth rate/% (X_{11})	0.0293	+
		Unemployment rate/% (X_{12})	0.0328	–
		Social insurance index① (X_{13})	0.0292	+
		Number of beds in medical institutions per 10,000 population/unit (X_{14})	0.0299	+
		Annual road passenger traffic/million passengers (X_{15})	0.0297	+
		Proportion of households with internet broadband access/% (X_{16})	0.0309	+
	Ecological sub-system	Sulfur dioxide emissions per square kilometer/(tons/KM^2) (X_{17})	0.0320	–
		Greenery coverage in built-up areas/% (X_{18})	0.0344	+
		Household waste disposal rate/% (X_{19})	0.0337	+
		Density of drainage pipes in built-up areas/(km/KM^2) (X_{20})	0.0316	+
		Integrated utilization rate of industrial solid waste/% (X_{21})	0.0298	+
Border system	Openness to the outside world sub-system	Total imports and exports of border cities/US$ billion (X_{22})	0.0413	+
		Actual amount of foreign investment utilized in border cities/US$ million (X_{23})	0.0828	+
		Number of foreign visitors received by border cities in a year/million (X_{24})	0.0373	+
		Border cities receive strong national policy support② (X_{25}) 1. The state council has approved the opening of a class of ports to the outside world. 2. Key development and opening-up pilot zones. 3. National ports along the border. 4. Border Economic Co-operation Zone (BECZ). 5. Cross-border economic cooperation zones.	0.0394	+
	Neighboring countries environment sub-system	Neighboring fragile states index (X_{26})	0.0308	–
		Neighboring countries UN human development index (X_{27})	0.0294	+
	Contact strength sub-system	Distance of border towns from the center of the administrative region/km (X_{28})	0.0302	–
		Distance of border cities from border crossing cities of neighboring countries/km③ (X_{29})	0.0297	–

①The social insurance index indicates the number of city residents with various types of insurance as a proportion of the total urban population. ②For measuring the strength of the city's support by national policies, a value of 1–5 was assigned according to the above five policy conditions, each corresponding to one point. ③The important border-crossing cities of neighboring countries were selected based on the UN database, foreign trade and economic information from the General Administration of Customs and the statistical yearbooks of each province and region, and the cities with the largest trade links and city size were selected comprehensively.

of their overall typological characteristics, the single "highest-resilience" city was observed in the north (Baotou), whereas "higher-resilience" cities were located in the northeast, namely Yanbian Korean Autonomous Prefecture and Dandong City. "Medium-resilience" cities were concentrated in the northwest region of the northern border and in the southwest region of southeastern Yunnan, extending to Guangxi; all other cities showed a low level of resilience.

TABLE 3 Classification standard of comprehensive measure of resilience of border cities in China.

	BCR value range	Classification
Grade 1	<0.286	Lowest resilience
Grade 2	0.287–0.323	Lower resilience
Grade 3	0.324–0.362	Medium resilience
Grade 4	0.363–0.409	Higher resilience
Grade 5	≥0.410	Highest resilience

The BCR values of border cities in 2015 were significantly different from those in 2010, with all cities showing an overall increase in resilience and more pronounced spatial differences, specifically in the northeast and northwest regions and in eastern Inner Mongolia. That is, cities in northeast and eastern Inner Mongolia showed significant increases in BCR values, whereas the southwest and Tibetan regions showed no significant improvement in resilience. During this year, border cities began to make a breakthrough in terms of resilience quantity and quality, transitioning from only one highest-resilience city and two higher-resilience cities in 2010 to three highest-resilience cities and six higher-resilience cities (Supplementary Table 1, Figure 2).

The resilience level of border cities in 2020 showed a relatively small change from that in 2015, except in the southwest region. The highest-resilience region was dominated by eastern Northeast China, northern Xinjiang, and western Guangxi, whereas the lowest resilience region included southwestern Xinjiang and Tibet, which showed no notable improvement effect. In Yunnan Province, the resilience level of border

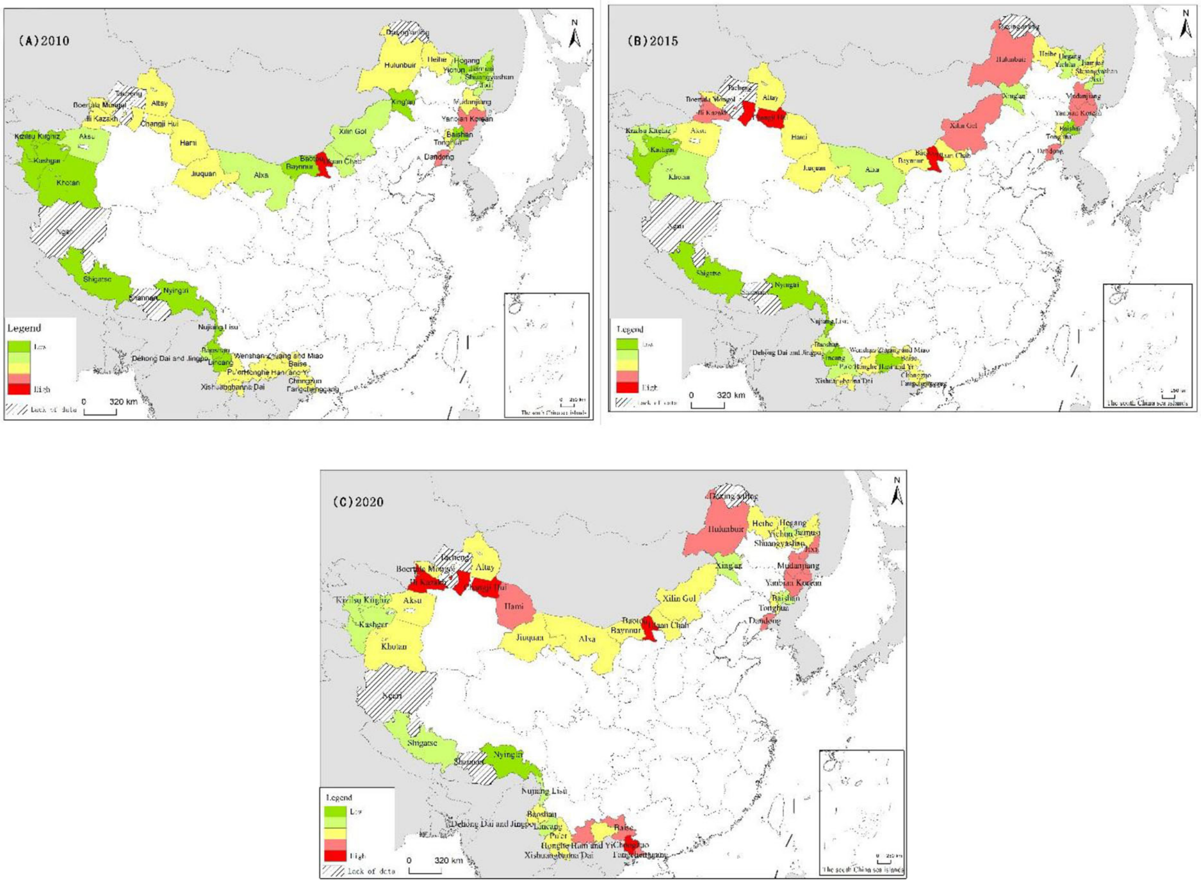

FIGURE 2
Spatial pattern of resilience for border cities in China in 2010 **(A)**, 2015 **(B)**, and 2020 **(C)**.

cities was significantly increased, with a transition from lower resilience to highest resilience and significant regional differences overall. The northern region had the largest average BCR of 0.3514, showing an increase of 0.011 from that in 2015, with the best overall regional resilience quality and the fastest rate of resilience improvement in Tibet, followed by the southwest region, with BCR values showing an increase by 11.4 and 5.52%, respectively, from 2015. In 2020, there were five border cities with the highest resilience and nine border cities with higher resilience. In the northeast, the cities of Jixi, Mudanjiang, Yanbian Korean Autonomous Prefecture, and Dandong had an average resilience index value of 0.3868. The northern region had the most balanced resilience level, with Baotou exhibiting the highest intra-regional resilience level of 0.447, which was decreased from that in 2015. The greatest variation in city resilience levels was found within the northwest region, with the highest resilience level in Yili at 0.4345 and the lowest resilience level in Kizilsu Kirgiz Autonomous Prefecture at 0.299, with a difference of 0.135 between the two, reflecting the huge gap in development between the north and south of Xinjiang. The resilience index of Yunnan border cities in the Tibetan and southwest regions is rising slowly, whereas cities in Guangxi Province have improved significantly, with the emergence of Chongzuo as a high-resilience border city (Supplementary Tables 1, 2).

Regarding the evolution of border city resilience from 2010 to 2020 in more detail (Figure 2), the resilience levels of the four major regions outside Tibet increased overall; however, individual cities within the region showed a decline in resilience. The three regions of Northeast China, the eastern part of Inner Mongolia, and the northern border, which developed significantly faster than other cities in 2010–2015, became the core regions of highest resilience in China. The period during 2015–2020 then marked a major breakthrough in the level of resilience of border cities in the southwest, with border cities in Yunnan Province making a leap from the lowest resilience to medium–high resilience and border cities in Guangxi Province transitioning from medium to high resilience across the board. In this decade, the western part of Inner Mongolia province, the southern part of Xinjiang province, and the Tibet Autonomous Region still showed low levels of resilience, making it difficult to form highest-resilience cities in these regions. In addition, the gap between the resilience levels of border cities gradually widened, and individual cities with high resilience continued to improve while expanding outward, forming a regional trend whereby high-resilience cities formed the nodes that spread to the periphery, whereas the original large clusters of low-resilience cities struggled to further develop their resilience.

4.2. Typical sample zones of resilience in Chinese border cities

In this study, three sample zones of border cities in Northeast China, Xinjiang, and Yunnan–Guangxi, which are located in three key development directions of China's border area, were selected to draw a trend line of the resilience level of each zone in 2010, 2015, and 2020 using the geostatistical trend line analysis method in ArcGIS 10.2 (Figure 3). This analysis further elucidated regional differences in the resilience of border cities in China from the perspective of the spatial gradient of geographical factors.

(1) Northeast China: Northeast Asia sample zone

The BCR values of northeast border cities, which span the three provinces of Heilongjiang, Jilin and Liaoning, were approximately arranged in an inverted "U" shape, i.e., BCR values were higher for the western side, mainly Heihe, the northeast side, including Jixi, Mudanjiang and Yanbian Korean Autonomous Prefecture, and the southern side, Dandong, than for the other cities. However, the three cities on the northeastern side have maintained high levels of resilience over time, increasing their differences from their neighbors and becoming more structurally prominent. Subject to the influence of the urban base and international environment, the northern side of Heilongjiang Province, as the border river between China and Russia, has convenient transportation and serves as a good basis for cooperation between the two countries. Jixi City and Mudanjiang City have their own urban volumes, which are greater than those of the surrounding cities, and have relied in recent years on the advantages of transportation, population, and national policies to improve the quality of development, in addition to port trade, foreign investment, and border tourism to optimize the economic structure, which has accelerated the resilience of these cities. The border cities in the north and east, as traditional forest and agricultural areas in the northeast, have good basic conditions for the development of agriculture and animal husbandry but a weak foundation for secondary and tertiary industries and face the dilemma of industrial structure defects and difficulties in transformation. Moreover, this part of the region has long belonged to the labor export outflow area and faced the pressure of negative population growth, with a high degree of aging and a high unemployment rate, relative to the cities in the northeast and Dandong City in the south, where the export of trade-oriented industrial development is constrained. Intra-regional development disparities have accelerated factor flows, with resources from cities with differing infrastructure flowing more to developed regions, large provincial cities, and the parts of neighboring countries that border China

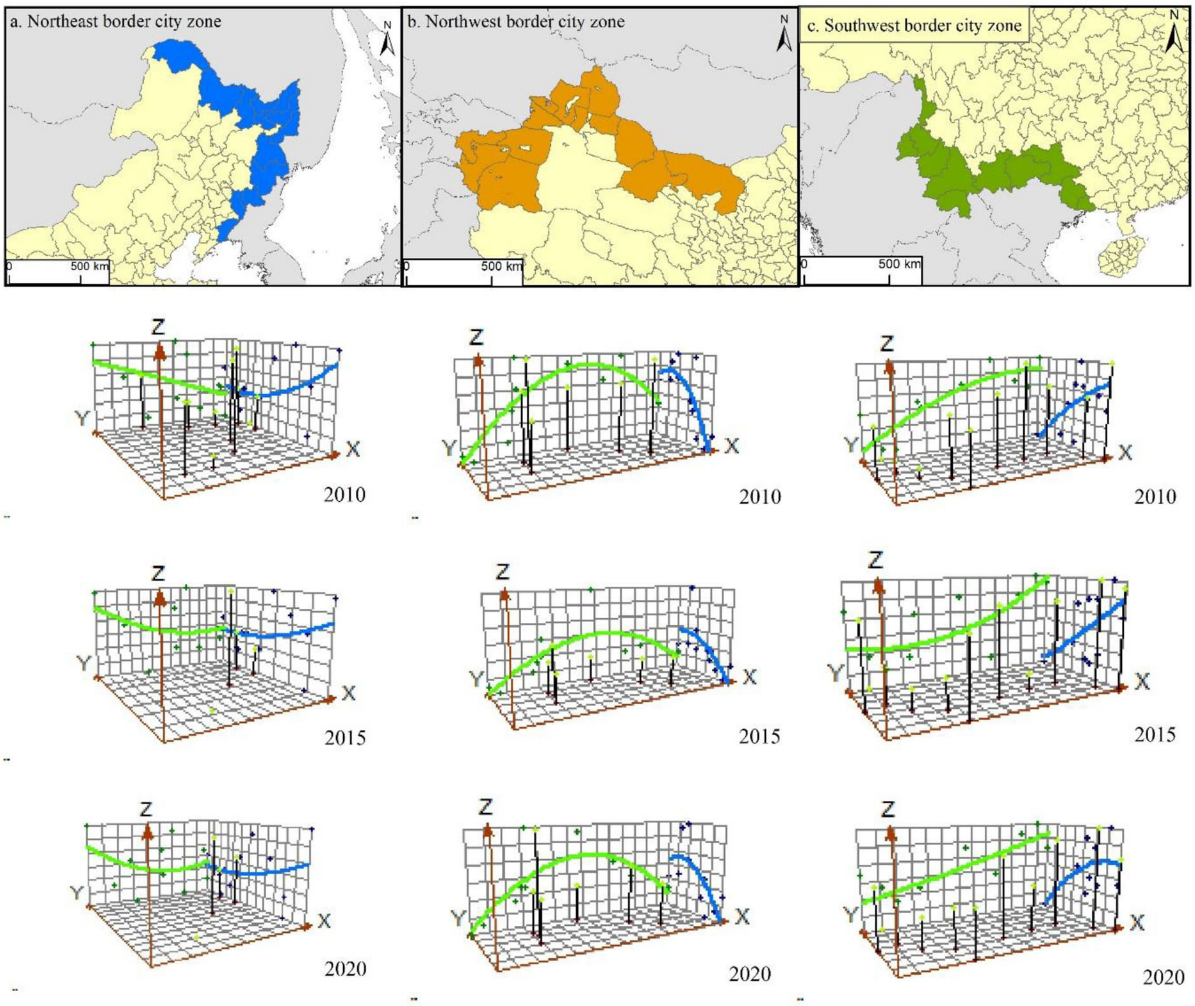

FIGURE 3
Trend lines showing the resilience level of China's border cities in three sample zones in 2010 **(a)**, 2015 **(b)** and 2020 **(c)**.

far from their own economic and political centers, which makes it difficult for Northeast China's border cities to prosper. In addition, the long-term population exodus, the existence of social problems such as aging urban infrastructure, low income of residents, and employment difficulties, as well as the low degree of openness of the neighboring Russian Far East and North Korea to the outside world, which reduces the development potential of border cities on the Chinese side, have led to large spatial differences in resilience of the border cities and unstable development trends in this sample zone.

(2) Xinjiang province: Central Asia sample zone

This zone includes border cities with high levels of resilience, consisting of various regions, cities, states, and leagues in northwest China, as well as those bordering Central Asian countries and Mongolia, including Xinjiang, Jiuquan in Gansu, and the Alashan League in Inner Mongolia. The difference in resilience between cities in the east and west of the sample zone was not significant, and its trend line is approximately a smooth curve, characterized by a "convex" structure with low levels in the east and west and high levels in the center. The difference in resilience levels between cities was greatest in 2010 and least prominent in 2015; in 2020, the curve became more pronounced, reflecting an increased difference in resilience levels between cities. This phenomenon is primarily caused by constraints of the natural environment. The northwest region straddles arid and semi-arid zones, with large areas covered by grasslands, deserts, the Gobi, and other land cover types that are relatively harsh. However, Xinjiang, Gansu, and Inner Mongolia rely on their rich resources of livestock, minerals, oil, and gas, coupled with increasing openness toward Central

Asian countries, four of which joined the SCO as early as 2001 and have a high degree of political mutual trust. Moreover, closer economic cooperation under the Belt and Road Initiative will, to a certain extent, make better use of the city's proximity to the border and make up for the inherent shortcomings of its natural geographical environment. Furthermore, the ecological environment of the southern border region and western Inner Mongolia still deserves protection, as overgrazing and reclamation of pastureland has led to ecological fragility and consequent severe weather conditions such as sand and dust storms, which directly threaten the normal functioning of the city. In addition, the economic development of the northern border region has long relied on mining mineral resources and petrochemical processing, resulting in pollution and a fragile industrial structure. We recommend that the region as a whole should restore its ecology while developing tourism and that multiple initiatives should be taken to improve the resilience of the city and achieve healthy and sustainable development of northwestern border cities.

(3) Yunnan–Guangxi: Myanmar–Laos–Vietnam sample zone

The sample zone extends from the Nujiang Lisu Autonomous Prefecture in Yunnan to Fangchenggang City in Guangxi and includes 11 cities bordering the Southeast Asian countries of Myanmar, Laos, and Vietnam. The resilience level of border cities in this sample zone increased from west to east, with an overall trend line of double smooth curves in parallel. The region covers three water systems, namely the Nujiang, Lancang, and Duijiang Rivers; cities in the Nujiang River Basin showed the lowest level of resilience, followed by cities in the Lancang River Basin, with cities in the "Youjiang" River Basin in Guangxi Province exhibiting the highest resilience. The Yunnan–Guangxi border area has good water and temperature conditions, high forest cover, and complex topography. Unlike the two sample zones mentioned above, the Yunnan–Guangxi sample zone lacks large areas of flat land conducive to urban-scale development, which limits the carrying space for urban production and living. In this environment, the inconvenience of geographic location becomes a challenging factor that hinders the comprehensive resilience of the city in terms of accessibility and the quality of life of residents. The trend line in 2020 was flatter than that in 2010, with the overall gap narrowing as the resilience of border cities in the southwest region increased across the board. Notably, the strength of national policy support for Yunnan and Guangxi provinces has reinforced the effective functioning of border cities across the border. We found an obvious role of each city in trade with Myanmar, Laos, and Vietnam. Moreover, these cities have attracted increasing attention in terms of good prospects for radiating ASEAN countries, as well as investment in talent, investment environmental management, and other related elements. This has led to an improvement in the quality of urban construction while actively promoting comprehensive construction of border cities with high levels of resilience.

5. Discussion

5.1. Research contributions and new discoveries

This study makes two major contributions to the research field. First, regarding theoretical knowledge, we construct a comprehensive, focused, and visual system for exploring the resilience and healthy development of border cities in China. This study differs from existing research in relation to the location conditions and development of border cities in China. Most existing studies start from macro-scale countries (regions), meso-scale cities (33), and micro-scale communities (ports, towns, etc.) and involve four main aspects: (1) Local urban problems at the border by focusing on certain categories of elements, such as the environment (34), crime (35), and immigration (36), which are prominent conflicts in the border area. (2) Research on major international and regional issues in border cities is often characterized by the global impact and problem-oriented issues, such as epidemic prevention and control in China–Russia border cities (23). (3) Urban connection in border areas, which focuses on geographical location characteristics, emphasizing the interaction between neighboring cities in the national border, such as the "twin Cities" development model (37). Most of these studies are policy-oriented, and national and local government policies play crucial roles. (4) Micro-scale studies on a specific border city, including ports and small border towns. This type of research can examine almost all the developmental elements of border cities and provide substantial development guidance and suggestions for local governments with local orientation (22).

In this study, we summarize the methods and processes of these four categories of research, which represent studies of "cities in the border" (38) and "the border outside the city" (39), to easily split the connection between border areas and urban spaces. Our research embodies the dual structure of "urban–rural" and the spatial mode of "border–inland," based on research into the border–city relationship (40), and starts from the concept of resilience, considering the three aspects of structure attributes, disturbance factors, and pressure response in the border city system and then constructs a comprehensive evaluation system of China's border cities. This model not only quantitatively evaluates the resilience of border cities in various periods and regions in China but also identifies weak items through data weights and visually determines the advantages and disadvantages of border cities from an overall perspective, which can be used to propose relevant regional development policies. According to the empirical measurements of this system, we showed that the resilience level of border cities differs significantly among different regions of China and has obvious temporal fluctuations. According to the characteristics of sample zones, different inter-regional border cities have different structures. In the future, this model can also be used to make development predictions and explore the functional combinations of border cities.

The second major contribution of this study is to provide guiding suggestions for the development of Chinese border cities in combination with government policies. The national government provides policy support to border cities, and local governments take measures to formulate effective development models according to local conditions. In this study, we explored the weaknesses of regional border cities through resilience measures and spatial differences in recent years and proposed measures to improve urban resilience. These measures include maintaining high-resilience border cities to optimize the urbanization structure, reasonably optimizing the urbanization quality, building a border area growth pole, actively undertaking the industrial transfer of developed areas, introducing emerging industries, paying attention to technological innovation, improving the product market and competitiveness, creating a good market investment environment, developing a series of investment promotion preferential policies to enhance city vitality, encouraging scientific and technological innovation, and promoting the development of border city transformation measures (41). For border cities with low resilience and stagnant upward trends, smart development strategies are required to improve the quality of development, for example, controlling the scale of urban land use, ecological reconstruction, strengthening social security, improving urban service functions, improving the happiness of urban residents, and relying on a good ecological environment and rich historical, cultural, and natural landscape to develop tourism. During the development of border city tourism, the industry should strengthen the construction of tourism service infrastructure, actively develop diversified tourism products, integrate tourism resources, strengthen publicity around their tourism resources, and improve the visibility and attraction of tourism resources. Furthermore, appropriate measures should be taken to promote the high-quality development of urban resilience. For various regional border cities in China, comprehensively improving the resilience of cities is an important guarantee for achieving sustainable urban development, improving infrastructure construction, and coordinating regional development. Moreover, to achieve complementary advantages between cities, measures are required to improve the resilience of border cities, such as attracting talent and appropriately encouraging fertility (42). In particular, the port economy in border cities maintains the status and growth of resilience, with ports making a vast economic contribution to the economic development of border cities; therefore, port development measures should explore new border trade preferential policies and consider policy changes with neighboring countries to ensure positive countermeasures.

5.2. Study limitations

The limitations of this study are predominantly related to data collection limitations and the complex factors affecting the resilience of border cities. As border cities are far less comprehensive than mainland capital cities and coastal cities in terms of data disclosure, the lack of data is a serious issue. Moreover, the reality of China's border cities is complex. China's border areas are vast, and border cities in different regions are faced with different levels of economic development and resource endowments; therefore, it is difficult to identify a unified development pattern. Although we deconstructed the concept and analytical framework of the resilience of China's border cities and then analyzed their spatio-temporal patterns and regional differences, we did not further explore the factors influencing the resilience of border cities because of objective factors such as the complexity of the main body of border cities and the difficulty of obtaining some data. We aim to conduct further research on this aspect in future. The development of China's border areas has attracted substantial attention from the international community and Chinese government. Various international, national, and local incentive policies have been introduced to encourage development (20, 43). In future, the development of this special region should be more closely related to the geopolitical environment and should build on the conclusions of this study through additional field research, dialogue, and interviews.

6. Conclusion

In this study, we collected urban panel data for 2010, 2015, and 2020, as well as data used to characterize internal and external city linkages, to analyze the spatio-temporal characteristics and evolution of resilience in border-level cities in China at the national scale. A city resilience system was constructed from the perspective of border city relationships, and the main interannual variations and spatial differences in the resilience of China's border cities were summarized by quantifying their resilience levels. The main findings are as follows:

(1) We observed significant spatial divergence in the level of resilience in Chinese border cities, with overall resilience decreasing the following order: Northeast China > Southwest China > Northwest China > North China > Tibetan China. Coastal border cities such as Dandong and Fangchenggang had greater resilience than inland border cities. The spatial differences in BCR values were

consistent with the economic level of border regions as well as the construction of ports and export-oriented trade orientation. Moreover, the spatial difference coincides with the level of economic and trade development of border areas, which directly influences investment in urban infrastructure and environmental management. The economy is not only an important component of the border system but also the basis for increased resilience of the urban system at border locations. However, gaps in the resilience level of border cities are inextricably linked to factors such as physical geography, historical foundations, population movements, and policies. Most border cities in China still rely on their geographical location and geopolitical advantages. In addition to forming an economic development model that focuses on foreign trade, close links between the main body of the city and the border crossing and its surrounding areas are strengthened. By ensuring the healthy and high-quality development of highly resilient cities, the quality of resilience in small- and medium-sized cities can be improved, and the geographical gap in resilience between cities can be gradually reduced.

(2) From 2010 to 2020, the overall resilience level of China's border cities showed an upward trend, with spatial disparities gradually increasing. In particular, 2010–2015 was a critical period for the resilience of border cities nationwide, and by 2015, the combined resilience of northeast China and the northern border region of northwest China had reached its highest level, becoming the most resilient areas of China. In 2020, the number of cities with medium and high levels of resilience dominated; however, concentrated contiguous areas of cities with medium to low levels of resilience still existed. For border cities, the elements between the border and urban systems cannot be separated, and the integration and matching of elements between systems is key to improving the resilience of border cities.

(3) According to its geographical proximity, the northeastern sample zone showed an inverted "U" shape, with western, northeastern, and southern parts exhibiting high and continuously increasing resilience and all other cities in the zone exhibiting reduced resilience. The Xinjiang sample zone showed no significant differences from east to west, and the resilience trend line was approximately a smooth curve, characterized by a "convex" structure with low levels in the east and west and high levels in the center and a "gentle to prominent" trend over time. The Yunnan–Guangxi sample zone showed an increasing level of resilience from west to east, with a double smooth curve parallel structure. Cities in different sample zones and stages of development face significantly different risks and shocks. The construction of a resilient city at the border must be tailored to the local conditions, that is, the regional nature of the border and the stage of urban development. Simultaneously, refined and dynamic coping strategies that consider the general environment and future urban development potential of border areas should be developed.

Data availability statement

The original contributions presented in the study are included in the article/Supplementary material, further inquiries can be directed to the corresponding author.

Author contributions

LS: form analysis, topic research, method proposal, progress management, and article writing. FP: fund acquisition, conception, supervision, review, and editing and modification suggestions. SW: conceptualization, methodology, theory proposal and verification, software application and visualization analysis, article writing, and data management. All authors contributed to the article and approved the submitted version.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Publisher's note

Supplementary material

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/fpubh.2022.1101799/full#supplementary-material

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Does the built environment of settlements affect our sentiments? A multi-level and non-linear analysis of Xiamen, China, using social media data

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Introduction: Humans spend most of their time in settlements, and the built environment of settlements may affect the residents' sentiments. Research in this field is interdisciplinary, integrating urban planning and public health. However, it has been limited by the difficulty of quantifying subjective sentiments and the small sample size.

Methods: This study uses 147,613 Weibo text check-ins in Xiamen from 2017 to quantify residents' sentiments in 1,096 neighborhoods in the city. A multilevel regression model and gradient boosting decision tree (GBDT) model are used to investigate the multilevel and nonlinear effects of the built environment of neighborhoods and subdistricts on residents' sentiments.

Results: The results show the following: (1) The multilevel regression model indicates that at the neighborhood level, a high land value, low plot ratio, low population density, and neighborhoods close to water are more likely to improve the residents' sentiments. At the subdistrict level, more green space and commercial land, less industry, higher building density and road density, and a smaller migrant population are more likely to promote positive sentiments. Approximately 19% of the total variance in the sentiments occurred among subdistricts. (2) The proportion of green space and commercial land, and the density of buildings and roads are linearly correlated with residents' sentiments. The land value is a basic need and exhibits a nonlinear correlation with sentiments. The plot ratio, population density, and the proportions of industrial land and the migrant population are advanced needs and are nonlinearly correlated with sentiments.

Discussion: The quantitative analysis of sentiments enables setting a threshold of the influence of the built environment on residents' sentiments in neighborhoods and surrounding areas. Our results provide data support for urban planning and implementing targeted measures to improve the living environment of residents.

KEYWORDS

neighborhoods, subdistricts, sentiment analysis, natural language processing, social media text data

1. Introduction

As an important comprehensive indicator to measure people's quality of life and mental health, subjective sentiments have attracted attention from various fields. According to the World Health Organization, 322 million people were affected by depression worldwide in 2017 (1). Due to rapid urbanization, the number of people with depression in China has reached 54 million; 73.6% are in a state of psychological sub-health, and 16.1% have psychological problems of varying degrees (2). Although residents' subjective sentiments are largely influenced by individual and family status, such as income, marriage, age, economic status, genetic indicators, and individual subjective indicators, environmental indicators comprise 40–50% of all factors affecting subjective sentiments (3). Studies have shown that people spend an average of 87% of their time indoors and about half of their time in their neighborhoods due to increasing urbanization (4). There is widespread awareness that improvements in the built environment of neighborhoods may improve the residents' sentiments. Research on the relationship between the living environment and psychological factors is a core topic in urban planning and environmental psychology, and the improvement of residents' sentiments is one goal of urban planning. Research on sentiments and living environments encompasses areas as diverse as inequality (5), space deprivation (6), and policy, which are critical to the health of rapidly urbanizing cities in developing countries.

Empirical studies based on questionnaires have shown that land prices (7, 8), location (9, 10), spatial form (11), and the built environment (such as the plot ratio, greening rate, property ownership, transportation organization, and density) (12–14) in neighborhoods may affect residents' sentiments. However, the largest challenge in this field is the large-scale quantification of sentiments. The concept of subjective sentiments has been typically used to evaluate an individual's sentiments (15). However, subjective sentiments are difficult to monitor or quantify in real time. For example, most studies relied on questionnaires, which have limitations, such as limited quantitative measurements, low coverage, recovery, and efficiency, and difficulty in replicating the results. In the past 2 years, few studies have used big data to quantify the sentiments of urban residents (16, 17). However, these data have rarely been used to conduct neighborhood-level research on residents' sentiments. More importantly, as discussed in the next section, objective, large-sample, non-discrete, and reproducible quantitative sentiment measurements may provide a detailed reference for studying multilevel and non-linear relationships between the built environment and sentiments.

This study uses social media text data and natural language processing (NLP) to quantify the residents' sentiments in Xiamen, China. A multilevel regression model is established at the neighborhood and subdistrict levels to investigate the relationship between the built environment and residents' sentiments at different levels. We use the gradient boosting decision tree (GBDT) model to evaluate the non-linear correlation between variables with a significant impact. We attempt to answer the following questions: (1) What is the sentiment difference between residents living in different subdistricts of the city? (2) Which are the built environment indicators affecting individual subjective sentiments at the neighborhood and subdistrict levels? (3) Is the relationship between the built environment indicators and the sentiments non-linear or linear? This study uses objective social media text data to quantify long-term sentiments instead of short-term happiness (18) to provide a reference for interdisciplinary research on urban planning and public mental health. In addition, determining whether the relationship between the sentiments and the built environment at multiple levels is linear or non-linear is critical for optimizing the built environment of neighborhoods to improve residents' sentiments.

The rest of this article is organized as follows. Section 2 is a literature review of the quantification of sentiments, the built environment at multiple levels, and non-linear studies of sentiments to identify current research problems. Section 3 introduces the data, sentiment quantification methods, variables of the built environment, and multilevel and non-linear regression modeling methods. Sections 4 and 5 present the results and discussions. The final section summarizes the paper and discusses policy implications.

2. Literature review

2.1. Research on the quantitative analysis of residents' sentiments

Questionnaires are commonly used in sentiment studies and social research (19). However, this method may not be objective and may not reflect the psychological state of the subjects. The results of psychological state studies are influenced by the subjective feelings of the research participants and by the questionnaire design. Uncertain and confounding indicators may exist, such as the same questions applicable to different environmental conditions and inappropriate measurement methods. Moreover, discrete variables are typically used in questionnaires (20). Thus, the results need to be reclassified and scored to conform to a normal distribution and meet the requirements of statistical inference. A reproducible quantitative method can avoid some of the shortcomings of traditional surveys.

A limited number of studies have used social media data for sentiment analysis to determine the objective sentiments of residents in cities. Social media capture thousands of interactions between individuals and large groups over a long period. Semantic analysis has been used to analyze large samples of highly objective and spatially and temporally resolved data to study the sentiments and wellbeing of individuals and societies. These data can be used to assess mental health and public sentiments (21, 22). One advantage of using social media data rather than questionnaires and interviews is the large sample size for analyzing sentiments (23). Text analysis and geographical analysis have been used to process social media data to obtain non-discrete and reproducible quantitative sentiment data with high spatial and temporal resolution (24). In general, the use of social media data to quantify sentiments is a widely used and accepted method in the academic community.

2.2. Complex relationship between the built environment and residents' sentiments

2.2.1. Multilevel analysis of the impact of the built environment on residents' sentiments

Studies on the influence of the built environment on residents' sentiments have been conducted primarily at two levels: the neighborhood and the surrounding environment (25). Baker and Steemers (26) stated that "In Britain, we spend, on average, as much as 90% of our time inside buildings, 70% of it in our own homes" (26). Therefore, the built environment of a neighborhood probably has the largest influence on residents' sentiments. Most studies are in agreement. For example, it has been shown that unsafe, inadequate facilities and poorly designed landscapes can significantly reduce residents' sentiments, potentially leading to psychological stress and mental problems. In contrast, environments with well-designed facilities, beautiful landscapes, low noise, and more daylight are more likely to evoke positive sentiments (27, 28). However, some disagreement exists on the effect of some indicators, such as the impact of building density indicators on sentiments. Most studies found that a higher building density is more unpleasant and results in negative sentiments (29, 30). However, a study conducted in Oslo reported that high building density might promote social relationships to improve residents' sentiments, provided that the environment is safe and not noisy (31).

Urban planning considers spaces outside neighborhoods (e.g., subdistricts, districts, towns) to enrich residents' daily activities (32). Research has focused on five aspects: land use, spatial form, development intensity, property ownership, and transportation organization (Table 1). (1) Early studies focusing on land use have consistently shown that neighborhoods far away from industrial areas have better public health. Safety and welfare can promote a clean environment and improve the quality of life (33, 34). A large amount of urban green space in neighborhoods can provide good air quality and landscape conditions to enhance sentiments (35–37). In contrast, disagreement has developed over the impact of commercial land use on residents' sentiments. Some studies have found that areas of commercial land around neighborhoods can promote travel, reduce the dependence on cars, and lower residents' travel time and costs (38). However, the proximity of commercial land to residential sites results in more litter, high traffic noise, and low visual quality, potentially evoking negative sentiments (37). (2) Studies on the spatial form found that a large proportion of mixed land use reduced the average walking distance of residents from their homes to sites of interest and increased social interaction, improving the residents' sentiments (39). However, some empirical studies did not produce consistent results. Foord (40) observed that mixed land use improved the convenience and diversity of amenities for residents to meet their lifestyle needs. Cao (41) found that mixed land use in the Twin Cities, MN, provided more amenities but also resulted in more noise, traffic congestion, and possibly stranger danger, resulting in positive and negative effects on the residents' sentiments. However, the overall impact was statistically insignificant. (3) Higher development intensity results in higher population density and diverse impacts on the residents' sentiments. Some studies reported that a higher population density caused overcrowding, unemployment, poverty, and mental stress (31, 42, 43). Other studies suggest that a higher population density may improve residents' sentiments by enabling them to walk through their neighborhoods (23, 44, 45). (4) Some studies on property ownership reported that the migrant population caused a sense of insecurity and instability, increasing the mental stress of residents. When the proportion of the migrant population reached a specific size, the formation of group identity caused a stabilization of the sentiments (46, 47). (5) Many studies have examined the impact of road design on residents' sentiments. Some found that a higher road density provided increased connectivity between neighborhoods and significantly reduced congestion, improving residents' sentiments. It has also been argued that a high road density in neighborhoods can reduce the quality of life in a subdistrict due to landscape fragmentation. Too many road crossings can reduce access efficiency and make residents' travel experiences less enjoyable (48, 49). It has also been found that residents' sentiments are considerably influenced by traffic efficiency (e.g., rush hour, and traffic lights) (50) and that transportation organization and sentiments may not be correlated.

Early empirical studies primarily used simple linear regression models to explore the impact of the built environment on residents' sentiments. Subsequently, more complex regression models, such as multiple linear regression and structural equations, were used (62, 63). Although theoretical and empirical evidence suggests that the impact of the built environment on sentiments is multilayered, most studies focused on a single level and individuals.

TABLE 1 Studies of the relationship between the built environment and residents' sentiments.

Indicators	Positive correlation	Negative correlation	Non-significance
Built environment of the neighborhood			
Land value	(8), (7), (20)*		
Plot ratio		(25), (10)	
Landscape	(27), (28), (20)*, (10)		
Land use			
Green space	(33), (34), (10)		
Industrial land		(51)	
Commercial land	(38)	(37)	
Spatial form			
Mixed land use	(40)	(10)	(41), (52)
Accessibility of facilities	(46), (47), (53)*		
Development intensity			
Building density	(31)	(43), (42)	
Population density	(54), (55)	(30), (53)*	
Property ownership			
Proportion of migrant population		(56), (57)	
Transportation organization			
Road density	(49), (58)	(59)	(50), (60)
Road intersections		(48), (61)	

*Indicates studies with non-linear correlations.

2.2.2. Studies on the non-linear correlation between the built environment and sentiments

Existing studies show that the built environment has non-linear relationships with overall sentiments (64). Referring to Maslow's theory, residents' needs regarding the environment can be divided into three categories: basic needs, intermediate needs, and advanced needs (65). Negative sentiments occur when basic needs are not met and vice versa. Positive sentiments occur when advanced needs are met, but negative sentiments do not occur when they are not met. Negative sentiments occur when intermediate needs are not met and vice versa (20, 66). Studies on residential environments found a non-linear relationship between negative sentiments and basic needs such as street lighting, residential safety, absence of noise, and nearby facilities (53, 67). A non-linear relationship was also observed between sentiments and advanced needs, such as diverse architectural styles, outstanding education, and good streetscape design (68, 69). However, questionnaire methods used in most sentiment analysis studies provide mostly discrete data, and there may be errors in analyzing non-linear relationships. Using an ordinal scale to classify the sentiments of residents is subjective and does not provide a trend, making it difficult to determine whether the variance in the data is the result of random errors or curve fitting when assessing non-linear relationships.

Although theoretical and empirical studies in public health and planning indicate a multilevel and non-linear correlation between the spatial environment and residents' short-term satisfaction, most multi-level analyses have focused on the individual and the environment. In contrast, the impact of multi-level differences in the spatial environment on residents' long-term sentiments has been based on theoretical approaches, and few empirical studies have been conducted. However, public health studies focused more on long-term sentiments than short-term satisfaction (18). Researchers started to use social media data to analyze the long-term sentiments of people ~2 years after the development of NLP techniques (70–72). These studies found complex relationships between people's sentiments and the built environment in boroughs with different region, no quantitative analysis was conducted. Furthermore, most studies used discrete data from questionnaires, which are highly subjective and contingent, making it difficult to replicate the results and assess the non-linear relationship between sentiments and the environment. Assessing the variable and non-linear relationship between the different elements of the built environment and the multi-level needs of residents requires more accurate and comprehensive data.

3. Data and methods

We use tweet text data from social media platforms and the sentiment knowledge enhanced pretraining (SKEP) algorithm to score the sentiments. Multilevel regression analysis and non-linear correlation analysis are used to assess the relationship between the built environment and residents' sentiments. The approach uses 4 steps: (1) Acquisition of social media tweet texts and data cleaning. (2) Using NLP to perform semantic analysis of the social media tweets. (3) Establishing a multilevel regression model to evaluate the correlation relationship between different levels of the urban built environment and residents' sentiments. (4) Using the GBDT model to determine the non-linear relationship between different indicators of the urban built environment and residents' sentiments (Figure 1).

3.1. Study area

The study area is Xiamen, China. Xiamen is located in East China in the southeast of Fujian Province; it has 50 subdistricts. The city covers an area of 1,699.39 square kilometers, and the permanent population of Xiamen was 4.01 million in 2017. Xiamen has repeatedly ranked first in China's

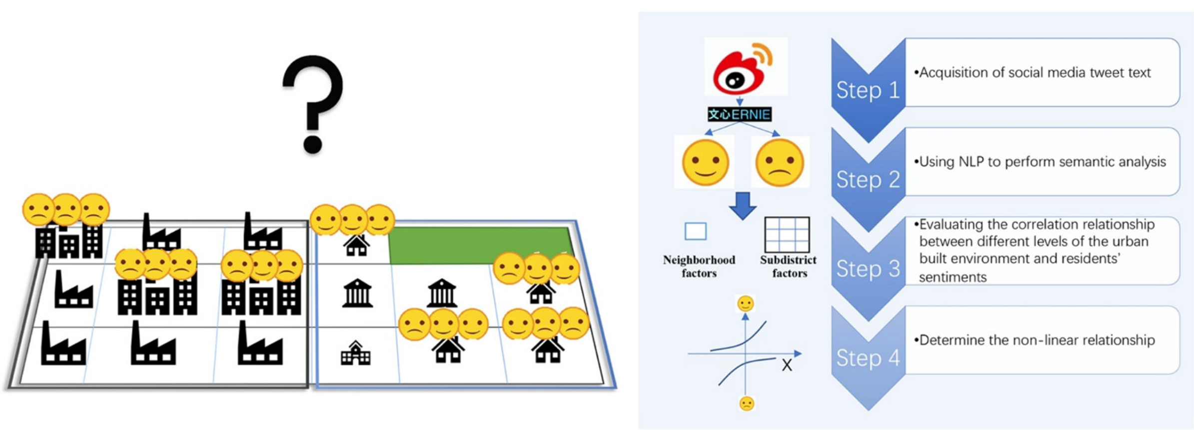

FIGURE 1
Technical route.

economic life survey as the happiest city in China. It has an excellent urban environment, a comfortable climate, and is a safe city with high urban development and numerous social and cultural activities (73). In addition, Xiamen's urban development ranks high in China, attracting a large migrant population for work. The complex population structure has also contributed to the formation of many urban villages, which are called *Chengzhongcun* in China (74). These are high-density villages surrounded by urban communities that have poor living conditions and are located in areas with high land prices. In addition, the old city of Xiamen is limited by the terrain, and the building density and housing prices are much higher than those of the new city. Therefore, the built environment of Xiamen is highly unbalanced and complex, making it ideal for this type of research. Many studies on the residents' sentiments and lives focused on tourism and housing have been conducted in Xiamen (70, 75, 76). We used the 2018 land-use map of Xiamen City to select the high-grade and medium-grade residential land (Code R1 and R2) and urban villages (Code R3) for this research (Figure 2).

3.2. Data sources

3.2.1. Data of residents' sentiments obtained from social media tweets

Social media tweet data include the social media user's geographic information (latitude and longitude coordinates), time, and text. Since check-in events are based on people's conscious behavior, people only post at a location if they stay for a relatively long time and think they have information worth recording. Thus, these tweets reflect the user's psychological state. The amount of data is larger than that obtained from questionnaires. Unlike mobile phone data and night lights, social media check-in data contain information on human sentiments; thus, they are more suitable for studying the state of residents (77, 78).

We used Sina Weibo check-in data. Sina Weibo is a widely used social networking platform in China. Users are encouraged to check in frequently, recording their daily activity patterns and behaviors. The data used in this article was obtained by crawling the annual Weibo tweet data using the Sina Weibo Application Programming Interface (API) in 2017, including public data, such as Weibo tweets, generation time, user ID, and location. The data were filtered to remove repetitive, garbled, and other meaningless text or symbols in the text, such as URLs, Html, tags, curly single or double quotes, email addresses, and non-ASCII characters (8, 79). The Weibo data with a neighborhood was extracted, and a total of 146,147 tweets were obtained. There were 1,096 neighborhoods with more than 10 tweets, exceeding the amount of data obtained from a questionnaire.

The quantification of the residents' sentiments was performed using deep learning classifiers. They can identify emojis and text in social media tweets, analyze subjective texts with sentiment overtones, and score the sentiments (70). We used the open access model SKEP based on ERNIE 3.0 to analyze the sentiments (80, 81). First, we used the pre-trained model dataset to build a learning platform based on sentiment knowledge. Then, we manually labeled 50,000 Weibo texts with sentiments. Machine learning based on pre-trained samples teaches computers how to quantify sentiments in tweets (82). Unlike scoring methods, such as sentiment dictionaries and cloud sentiment analysis (8, 83), the SKEP method is similar to human subjective thinking, and the method is reproducible. The sentiment scores of the tweet text have a range of [0, 1]. The closer the score is to 1, the more positive the sentiments are, and vice versa. The sentiment analysis preprocessing model was shared in

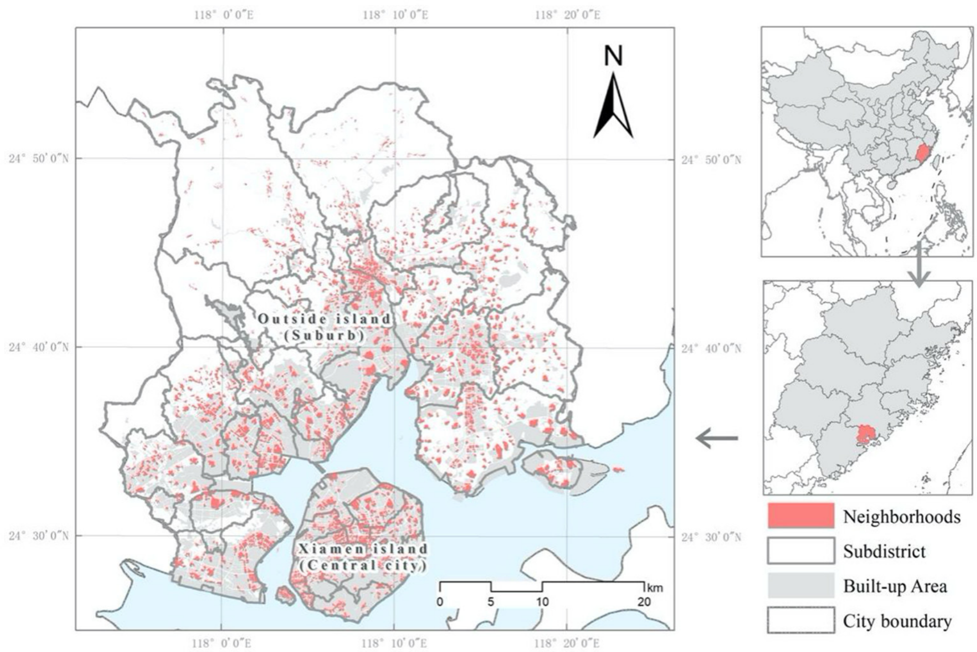

FIGURE 2
Study area.

Figshare (https://doi.org/10.6084/m9.figshare.21524391). A comparison of the publicly available Chinese corpus (https://console.bce.baidu.com/ai/?_=1667982697826&fromai=1#/ai/nlp/sentiment/dict/list) annotated by Baidu Intelligent Cloud Sentiment analysis showed that the classification accuracy of the SKEP model was 95.8%. The precision and recall for the positive sentiments were 95.7 and 96.4%, and those for the negative sentiments were 96 and 95.1%, respectively, demonstrating the reliability of the sentiment classification results are reliable.

3.2.2. Built environment data

We obtained statistical data for the neighborhood and subdistricts (Table 1). In China, a neighborhood is the smallest residential unit for urban planning and management. It is constructed by a developer or the village collective, and the boundaries of the neighborhood determine in urban planning depend on the land granted. A subdistrict consists of several neighborhoods and is an administrative unit in China. It is subject to the urban planning goals of the government.

The neighborhood data was obtained from the website of *Fangtianxia,* a Chinese real estate market website (https://www.fang.com/). Typically, Internet real estate data are collected by designated staff and uploaded to the Internet by relevant institutions. The data include neighborhood construction information, such as neighborhood location, boundary, land value, number of households, building density, plot ratio, and greening rate. We extracted the neighborhood boundaries from the current map of the urban master plan and calculated the information on living facilities, population, public facilities, and other information within 1 km of the neighborhood.

Urban dwellers spend most of their time in neighborhoods that provide the most important functions of daily life. Multiple indicators affect sentiments (Table 1). For example, the housing area, building density, plot ratio, and greening rate may affect the living experience of residents. The number of households, the proportion of the migrant population, and population density affect residents' social activities. Property fees and land values affect the living expenses of residents. Cultural, public, and transportation facilities affect the living experience of residents. We used two types of indicator statistics; one is a numerical variable for the number of neighborhoods, population structure, and land value. The other is a categorical variable, e.g., for cultural facilities and proximity to water.

The subdistrict characteristics were extracted from the 2018 land-use map of Xiamen City, including the subdistrict area, name, and region. We derived statistics for the subdistrict, including land use, spatial form, development intensity, property ownership, and transportation. The average of the sentiments for each neighborhood was used as the dependent variable.

Since a subdistrict is used by urban residents for jurisdiction and communication activities, the spatial elements have the largest impact on the residents' sentiments. For example, different land-use types of the subdistrict can provide different functions. The public service facilities may affect the residents' accessibility, and the building density may reflect the development level of the subdistrict. The proportion of the migrant population in the subdistrict may affect the interpersonal experiences of residents, and road density may affect traffic quality.

The indicators and their calculation are listed in Table 2; X_n is a neighborhood-level indicator, and S_n is a subdistrict-level indicator.

3.3. Statistical analysis of the correlation between residents' sentiments and built environment indicators

3.3.1. Multilevel regression model

The sentiments of urban dwellers may have a multilevel relationship with the built environment. Some scholars have conducted hierarchical studies on the built environment at different administrative levels and under different development conditions to determine the impact of the built environment factors on residents' sentiments at multiple levels (20, 84). Our sample data had a hierarchical structure, with low-level neighborhood data nested within high-level subdistrict data. The objective of this study is to determine the effect of the built environment on the population's happiness. Thus, we focus more on public health (18) than individual attributes or satification (85). Therefore, a multilevel regression model was used to analyze the differences between subdistricts and neighborhoods. Multi-level regression models can also explain the relationship of variables at different levels with the dependent variable. As a result, we used neighborhood-level indicators and subdistrict-level indicators to construct a two-level regression model.

The first step is to analyze the data hierarchy using an empty model with no explanatory variables. In this case, there are two levels; i is the neighborhood, and j is the subdistrict. Y_{ij} represents the observed variable of neighborhood i in subdistrict j. The model is defined as:

$$Y_{ij} = \beta_{0j} + \varepsilon_{ij}. \quad (1)$$

The change in the intercept between neighborhoods can be expressed as:

$$\beta_{i0} = \gamma_{00} + u_{i0}. \quad (2)$$

The empty model is defined as:

$$Y_{ij} = \gamma_{00} + u_{i0} + \varepsilon_{ij}. \quad (3)$$

where γ_{00} is the mean intercept, β_{i0} is the neighborhood-level intercept, u_{i0} is the random effect of the neighborhood-level intercept, and ε_{ij} represents the estimated neighborhood-level difference in the built environment.

The inter-group correlation coefficient (ICC) can be calculated using the empty model. It is defined as the ratio of the variance between groups to the total variance:

$$ICC = \frac{\sigma_{0j}^2}{\left(\sigma_{0j}^2 + \sigma^2\right)}. \quad (4)$$

The empty model [Equation (3)] can estimate the variation across all subdistricts. σ_{0j}^2 is the neighborhood-level variance, and σ^2 is the subdistrict-level variance. The significance of $\hat{\sigma}_{0j}$ and the size of the ICC determines whether the sentiment difference is significantly affected by the subdistrict and whether a multi-level model is required.

If there is a difference, a subdistrict-level variable is added to Equation (3) to create Equation (5). Five models are constructed: land use, spatial form, development intensity, property ownership, and transportation organization. The significant built environment variables at the neighborhood level are retained, and the subdistrict-level variables are added.

$$\beta_{i0} = \gamma_{00} + \gamma_{i0}S_j + u_{i0}. \quad (5)$$

$$Y_{ij} = \beta_{i0} + \gamma_{0j}X_i + \varepsilon_{ij}. \quad (6)$$

Equations (5) and (6) are combined to obtain the final model:

$$Y_{ij} = \gamma_{00} + \gamma_{0j}X_i + \gamma_{i0}S_j + u_{i0} + \varepsilon_{ij}. \quad (7)$$

where X_j denotes the neighborhood variables, and S_i denotes the subdistrict-level variables that remain in the final model only if they are significant. $\gamma_{00} + \gamma_{0j}X_i + \gamma_{i0}S_j$ is the fixed effect, γ_{0j} is the main effect of explanatory variable X_i at the neighborhood level, γ_{i0} is the main effect of the explanatory variable S_j at level 2, and $u_{i0} + \varepsilon_{ij}$ is the random effects.

An empty model was constructed to determine the difference in people's sentiments between neighborhoods and subdistricts. We established a single-level model with five indicators at the neighborhood level. We then added variables at the subdistrict level (land use, spatial form, development intensity, property ownership, and transportation organization) to establish different models. Several indicators were removed to prevent multicollinearity (86, 87).

3.3.2. Non-linear GBDT regression model

The sentiments of city dwellers may have a non-linear relationship with the built environment. We used the GBDT method to describe the non-linear relationship between sentiments and neighborhood spatial features. The GBDT uses decision trees and gradient boosting regression trees.

TABLE 2 Research variables and their calculation methods.

Level	Type	Indicator	Code	Unit	Calculation method
Dependent variable		Sentiment score	Y	-	Quantitative analysis of social media tweet data, details in 3.2.
Neighborhood level	Land value	Land value	X_1	10,000 RMB yuan	Average housing prices in public neighborhoods obtained from real estate websites (https://www.fang.com/). The price of houses that cannot be sold, such as urban villages, are estimated using spatial interpolation.
	Neighborhood built environment	Plot ratio	X_2	-	Total neighborhood building area/neighborhood land area. The data was obtained from real estate websites (https://www.fang.com/).
		Population density	X_3	Number of people per hectare	Neighborhood population/neighborhood land area. The data was obtained from real estate websites (https://www.fang.com/).
		Proximity to water	X_4	-	0 = Close to the water. 1 = Not close to the water.
Subdistrict level	Land use	Proportion of green space	S_1	%	Total area of green space/total area of the subdistrict. The data was obtained from land-use maps.
		Proportion of industrial land	S_2	%	Total area of industrial land/total area of the subdistrict. The data was obtained from land-use maps.
		Proportion of commercial land	S_3	%	Total area of commercial land / total area of the subdistrict. The data is derived from land-use maps.
	Spatial form	Mixed land use	S_4	-	We used the information entropy Shannon-Wiener Index to calculate it: $H = -\sum (P_i)(\ln P_i)$, where P_i is the proportion of land use derived from land-use maps.
		Number of public service facilities	S_5	Number	The number of public services in the subdistrict derived from the facilities in the current map.
	Development intensity	Building density	S_6	%	Subdistrict floor area/total subdistrict area. Building density is derived from housing boundaries calculated by the Housing and Urban-Rural Development Bureau.
	Property ownership	Proportion of migrant population	S_7	%	Number of migrant population/total subdistrict population. The data was obtained from the 2017 Population Census.
	Transportation organization	Road density	S_8	m/km^2	Total subdistrict road length/total subdistrict area. The data was obtained from the Traffic Bureau's road status map.

- Indicates that the indicator is dimensionless.

The gradient boosting is based on the residuals of the previous tree (53). We used the mean of the response variable to predict and calculate the residuals and determine the difference between the observed and predicted values. Then, a tree was added to predict the residuals. The new predicted value of the response was the sum of the predicted values from the previous step. The predicted residuals were multiplied by the learning rate (a number from 0 to 1), and the new residuals were obtained by subtracting the new predicted values from the observed values. We repeated the second step until the addition of a tree did not improve the prediction result or the maximum number of trees was reached. The GBDT method uses additive regression models by sequentially fitting a simple parametric function to the current residuals using least squares at each iteration (88). We selected index x_i with a significant correlation in the multi-level regression model.

First, the optimal constant model (Equation 8) was initialized to minimize the loss function $L(Y_{ij}, \gamma)$.

$$f_0(x) = \arg\min_{\gamma} \sum_{N} L\left(Y_{ij}, \gamma\right). \quad (8)$$

In the second step, each iteration of m had four sub-steps (a - d). First, we calculated the negative gradient using Equation (9). Next, we fit a regression tree to the target. The third sub-step was to calculate the gradient descent step size based on different tree expansions using Equation (10). In the last sub-step, Equation 11, the model was updated based on the results of Equation (10).

For m = 1 to M:

(a) For i = 1, 2, ..., N, calculate the pseudo-residuals

$$r_{im} = -\left[\frac{\partial L\left(Y_{ij}, f\left(x_i\right)\right)}{\partial f\left(x_i\right)}\right]_{f=f_{m-1}}. \quad (9)$$

(b) Fit the target edge of the regression tree and determine the terminal area $R_{jm}, j = 1, 2, \ldots, m$.

(c) For j = 1, 2, ..., m, compute

$$\gamma_{jm} = \arg\min_{\gamma} \sum_{x \in R_{jm}} L\left(Y_{ij}, f_{m-1}\left(x_i\right) + \gamma\right). \quad (10)$$

(d) Update

$$f_m\left(x_i\right) = f_{m-1}\left(x_i\right) + \sum_{j=1}^{J_m} \gamma_{jm} I\left(x_i \in R_{jm}\right). \quad (11)$$

The third step is to generate the final model as follows:

$$\hat{f}\left(x_i\right) = f_M\left(x_i\right). \quad (12)$$

where Y_{ij} is the sentiment mean, γ is the step size, r_{im} is the pseudo-residual, R_{jm} is the terminal region, M is the number of iterations, N is the number of eigenvalues, and J is the size of each constituent tree.

The regression curve was plotted according to the model fitting results, and the influence of different indicators on the sentiments was assessed. Positive sentiments occur when an intermediate need is met and vice versa. According to the three-factor theory, positive sentiments also occur when advanced needs are met, but negative sentiments do not occur when they are not met (89). The thresholds in the non-linear relationships were analyzed (Figure 3).

4. Results

4.1. Results of variable preprocessing

Table 3 list the descriptive statistics of the mean sentiments and variables at different levels. Figure 4 illustrates the high accuracy of the tweet data classification and the distribution of the non-discrete sentiment data. It was verified that the mean sentiments of the neighborhood followed a normal distribution, and the sample size was sufficiently large to reflect the sentiments of the neighborhood residents.

The average sentiment in Xiamen is 0.66, representing an average of 66 positive sentiments per 100 Weibo texts. The average sentiment on Xiamen Island is 0.67, and the average value outside of the island is 0.63, indicating a higher sentiment level on the island than outside the island. Figure 5 depicts the difference in the sentiments for different subdistricts. Therefore, it is necessary to perform multilevel regression.

4.2. Multilevel regression results

The multi-level regression results in Table 4 show that in the empty model, the intergroup variance of the two-level regression model is 0.1986, the within-group variance is 0.8270, the ICC is 0.1937, and the $p < 0.001$, indicating that ~19% of the total variance in the sentiments occurred among subdistricts. The variance inflation factor (VIF) of model 1 is <1.5, indicating no multicollinearity between the indicators. At the neighborhood level, the land value and proximity to water are significantly positively correlated with the sentiments. The plot ratio and population density are significantly negatively correlated with the sentiments. At the subdistrict level, the proportion of green space, the proportion of commercial land, building density, and road density are significantly positively correlated with the sentiments. The proportion of industrial land and the proportion of the migrant population are significantly negatively correlated with the sentiments. Mixed land use and the number of public service facilities were not significantly correlated with the sentiments.

4.3. Non-linear regression results obtained from GBDT model

According to the results of the multilevel regression model, we selected indicators with significant correlations and used them in the GBDT model to assess the non-linear relationship between different indicators on residents' sentiments.

We set the parameters in the GBDT model by focusing on the key parameters, such as the number of trees and the shrinkage, following Fan et al. (89). We used the following GBDT model parameters: the number of trees was 10,000, the shrinkage was 0.0001, and the minimum number of observations in the terminal nodes of the trees was 20. The results are plotted in Figure 6. Since there were positive and negative correlations between different indicators, we plotted the growth of the built environment in the positive direction of the horizontal axis. The larger the indicator value, the more influence it has. We observed different degrees of non-linear correlations between the neighborhood and subdistrict variables that significantly affected the sentiments (Figure 6, Table 5). The land value had a greater impact on sentiments when the indicator value was low, and it was difficult to meet residents' needs. This is referred to as a basic need in the non-linear relationship. Population density, the proportion of industrial land, building density, and the proportion of the migrant population had a larger influence on sentiments when the indicator values were high, i.e., an advanced need in a non-linear relationship. A linear relationship was observed between the sentiments and the proportion of green space and the proportion of commercial land. Table 5 summarizes the non-linear characteristics and thresholds.

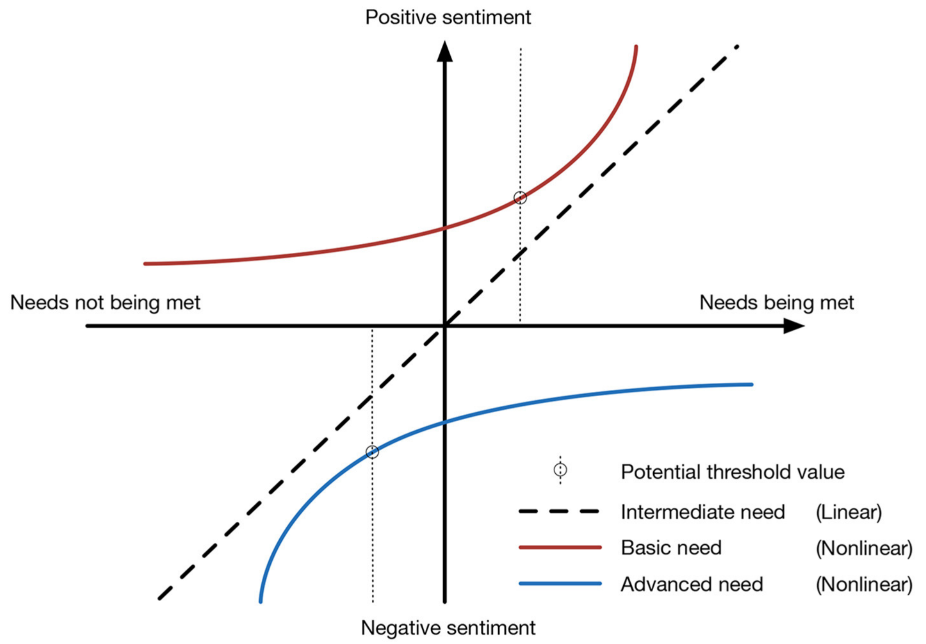

FIGURE 3
Three correlations between residents' needs and sentiments.

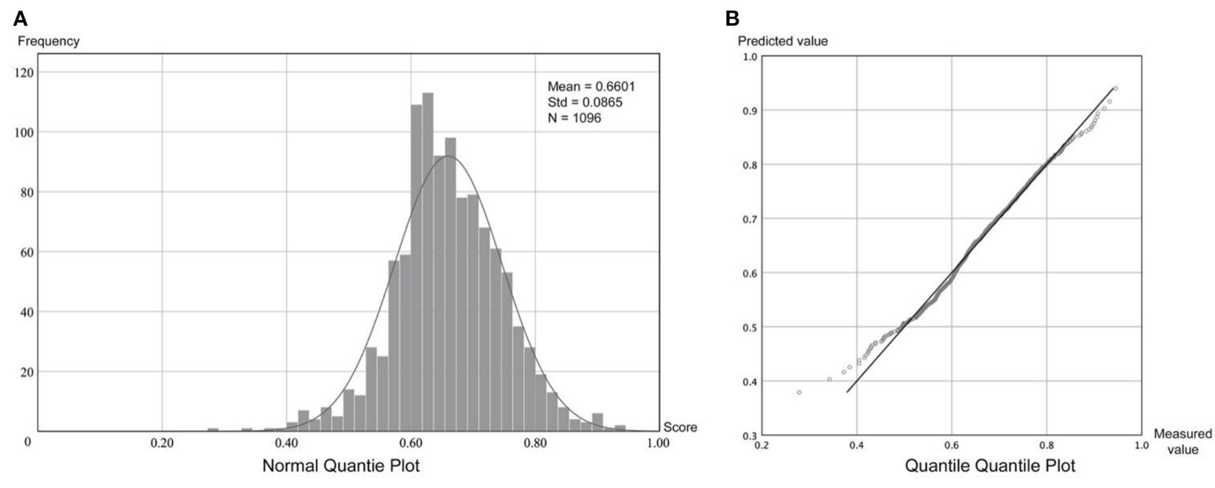

FIGURE 4
Frequency distribution and normal distribution of residents' sentiments. **(A)** Normal quantile plot. **(B)** Quantile quantile plot.

5. Discussion

5.1. Advantages of using social media data for sentiment quantification

The data used in previous related studies had either low spatial resolution (or a fuzzy classification was used) or lacked quantitative information. Using questionnaires to survey residents' sentiments is costly and provides small sample sizes, making it difficult to capture residents' sentiments objectively. Inconsistent results may be obtained, and it is not possible to analyze the non-linear correlation between the built environment and sentiments. Using social media data for sentiment analysis allows for quantitative analysis

TABLE 3 Descriptive statistics of research variables.

Code	Indicator	Number	Min	Max	Mean
Y	Average sentiment score	1,090	0.28	0.94	0.66
X_1	Land value	1,090	0.70	14.20	4.57
X_2	Plot ratio	1,090	0.00	9.20	1.88
X_3	Population density	1,090	0.00	0.05	0.02
X_4	Proximity to water	1,090	0	1	0.28
S_1	Proportion of green space	50	0.01	52.04	18.01
S_2	Proportion of industrial land	50	0.00	27.48	6.51
S_3	Proportion of commercial land	50	0.00	14.53	5.92
S_4	Mixed land use	50	0.16	3.54	2.43
S_5	Number of public service facilities	50	27	211	102
S_6	Building density	50	0.36	30.16	13.19
S_7	Proportion of migrant population	50	7.40	84.47	45.87
S_8	Road density	50	936.64	27,989.16	13,000.30

of urban sentiments. Questionnaires may be subjective, with leading questions and a specific survey context. In contrast, social media data capture the residents' sentiments (90). The SKEP model enables the efficient quantification of the sentiments of urban residents. It provides a score of the sentiments and has the advantages of low cost, a large sample size, and quantitative and reproducible results (80).

5.2. Multilevel relationships between sentiments and the built environment

We observed differences in the relationships between sentiments and the built environment between the neighborhood and subdistrict.

At the neighborhood level, housing with a high land value and close proximity to the waterfront evoked positive sentiments, consistent with previous research (7, 8, 28). A low plot ratio and low population density resulted in negative sentiments, which is in line with residents' needs for high-quality housing. Our research also revealed the relationship between population density and sentiments. Previous research found that a high-population density worsened environmental conditions and increased noise, causing negative sentiments (30, 53). However, several studies found that an increase in population density in low-density areas improved the residents' sentiments by increasing opportunities for interpersonal interactions (54, 55). However, in compact cities like Xiamen, residents prefer low-density settlements. Reducing the population density of residential areas can

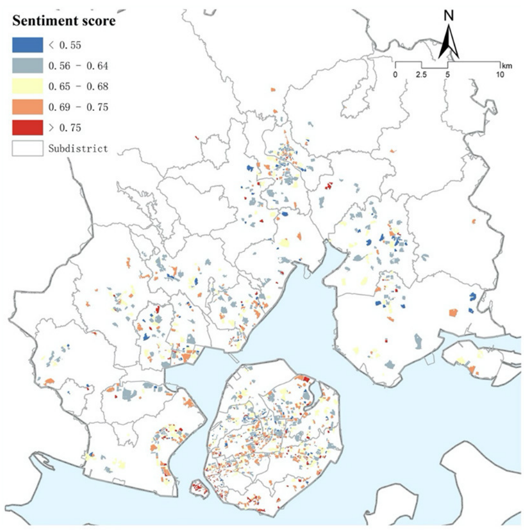

FIGURE 5
Neighborhood sentiment scores in Xiamen City.

improve the quality of life; thus, it is one objective of urban planners (91).

At the subdistrict level, more green spaces and commercial land improved the sentiments of the residents, whereas a large proportion of industry resulted in negative sentiments. An increase in the proportion of commercial land use significantly improved residents' sentiments, suggesting that residents enjoy the convenience offered by nearby commercial facilities (38) and are not bothered by the negative impacts, such as traffic congestion and noise, that some studies have associated with

TABLE 4 Two-level regression results for neighborhoods and subdistricts.

Level	Dimension	Indicator	Empty model	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
Level 1:	Land value	Land value		0.290***	0.173***	0.143***	0.299***	0.243***	0.221***	0.256***
Neighborhood	Neighborhood built environment	Plot ratio		−0.097***	−0.073*	−0.078**	−0.093**	−0.096***	−0.075*	−0.097***
		Population density		−0.085*	−0.092**	−0.143***	−0.082*	−0.135***	−0.071*	−0.132**
		Proximity to water		0.152*	0.150*	—	0.150*	0.144*	0.140*	0.147*
Level 2:	Land use	Proportion of green space			0.116***					
Subdistrict		Proportion of industrial land			−0.127***					
		Proportion of commercial land				0.262***				
	Spatial form	Mixed land use					—			
		Number of public service facilities					—			
	Development intensity	Building density						0.106*		
	Property ownership	Proportion of migrant population							−0.170***	
	Transportation organization	Road density								0.092*
		ICC	0.194							
		AIC	2,959.54	3,035.07	3,008.43	2,997.26	3,043.21	3,034.57	3,010.45	3,035.28

— Indicates no significant effect.

*** Represents significant at the 0.001 level, ** represents significant at the 0.01 level, and * represents significant at the 0.05 level.

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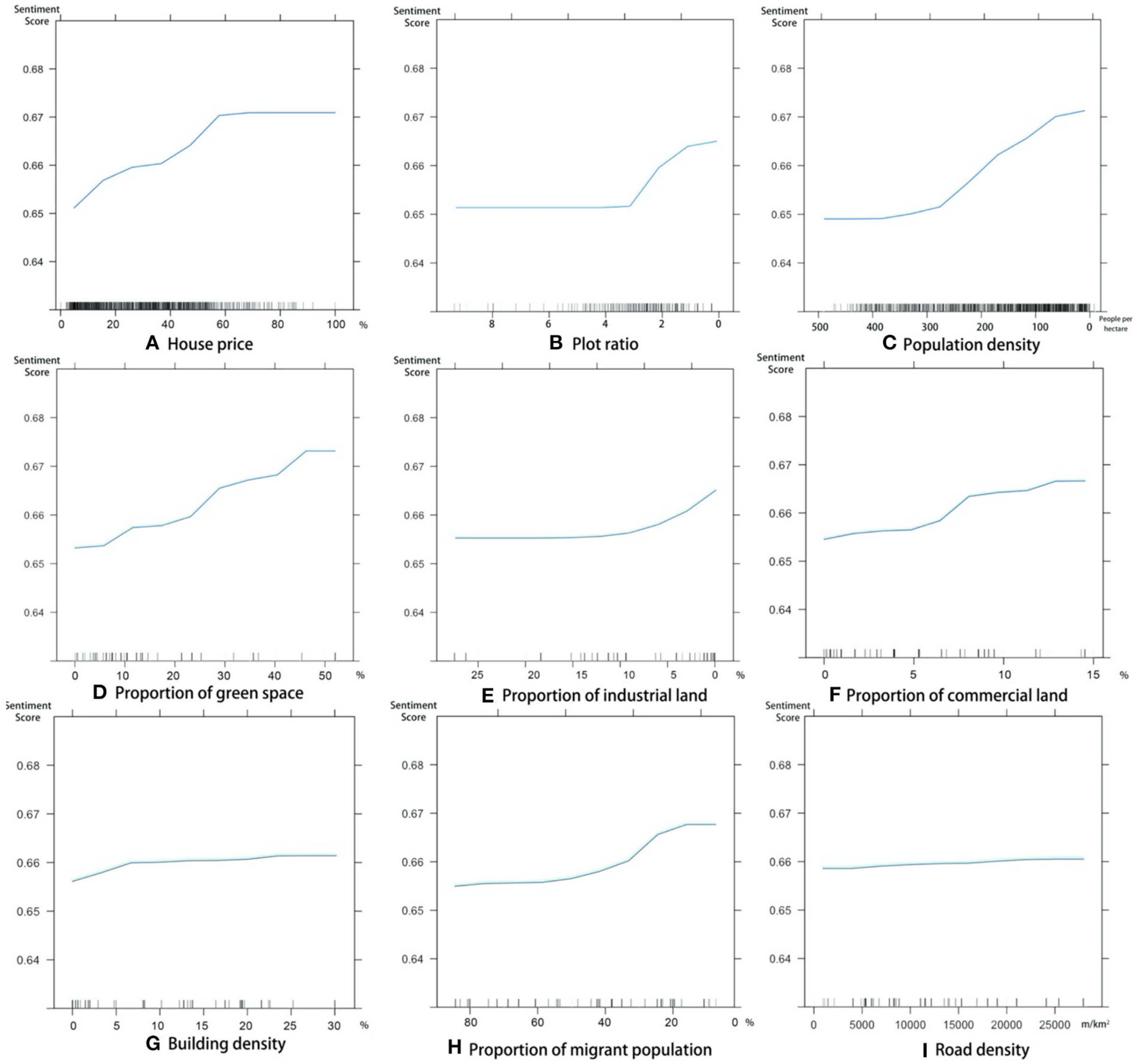

FIGURE 6
Non-linear correlation between sentiments and different independent variables. [**(A)** land value (percentile); **(B)** plot ratio*; **(C)** population density*; **(D)** proportion of green space; **(E)** proportion of industrial land*; **(F)** proportion of commercial land; **(G)** building density; **(H)** proportion of the migrant population*; **(I)** road density]. *The variable is negatively correlated with sentiments; therefore, we plotted the growth of the built environment in the positive direction of the horizontal axis.

commercial land use (37). A higher proportion of the migrant population in the neighborhood significantly worsened the residents' sentiments. Previous studies have also concluded that too many foreign renters affected the living experience of local residents and made it difficult for outsiders to integrate into local life (56, 57), resulting in negative sentiments. A high road density in a subdistrict indicates a higher level of development (49), increasing traffic and meeting the travel needs of more residents.

5.3. Non-linear correlation between sentiments and the built environment

The GBDT model can predict complex non-linear associations and is particularly efficient when the non-linear associations differ for different independent variables (89). Figure 6 shows the relationship between different indicators and the sentiments.

TABLE 5 Summary of relationships.

Level	Code	Indicator	Type	Threshold
Neighborhood	X_1	Land value	Basic need	60%
	X_2	Plot ratio	Advanced need	3
	X_3	Population density	Advanced need	300
Subdistrict	S_1	Proportion of green space	Intermediate need	*
	S_2	Proportion of industrial land	Advanced need	10%
	S_3	Proportion of commercial land	Intermediate need	*
	S_6	Building density	Intermediate need	*
	S_7	Proportion of migrant population	Advanced need	40%
	S_8	Road density	Intermediate need	*

*Indicates that the indicator has no threshold.

The land value is a basic need of residents. These indicators had non-linear relationships with sentiments. The home owners' sentiments can be significantly affected by a change in the housing price when the price is <60% of the maximum value (about 60,000 yuan per square meter in Xiamen). At this price, most people in low-income and middle-income groups can own a house. Home owners are not affected by a change in house prices it the price is higher than 60% of the maximum value.

In contrast, the plot ratio, population density, proportion of industrial land, and the proportion of the migrant population were advanced needs and had a non-linear correlation with sentiments. The plot ratio had a threshold of 3. A plot ratio of 0–3 usually indicates low-rise and middle-rise housing. The lower the plot ratio in this range, the more spacious the living place; thus, a decrease in the plot ratio improved the residents' sentiments. When the plot ratio was more than 3 in middle-rise and high-rise residential houses, an increase in the plot ratio did not affect the housing type; therefore, there was a negligible effect on the sentiments. The lower the population density in the neighborhood, the more positive the sentiments of the inhabitants were at densities of <300 people per hectare. At greater densities, the sentiment remained relatively stable. The threshold for the proportion of industrial land within the subdistricts was 10% (e.g., industrial workers' living quarters, industrial attached neighborhoods). Above this threshold, the sentiments of the residents were not significantly affected. In contrast, below 10%, as the percentage decreased, the sentiments of the residents improved substantially, which is in line with the planning and construction criteria of keeping neighborhoods away from industrial areas to improve their quality (33, 34). When the migrant population in the neighborhood was <20%, the sentiments of the residents were largely unaffected and remained high. Between 20 and 40%, a significant increase in the migrant population caused a significant decrease in the sentiments in the neighborhood. The residents exhibited more xenophobia, and the migrant population showed a decrease in their sense of belonging (56, 57). When the proportion of the migrant population exceeded 40%, the sentiments stabilized.

In general, advanced need represents the residents' desire for a high-quality residential life and should be the focus of high-quality construction in urban renewal projects. The findings of this article indicate inequalities in the sentiments in Xiamen due to differences in the built environment of neighborhoods and subdistricts. These differences may lead to inequalities in the health of residents (92). Therefore, planners and designers should focus on meeting the various needs of urban residents to promote health equity (93). High-density development in Xiamen currently meets the needs of residents at the middle and lower levels, although residents desire a high-quality built environment with low plot ratios, low population density, low proportion of industrial land, and low proportion of the migrant population in the neighborhood and district. These factors are considered in the current people-oriented urban renewal and transformation projects in Xiamen. The non-linear correlations and thresholds obtained in this study (Table 5) can inform decision-makers in other cities to meet the needs of residents at different stages of development. This information enables the use of planning and design tools in a targeted manner to improve the living experience of residents.

6. Conclusion

We used social media data and the SKEP model to quantify residents' sentiments in Xiamen, China. Multilevel regression models and GBDT models were used to investigate the effects of various indicators on sentiments in the neighborhood and subdistrict and determine the non-linear correlation between different indicators and sentiments. The multilevel regression results showed that neighborhoods with a higher land value, lower plot ratio, lower population density, and water frontage were more likely to evoke positive sentiments. At the subdistrict level, more green spaces and businesses, less industry, higher building and road densities, and a smaller migrant population were more likely to result in positive sentiments. Approximately 19% of the variability in the residents' sentiments was explained by the subdistrict indicators. We used the GBDT model to derive the non-linear correlations between the sentiments and different indicators. The proportion of green space and commercial land and building and road density were linearly correlated with residents' sentiments. The land value is a basic need and exhibited a non-linear correlation with sentiments. The plot ratio, population density, the proportion of industrial land, and the proportion of the migrant population were advanced needs and had non-linear correlations with sentiments. The basic needs should be met first during planning and construction, whereas advanced needs are a direction for developing a high-quality living environment.

Quantitative analysis of sentiments can provide powerful data support for urban planners and decision-makers. This analysis is superior to using traditional questionnaires, which provide discrete data that do not reflect global attributes. Combining social media data and intelligent sentiment analysis algorithms can greatly improve the efficiency and accuracy of sentiment quantification. Priorities for planning and construction can be determined based on the needs of residents at different levels. Decision-makers should consider the correlation of different indicators with sentiments to optimize resource allocation. Future research should focus on assessing sentiments with larger sample sizes and including more built environment variables (e.g., climate, city size, etc.) to reveal the complex relationship between the urban built environment and residents' mental health from a people-centered perspective. In addition, our study on the relationship between environment and human emotions is exploratory in nature. There are currently no models that explain both multilevel and non-linear relationships. Further analyses of multilevel and non-linear relationships are needed.

Data availability statement

The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding author.

Author contributions

CF led the project and provided the idea for this research. CF and ZG designed the research and wrote the paper. CF, ZG, SL, and CJ collected, analyzed, and validated the data. ZG created the figures. LZ revised and supervised the manuscript. YC, YGu, CJ, YZ, and YGe helped with the programming. All authors contributed to the article and approved the submitted version.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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Emergency shelter allocation planning technology for large-scale evacuation based on quantum genetic algorithm

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Introduction: Shelter allocation is one of the most important measures in urban disaster prevention and mitigation planning. Meanwhile, it is essentially a comprehensive planning problem combining resource allocation and traffic routing. A reasonable allocation scheme can avoid congestion, improve evacuation efficiency, and reduce the casualty rate. Owing to the large region and large evacuation population demand, quickly solving the complex allocation problem is somewhat challenging, and thus, the optimal results are difficult to obtain with the increase of evacuation scale by traditional allocation methods.

Methods: This article aims to establish a shelter allocation model for large-scale evacuation, which employs an improved quantum genetic algorithm (IQGA) based on spreading operation and considering the total evacuation distance, the capacity constraint of evacuation sites, and the dispersion of allocation results, and compare allocation schemes of the spreading model with those of models that consider different constraints.

Results and discussion: Results show that the allocation model with the spreading operation has better allocation results than that without the spreading operation. For the allocation model with spreading operation, the spreading model with different spreading speeds is more reasonable than that with the same spreading speed, and the allocation results are closer to the ideal results with the increase of constraints. In addition, according to the allocation results, the evacuation route map and the evacuation heat map are drawn to intuitively understand the distribution scheme of each shelter.

KEYWORDS

urban safety, emergency shelter, allocation planning, evacuation, quantum genetic algorithm

1. Introduction

Many areas of the world are vulnerable to disasters, threatening the lives of urban residents and causing major property damage to the country (1). These disasters include natural disasters, such as the 2011 earthquake in Japan, the super typhoon "Lekima", and the Indian Ocean tsunami, and man-made disasters, such as the explosion accident in Tianjin Binhai New Area and the Chernobyl nuclear disaster. Emergency shelters are ordinarily established as disaster prevention and mitigation facilities in economically developed urban areas, they are the evacuation areas that provide safe assembly spaces and essential for the rescue of the wounded (2, 3). Therefore, when disasters or accidents occur, there would be tremendous amounts of urban residents who need quick allocation of shelters. In this context, developing models for optimizing urban emergency shelter planning is significant for urban disaster prevention and mitigation and people's life safety protection (4). Location selection, evacuation route planning, and shelter allocation are the most crucial issues correlated to emergency shelter planning. Therefore, in recent years, numerous studies have emerged on the modeling or methods for shelter location selection, evacuation route planning, and shelter allocation.

Regarding shelter location selection models, in early research, most of the studies on humanitarian emergency facility location problems prefer to apply mathematical programming methods such as P-Center (5), P-Median (6), and Max covering approach (7, 8). But, in this way, models are built to consider a single factor, while realistic situations are far more complicated. Therefore, some studies considering multiple factors or multiple methods have begun to emerge. Trivedi and Singh (9) presented a hybrid algorithm for shelter location selection by proposing a hybrid multi-objective decision model based on the analytic hierarchy process (AHP), fuzzy theory, and goal programming approach; the model considered evacuation demand, shelters utilization, budgetary cost, and subjective vagueness of decision-makers and finally explored the applicability of theories of multi-criteria decision-making support in emergency shelter location selection. Xu et al. (10) put forward seven principles for shelter location selection, constructed a multi-objective location model and program with these principles, extended the P-Median model and location set-covering problem model, and finally selected the city of Yangzhou to verify this model and location program. Song et al. (11) developed an integrated method by combining the qualitative flexible multiple criteria (QUALIFLEX) method and the rough set theory to solve the sustainable shelter location selection problem, and the Wenchuan county was employed to verify the efficiency and practicability of the method.

Regarding evacuation route planning methods, the mainstream research methods include cellular automata modeling (12, 13), agent-based modeling (14, 15), and mathematical optimization methods such as linear programming methods (16, 17) and intelligence/ heuristic algorithms (18–21). The cellular automata and agent-based models could reflect human psychology and behavior, be closer to the real situation, and present more accurate results, while the modeling process is usually complex. The optimization methods could employ a series of mathematical models to replace complex practical problems and then produce optimal solutions through tools or methods such as intelligent algorithms, CPLEX, and LINGO. Compared to the modeling approaches, optimization methods could produce optimal solutions for evacuation route planning with a short solving time.

Regarding shelter allocation models, there are two main categories, namely, the Euclidean distance model and the Network distance model. Buffer or radius methods (22), ordinary Voronoi diagram (OVD), and weighted Voronoi diagram (WVD) (23, 24) are three typical methods that adopt Euclidean distance. They employ straight-line distances to produce allocation solutions for shelters and thus cannot represent the actual evacuation routes. As for network distance, some scholars incline to employ ArcGIS network analysis tools (25, 26) to produce allocation solutions, which are closer to the real evacuation route but ignore the capacity limit of shelters and thus may cause too many people to evacuate toward the same shelter. Other scholars also adopt integration methods to consider shelter capacity. Jiang et al. (27) established a hierarchical UHM network based on central place theory, and the shelter allocation is solved by a series of geographic information system technologies. Li et al. (28) designed a two-stage mathematical programming model for shelter allocation; in the second-stage model, the shelter allocation was solved by minimizing the total evacuation distance and considering the capacity of the shelter. Li et al. (29) developed an algorithm for shelter allocation, in which a shift insertion mechanism to reduce total evacuation distance and to improve the spatial continuity of allocation results was employed, taking into account the capacity constraints of the shelter. It is worth noting that most studies prefer to apply adjacent communities or streets as evacuation demand regions, less investigate discrete regions like buildings. From the macroscopic view, the shelter allocation problem can be treated as the knapsack problem, which is known as an NP-complete problem. To solve the problem, intelligent algorithms such as the genetic algorithm (30), tabu search algorithm (31), and particle swarm optimization algorithm (32) have been applied in some studies. However, the high computational complexity would cause these algorithms to fall into local optimum easily if they were not improved before solving the large-scale scenario problem.

The purpose of this study is to develop a realistic and objective model to solve the shelter allocation problem quickly and effectively. Therefore, an improved spreading quantum genetic algorithm (ISQGA) considering discrete regions and capacity constraints is proposed and elaborated in detail with case application. It is hoped that the method could provide an effective and quick planning scheme for the emergency commander and urban managers. This article is arranged as follows. In Section 2, a shelter allocation model considering discrete regions and capacity constraints is established. In Section 3, the improved algorithm for solving the model is explained. In Section 4, a case application is presented and discussed. Finally, in Section 5, the whole study is summarized and concluded.

2. Shelter allocation model development

2.1. Shelter allocation problem

The shelter allocation problem can be considered a planning problem. Suppose there are some residential buildings and several shelters in a certain city space, the task of allocation is to plan the evacuation destination shelter for each building and the evacuation paths in the road network. In the study, capacity limitation of shelters, continuity and rationality of results, and the shortest total evacuation distance are also needed to be considered in the problem.

2.2. Shelter allocation model

Before developing the allocation model, specifying the factors or variables related to the problem is necessary, and Table 1 shows the definitions for sets, indexes, and variables that would be used in the model.

In this model, shortening the evacuation routes and keeping contiguity are two important objectives. To minimize the total distance of all evacuation routes from each building to its assigned shelter, the first objective function F_1 can be set up as follows:

$$\min F_1 = \sum_{i \in SS} \sum_{j \in BS} D_{ij} X_{ij} \tag{1}$$

In the planning of shelter allocation, if we only consider the factor of total evacuation distance, the distance between the two buildings assigned to the same shelter may be too large in the allocation results, as shown in Figure 1, which would induce a high probability of congestion during evacuation. Therefore, to avoid the generation of congestion in the evacuation process, the continuity of the allocation is also necessary. Considering the buildings are not connected to each other in the discrete layout, we introduce a discrete penalty function F_2 to reduce the occurrence of discrete points:

$$\min F_2 = \sum_{i \in SS} \sum_{j,k \in BS} BD_{jk} X_{ij} Y_{jk} \rho^2 \tag{2}$$

$$\rho = floor\left[\frac{BD_{jk} - DC}{DC}\right] \tag{3}$$

Considering the capacity of the shelters located within a certain city space may not be able to meet the need of the residential buildings, some other shelters located outside the space should be introduced into the scope of shelters for allocation. Compared with internal shelters, each external shelter has a longer useless distance to find the first service object. When using the spread method proposed in this study, if the location of the initial point is not constrained, the distance between the initial point and its corresponding shelter may be too large when the total distance is the same, as shown in Figure 2.

Therefore, we introduce a penalty function of spread initial point F_3 to reduce the occurrence of unreasonable starting points in Figure 2:

$$\min F_3 = \sum_{a \in SS} SI_a \mu^2 \tag{4}$$

$$\mu = floor\left[\frac{SI_a - SC}{SC}\right] \tag{5}$$

Combining the three objective functions, as well as considering the capacity limitation of shelters, we propose the following model to solve the shelter allocation problem:

$$\min F = F_1 + F_2 + F_3 \tag{6}$$

$$s.t.$$

$$\sum_{j \in BS} X_{ij} BP_j \leq CC_i \ \forall i \in SS \tag{7}$$

$$\sum_{j \in BS} X_{ij} = 1, \forall i \in SS \tag{8}$$

$$X_{ij} = \{0, 1\}, \forall i \in SS \forall i \in BS \tag{9}$$

TABLE 1 Definitions for sets, indexes, and variables of the problem.

Type	Symbol	Definition
Sets	BS	The set of buildings within the study area
	SS	The set of emergency shelters
Indexes	i,a	The i^{th} or a^{th} shelter, i,a ∈ BS
	j,k	The j^{th} or k^{th} building, j,k ∈ BS
	tn	The number of buildings within the study area
Variables	DC	The constraint value of discrete distance
	SC	The constraint value of spreading initial points
	CC_i	The capacity of the i^{th} shelter
	SI_i	The distance of spreading initial point of the i^{th} shelter
	BD_{jk}	Distance between the j^{th} building and the k^{th} building
	D_{ij}	The distance between i^{th} buildings and j^{th} shelter
	X_{ij}	1, if the j^{th} building is assigned to the i^{th} shelter; 0, else
	Y_{ij}	1, if $BD_{jk} \geq$ DC; 0, else
	BP_j	The population within the j^{th} building
	TP	The total population within study area

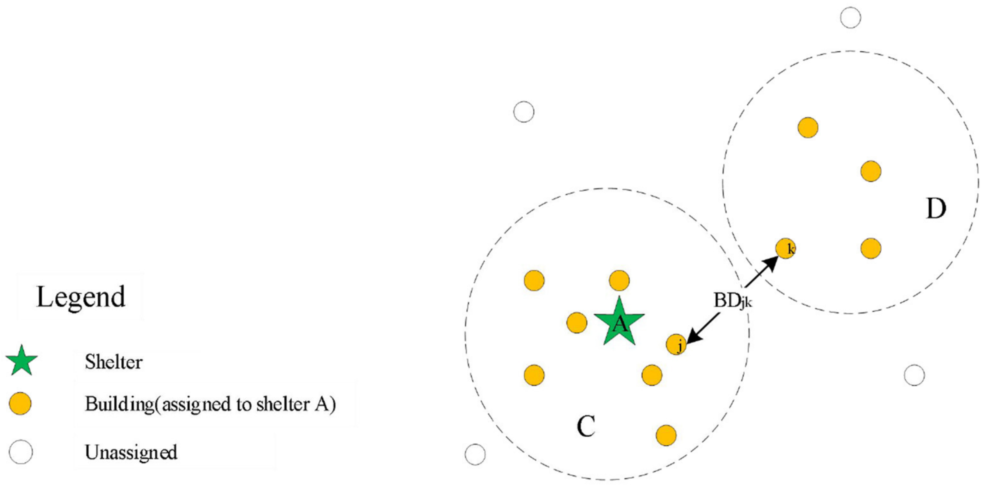

FIGURE 1
The scenario analysis of discrete allocation result.

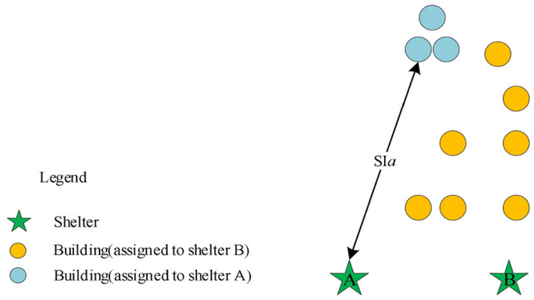

FIGURE 2
The scenario analysis of the spread initial point.

Formula (6) is the total objective function, which is employed to minimize the total evacuation distance and improve the continuity and rationality of the allocation results. Formula (7) indicates that the number of people allocated to each shelter cannot exceed its capacity limit. Formula (8) means that each building can only be allocated to a single shelter. Formula (9) produces the binary constraints.

In addition, considering the difficulty of obtaining the population data of each building, in this study, we adopt a strategy of randomly generating the population for each building by the following formula:

$$EBP_j = FP + RP_j \; j \in BS \tag{10}$$

$$FP = round(\frac{TP}{2tn}) \tag{11}$$

$$RP_j = randi \; j \in BS \tag{12}$$

$$TP - FP \cdot tn = \sum_{j \in BS} RP_j \tag{13}$$

Formula (10) is the random population of each building, which is composed of two variables, namely, fixed population (FP) and random population (RP_i). For population data in each building, it is difficult to get them directly from the statistical department, but it is obviously not realistic to set the same population in all the buildings. Therefore, a randomness method for generating the number of populations in each building is proposed. Half of the population in the area was evenly distributed to each building, and the other half was randomly assigned to each building. Although this scheme may not fully describe reality, it does reflect the characteristics of the randomness distribution of the real population. Formula (11) shows the fixed population, which is obtained by rounding the ratio of half of the total population to the number of buildings. Formulas (12) and (13) represent the generation method of the random population, which is obtained by randomly assigning the remaining number of people to each building. In addition, for FP, RP_j, and EBP_j, their values are all integers.

3. Shelter allocation algorithm

3.1. The spread principle for the emergency shelter allocation model

The spread principle proposed in this study is relatively simple, just as water flows in the pipeline; we regard each shelter as the source of water and the road network as a pipeline. If each shelter is given a spread speed S, the shelter will spread along the road to find the service objects, and whenever the distance of the outward spread reaches S, the expansion is paused and all the buildings within [SR,SR-S] range are recorded, where SR represents the distance between the pause location and its belonging shelter, and then the evacuation destination of these buildings is analyzed based on the distance. The shelters continue to spread out in this way until all buildings are assigned to the shelter after the allocation. To be clarified, the spread process proceeds along the actual road network, so that the boundary of each pause is not a standard circle, but possibly an irregular regional boundary, where the speed S actually specifies the outward spread distance of each step of the operation.

The following situations may be encountered during the spread process:

In *situation 1*, as shown in Figure 3, there is no intersection region between the spread ring of the two shelters, that is, there are no duplicate buildings within the current spreading of the two shelters. Therefore, we only need to consider the capacity constraints of shelters for the allocation of buildings within the spread ring to the shelter where the spread ring belongs. First, in order to keep continuity, we sequence the buildings within the spread ring from small to large according to the distance and then assign the buildings one by one to the designated shelter according to this sequence, until the

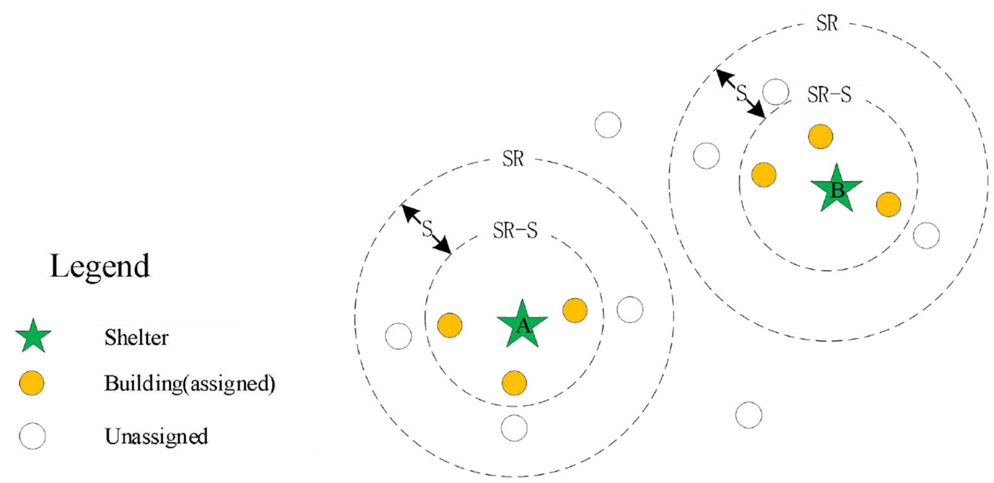

FIGURE 3
The scenario analysis of without intersecting area.

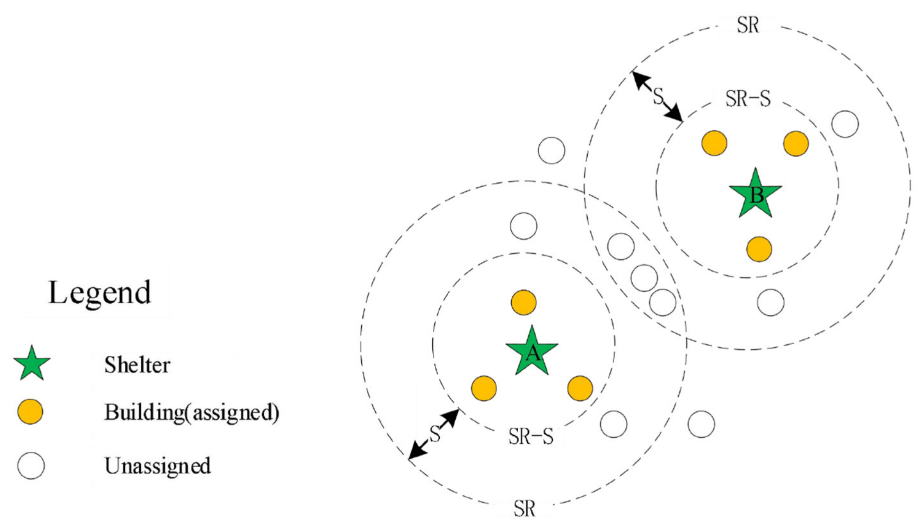

FIGURE 4
The scenario analysis of with intersecting area.

maximum capacity of the shelters is reached or all buildings have been allocated. When the maximum capacity of the shelters is reached, the shelters stop spreading and then remove these shelters from the set U (the set of shelters with remaining capacity). If there are any shelters in the set U, they will continue to spread outward; otherwise, the spreading operation will be ended and then the results of shelter allocation will be analyzed.

In *situation 2*, as shown in Figure 4, there is an intersection region between the spread ring of the two shelters, that is, there are some duplicate buildings within the current spreading of the two shelters. Therefore, we need to solve the assigned problem of duplicate buildings in the intersection region. First, we pre-assign the duplicate buildings to the shelter according to the distance, that is, if the building is close to the shelter A, it will be pre-assigned to the shelter A. If the building is close to the shelter B, it will be assigned to the shelter B. Based on this principle, all duplicate buildings in the intersection region are pre-allocated. Then, the buildings pre-allocated are merged into the shelter A, and the buildings that do not intersect with other shelters are into the same set MG. Finally, the buildings in the set MG are assigned according to the allocation method of Situation 1. In addition, for the end condition of the spreading operation, when there are no shelters in the set U or all buildings within the study region are allocated, it is regarded as the end of the spreading operation.

3.2. Improved quantum genetic algorithm (IQGA)

The quantum genetic algorithm (QGA) was first proposed by Narayanan and Moore in 1996 (33), which is a newly developed probability evolution algorithm combining the genetic algorithm and quantum computing, and it introduces qubit as the minimal unit of the chromosome. To a certain extent, traditional genetic algorithm (GA) easily falls into local maxima, and slow convergence speed and poor accuracy of search results are overcome. The QGA could very well overcome these deficiencies and therefore has been widely used in various optimization problems in the last 10 years. A conventional QGA mainly includes quantum bit coding, chromosome measurement, fitness calculation, and evolutionary operation based on a quantum rotating gate (34). Therefore, qubit coding and quantum rotating gate are two key elements to distinguish quantum genetic algorithm and traditional genetic algorithm.

3.2.1. Quantum bit coding

In quantum theory, there is a fundamental property that a qubit can be expressed as a linear superposition of $|0\rangle$ and $|1\rangle$, as shown in Figure 5 (35). Its formula is expressed as follows:

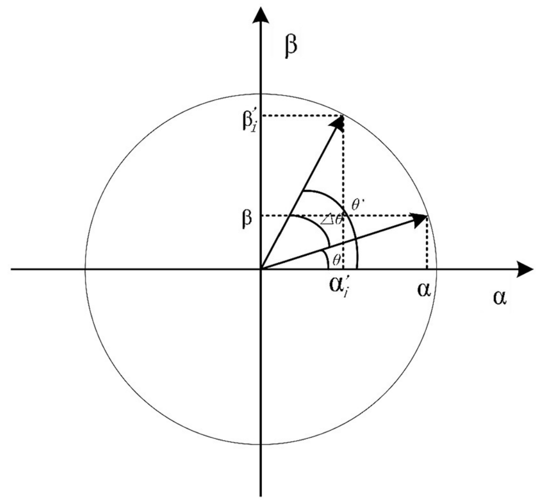

FIGURE 5
The polar plot of qubit state in QGA.

$$|\varphi\rangle = \alpha\,|0\rangle + \beta\,|1\rangle \quad (14)$$

$$|\alpha|^2 + |\beta|^2 = 1 \quad (15)$$

where α and β are complex numbers that specify the probability amplitudes of the corresponding states. $|\alpha|^2$ and $|\beta|^2$ are probabilities that the qubit will be translated into a '0' state and '1' state, respectively. Formula (15) represents the normalization condition in which α and β satisfy.

For example, a quantum chromosome with four qubits can be shown as follows:

$$q = \begin{bmatrix} \alpha_1\alpha_2\alpha_3\alpha_4 \\ \beta_1\beta_2\beta_3\beta_4 \end{bmatrix} = \begin{bmatrix} \frac{1}{\sqrt{2}} & -\frac{1}{\sqrt{3}} & \frac{\sqrt{3}}{2} & -\frac{\sqrt{3}}{2} \\ -\frac{1}{\sqrt{2}} & \frac{1}{2} & \frac{1}{2} & -\frac{1}{\sqrt{3}} \end{bmatrix} \quad (16)$$

For Formula (16), the probability of each qubit converting to a '0' state and a '1' state is shown in Table 2.

TABLE 2 The probability table for producing the state of each qubit.

Sate	First qubit	Second qubit	Third qubit	Fourth qubit
0	1/2	1/3	3/4	3/4
1	1/2	1/4	1/4	1/3

Therefore, the four-qubits quantum chromosome will take the states of $|0000\rangle$, $|0100\rangle$, $|0010\rangle$, $|0001\rangle$, $|1000\rangle$, $|1100\rangle$, $|1010\rangle$, $|1001\rangle$, $|0110\rangle$, $|0101\rangle$, $|0011\rangle$, $|1110\rangle$, $|1011\rangle$, $|0111\rangle$, $|1101\rangle$, and $|1111\rangle$, in the probabilities of 3/32, 9/128, 1/32, 1/24, 3/32, 9/128, 1/32, 1/24, 3/128, 1/32, 1/72, 3/128, 1/72, 1/96, 1/32, and 1/96, respectively. Thus, the state of the quantum chromosome can be expressed as follows:

$$\begin{aligned}|\varphi_q\rangle = & \tfrac{3}{32}|0000\rangle + \tfrac{9}{128}|0100\rangle + \tfrac{1}{32}|0010\rangle + \tfrac{1}{24}|0001\rangle \\ & + \tfrac{3}{32}|1000\rangle + ...\tfrac{9}{128}|1100\rangle + \tfrac{1}{32}|1010\rangle + \tfrac{1}{24}|1001\rangle \\ & + \tfrac{3}{128}|0110\rangle + \tfrac{1}{32}|0101\rangle + \tfrac{1}{72}|0011\rangle + ...\tfrac{3}{128}|1110\rangle \\ & + \tfrac{1}{72}|1011\rangle + \tfrac{1}{96}|0111\rangle + \tfrac{1}{32}|1101\rangle + \tfrac{1}{96}|1111\rangle\end{aligned} \quad (17)$$

3.2.2. Improved rotation gate

Compared with the genetic algorithm (GA), QGA employs a rotation gate to replace the variation operator of GA to guide the evolution of chromosomes. For the rotation gate of QGA, it is used to convert the qubit state of the current chromosome to the corresponding qubit state of the chromosome with the best fitness. In addition, with the rotation gate, QGA has a greater possibility than GA to obtain the global optimum, since quantum chromosomes have various linear combinations transformed into binary (36).

According to Liu et al. (37), the conventional rotation gate operation is achieved through a fixed rotation angle θ, as shown in Figure 5. To enhance the computational efficiency of rotation gate operation, and as far as possible avoid that fall into the local optimum due to the angle selection being too small, or missing the global optimum due to the angle selection being too large, an improved rotation gate is proposed based on Formulas (18)-(22). It modifies the angle θ by a dynamic updating operation. The formula for qubit dynamic updating is given as:

$$\Delta\theta = \theta_{\min} + f^{'} * (\theta_{\max} - \theta_{\min}) \quad (18)$$

$$f^{'} = \frac{f_x - f_{best}}{f_x} \quad (19)$$

$$S(\theta) = sign(\Delta\theta) = \begin{cases} 1 \; s_{best} > s \\ -1 \; s_{best} < s \\ 0 \; s_{best} = s \end{cases} \quad (20)$$

$$\theta^{'} = S(\theta) * \Delta\theta \quad (21)$$

$$\begin{bmatrix} \alpha_i^{'} \\ \beta_i^{'} \end{bmatrix} = U\left(\theta^{'}\right)\begin{bmatrix} \alpha_i \\ \beta_i \end{bmatrix} = \begin{bmatrix} \cos\left(\theta^{'}\right) & -\sin\left(\theta^{'}\right) \\ \sin\left(\theta^{'}\right) & \cos\left(\theta^{'}\right) \end{bmatrix}\begin{bmatrix} \alpha_i \\ \beta_i \end{bmatrix} \quad (22)$$

where $\theta^{'}$ is the qubit angle to update chromosome, S is the qubit individual state of current fitness, S_{best} is the qubit individual state of the optimum fitness, $[\alpha_i\beta_i]^T$ and $[\alpha'_i\beta'_i]^T$ are the probability amplitude before and after the i^{th} qubit update, $\Delta\theta$ is the rotation angle, and $S(\theta)$ is the direction of quantum gate rotation, f_x is the fitness value of current chromosome, f_{best} is the global optimal fitness value of records, $U\left(\theta^{'}\right)$ is the adjustment operation of quantum rotation gate, and $\theta_{\min}(\theta_{\max})$ is the minimum (maximum) value of the given rotation angle range, which is given in the next paragraph.

The value of the rotation angle range $[\theta_{\min}, \theta_{\max}]$ has a significant influence on searching the global optimum, which determines the value of $\Delta\theta$ the larger $\theta_{\max}$ is, the larger $\Delta\theta$ is, the smaller $\theta_{\min}$ is, and the smaller $\Delta\theta$ is. A large rotation angle $\Delta\theta$ may lead to missing the global optimum; conversely, too small $\Delta\theta$ may lead to slow convergence and cannot jump out of the local optimum. We usually set the value $\Delta\theta$ to be between 0.001π and 0.05π (38).

3.2.3. Algorithm flow based on spread operation

For the spread strategy, it is necessary to give an initial speed for shelters to spread outward. Therefore, in this study, the spreading speed of the shelter is taken as a variable, and the IQGA is used to solve the optimal spreading speed; using the objective function as a fitness function of IQGA satisfies the constraints of Formulas (7)-(9). In addition, there are two ways to employ spreading speed as a variable: each refuge uses the same diffusion velocity, and thus, there is only one variable; each shelter uses a different spreading speed. Therefore, the number of variables is equal to the number of shelters, and we will compare the results of the two ways in the later context.

The concise flow of the IQGA considering spread operation can be summarized as follows:

(1) Initialize population Q(t) and randomly generate n quantum chromosomes.
(2) Measure each individual quantum chromosome in the Q(t) and obtain the same spreading speed S or a different spreading speed S_i.
(3) Employ S or S_i to obtain fitness. Take S or S_i as the spreading speed and then obtain the objective function, namely, the fitness value, according to the diffusion result.
(4) Record the optimal spreading speed and its corresponding fitness value.
(5) New population Q(t+1) is obtained by employing a quantum rotation gate to update the quantum chromosome.

The corresponding algorithm flow chart is shown in Figure 6.

4. Case application

4.1. Study region selection

Wuhan, the megacity and the central city in China, is located in the middle reach of the Yangtze River. In this study, a central urban region with a dense population in Wuhan, i.e.,

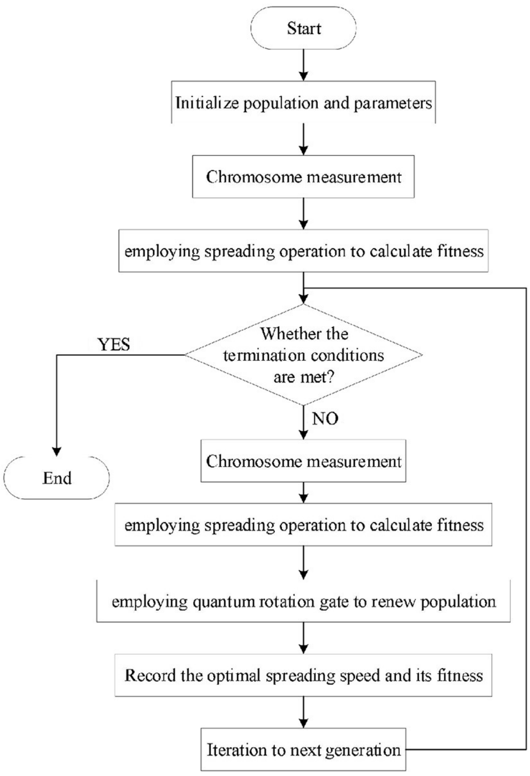

FIGURE 6
The flow chart of IQGA, considering a spread operation.

FIGURE 7
The Yangyuan Street area in the satellite image.

the Yangyuan Street region, was selected to study, as shown in Figure 7, which covers an area of 5.24 square kilometers, a large number of chemical plants and a resident population of 109,485.

FIGURE 8
Facilities distribution of the Yangyuan Street region.

TABLE 3 Parameter setting value table.

Parameter	Set value	Parameter	Set value
Chromosome length *len*	10	Initial point distance *SC*	1,000 m
Iteration times *Gen*	500	Discrete distance *DC*	300 m
Population size *n*	20	Number of buildings *BS*	1,980
Number of shelters *SS*	17		

4.2. Data preparation

The essential data were digitized base on the tile map of Baidu Map, including roads, emergency shelters, and building outlines, as shown in Figure 8.

In addition, when drawing roads outside the study area, we only consider the trunk roads outside the study area as a result of no evacuation demand for the people outside the region. Therefore, the roads outside the study region are much simpler than the roads inside the study region. This study mainly aimed at the temporary shelter of flood disasters for residents by river banks. Therefore, although there are many places in the Yangyuan Street region that can be used as emergency shelters, such as school playgrounds, green parks, and community squares, in order to reduce the computational

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amount, only large parks and green areas in the region were selected to be temporary emergency shelters. Meanwhile, the shelters adjacent to the Yangtze River were excluded to avoid environmental pollution and flood impact. For the capacity of shelters, the data were obtained from the website introduction and the space measurement of the shelters. In addition, the total capacity of the shelters in the study region was unable to accommodate such a large amount of people, thus several shelters outside the region to meet the evacuation demand of the whole street area were set up. The model parameters and the capacity of each shelter are shown in Tables 3, 4. The model parameters are set based on the general settings of the algorithm. The capacity of the shelter is computed by the ratio of the available area of the shelter to the occupied area per capita, in which the occupied area per capita is 2 m^2, and the available area is 60% of the land area of the shelter. For discrete distance limit D, we think that when $D > 300$, the two buildings are discrete and be punished with Formula (2). For the initial point limit L, we think that when $L > 1,000$, it is punished by Formula (4). In addition, we also randomly assigned the evacuated population to each building through Formulas (10)-(13), as shown in Figure 9.

4.3. Simulation

In this study, we constructed five scenarios simulation by means of adopting the improved quantum genetic algorithm considering the unchangeable spreading speed S and changeable spreading speed S_i. The unchangeable speed means that all shelters are spreading at the same speed, and the changeable speed means that each shelter spreads outward at a different speed. In other words, unchangeable speed means setting only one variable in IQGA, and changeable speed means setting the same number of variables as the number of shelters in IQGA. The five simulation scenarios can be described as follows:

Scenario 1, as shown in Figure 10, illustrates the planning of shelter allocation adopting IQGA with changeable spread speed, which considers the total evacuation distance, dispersion, spread initial distance, and capacity constraints.

Scenario 2, as shown in Figure 10, illustrates the planning of shelter allocation adopting IQGA with changeable spread speed, which considers the total evacuation distance, discreteness, and capacity constraints.

Scenario 3, as shown in Figure 10, illustrates the planning of shelter allocation adopting IQGA with changeable spread speed, which only considers the total evacuation distance and capacity constraints.

Scenario 4, as shown in Figure 10, illustrates the planning of shelter allocation adopting IQGA without spreading operation, which considers the total evacuation distance, dispersion, spread initial distance, and capacity constraints.

Scenario 5, as shown in Figure 10, illustrates the planning of shelter allocation adopting IQGA with unchangeable spread speed, which considers the total evacuation distance, dispersion, spread initial distance, and capacity constraints.

The corresponding numeric results are listed in Table 5.

As shown in Figure 10, the buildings with the same color represent they are assigned to the same shelter. In terms of color distribution, *Scenario 4* has a chaotic color layout, buildings with the same color are far away, and the discreteness is the highest. Compared with *Scenario 4*, the color layout of other scenes is basically the same, and buildings with the same color are adjacent to each other, so there is a high continuity. To visually compare the allocation results of

FIGURE 9
The population distribution of each building.

TABLE 4 The capacity of each shelter.

Shelter	ES 1	ES 2	ES 3	ES 4	ES 5	ES 6	ES 7	ES 8	ES 9
Capacity/hm^2	5.6	0.3	0.6	0.3	0.6	0.3	1.6	0.3	0.3
Shelter	ES 10	ES 11	ES 12	ES 13	ES 14	ES 15	ES 16	ES 17	
Capacity/hm^2	0.6	7	1.2	1.6	0.3	0.3	0.8	0.6	

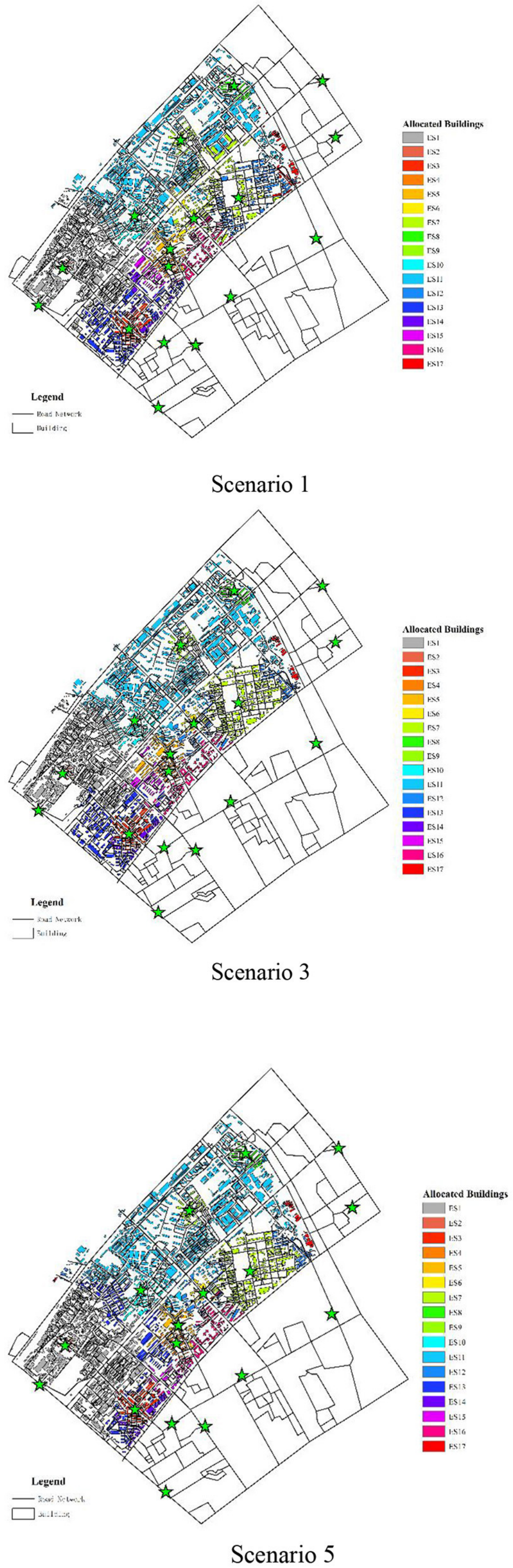

FIGURE 10
The allocation results of shelters for five scenarios.

each scenario, convert the color layout of each scenario in Figure 10 into corresponding numerical results and iteration curves, as shown in Table 5 and Figure 11, and each column data into dimensionless processing, as shown in Table 6. We can observe that *Scenario 4* and *Scenario 5* have the largest fitness values, far exceeding the first three scenarios. The first three scenarios are solved by employing an improved spreading quantum genetic algorithm with changeable speed, and their fitness is not much different. In addition, from the perspective of the number of discrete points, *Scenario 3* has the largest number of discrete points, with stronger discreteness. In terms of the Max-distance of the spread initial point, *Scenario 2* has the largest Max-distance of the spread initial point value, the evacuation completion time will also be greatly extended. Therefore, the results obtained by employing the spreading quantum genetic algorithm considering four factors are more reasonable; as the result, the effectiveness of the method in solving the problem of shelter allocation is proved.

4.4. Evacuation route and heat map

Reasonable route planning can effectively shorten evacuation time and reduce casualties. From a micro perspective, after a disaster, residents do not know where to evacuate or which road to take, and they tend to follow the crowd, which will cause the number of people serving in some shelters to exceed their maximum capacity, and the possibility of stepping accident will be greatly increased. Therefore, according to the allocation results of shelters, the evacuation route of each shelter is analyzed with the help of the ArcGIS network analysis tool, as shown in Figure 12, in which the green stars represent the shelters, the light green rectangles represent the residential buildings, and the black and red lines represent the actual road network and the evacuation paths covered by the shelters, respectively. Assigning an evacuation destination to residents and helping them draw an evacuation route map can let residents know where to go and which road to take, thereby forming an orderly evacuation. From a

TABLE 5 The digitized results for each scenario.

Scenario	Min-fitness	Max-distance of spread initial point	The number of discrete points
1	2378,406	1,060.88	36
2	2367,088	3,595.46	30
3	2335,391	936.99	106
4	2.2 E + 07	1,327.24	564
5	1.2 E + 07	778.51	196

TABLE 6 The digitized results dimensionless processing.

Scenario	Min-fitness	Max-distance of spread initial point	The number of discrete points
1	0.0022	0.1002	0.0112
2	0.0016	1	0
3	0	0.0563	0.1423
4	1	0.1948	1
5	0.5171	0	0.3109

FIGURE 11
Fitness iteration graph under different scenarios.

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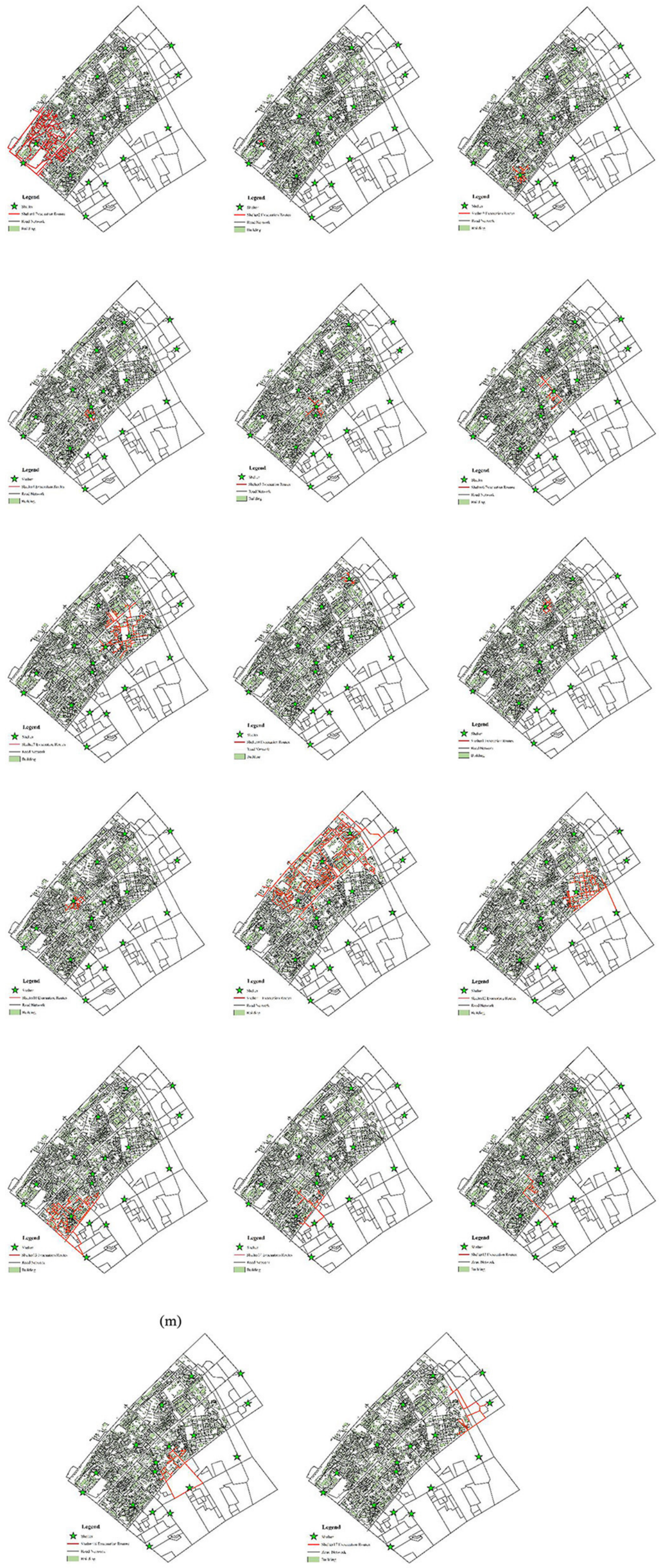

FIGURE 12
Evacuation routes to each shelter.

FIGURE 13
Evacuation heat map of the road network.

macro perspective, the evacuation heat map is drawn according to the number of times each road is used as an evacuation route, as shown in Figure 13, we can formulate corresponding management measures according to the road color. When the road color tends to red, the road sections have the largest traffic volume, which is more prone to congestion, and the traffic flow of these road sections can be diverted to the road sections with green. The road sections with orange color have a large traffic volume, which are potential congestion areas. To avoid congestion, we can maintain the road unobstructed through traffic controllers.

5. Conclusion

The main contribution of this study is to solve the problem of the distribution of shelters and to make a plan of evacuation routes for each building. Appropriate shelter allocation can improve evacuation efficiency. To solve the problem of shelter allocation, we propose a mathematical model, in which three objectives and one constraint are considered, which are to minimize the evacuation distance F1, to minimize the discrete distance F2, to maximize the combined rationality F3, and to meet the capacity constraint, so as to describe the problem of shelter allocation.

In this study, we propose an integrated method combining spreading operation and a quantum genetic algorithm to solve the problem of shelter allocation. To improve the efficiency and reduce the complexity of the analysis, it is converted from the evacuation demand point as an analytical variable to the evacuation site as an analytical variable. In each iteration, the spreading operation is used to calculate the fitness of the improved quantum genetic algorithm, and the shelter allocation scheme is gradually generated. In addition, we also analyze the rationality of the shelter allocation scheme in different scenarios. The results show that the QGA generated by spreading operation is more reasonable and the optimization efficiency is better. Finally, we analyze the evacuation route of each shelter according to the allocation scheme and then calculate the number of times that each path is the shortest path in the evacuation process; as a result, we have drawn the evacuation heat map.

In this study, we assume that every road is reliable optimization, but after a disaster, the road is more likely to be damaged. Therefore, we need to consider the probability of road damage in future work. In addition, we should consider the influence of congestion, safety, fairness, and other factors in the evacuation process in order to build a multi-objective optimization function. Furthermore, the disasters faced by humans are often not single, but diverse or even simultaneous. Therefore, shelters against comprehensive disasters are important and necessary. In urban disaster prevention planning, the design and construction of comprehensive shelters need more in-depth discussion.

Data availability statement

The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding author.

Author contributions

WL: funding acquisition, revision discussion, and review and editing. YY and XZ: conceptualization and writing—original draft. YY: formal analysis, methodology, and revising. All authors contributed to the article and approved the submitted version.

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Conflict of interest

XZ was employed by Shandong Hi-Speed Urban & Rural Development Group Co., Ltd.

The remaining authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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A novel method for quantifying human disturbances: A case study of Huaihe River Basin, China

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Human disturbances have become the main factors affecting the ecological environment. Therefore, evaluating the intensity of human disturbances is of great significance for ensuring effective regional conservation and ecosystem management. In this study, we constructed a novel method to quantify human disturbances based on three components of human disturbances into three types, namely naturalness transformation, natural resource consumption, and pollutant emissions. These components were quantified using the land use naturalness index (LNI), resource consumption index (RCI), and pollution emission index (PEI). Based on these three indicators, the human disturbances index (HDI) was calculated to reflect the intensity of human disturbances. In addition, remote sensing (RS), geographic information system (GIS), and multisource data were combined in the HDI method, taking into account the temporal variability of input parameters to achieve more convenient and comprehensive dynamic monitoring and evaluation of human disturbances. The applicability and effectiveness of the HDI method were assessed in the Huaihe River Basin, China. The obtained results revealed an increase and decrease in the intensities of human disturbances in the Huaihe River Basin from 1990 to 2005 and from 2010 to 2018, respectively. In addition, areas with a high level of human disturbances in the 1990–2005 period were mainly concentrated in the agricultural and industrial areas, while those in the 2010–2018 period were mainly observed in urban areas. This change was mainly due to a decrease in the pollutant emission amounts from agricultural and industrial lands and a marked increase in resource consumption in urban areas. This study provides theoretical guidance for regional conservation in the Huaihe River Basin and a new method for quantifying human disturbances.

KEYWORDS

human disturbances, HDI, land use naturalness, resource consumption, pollutant emissions, spatiotemporal change, Huaihe River Basin

1. Introduction

Human activities have exerted considerable anthropogenic influences on the earth system since the Anthropocene (1–3). Indeed, the increase in human activities through the rapid growth of population and urbanization has gradually become an important driving factor affecting the ecological environment on a global scale (4–7). According to previous studies, over 75 and 90% of the earth's land surface and riverine systems, respectively, have been altered as a result of human activities (8–12), resulting in a series of eco-environmental problems, such as global warming, water pollution, and land degradation (13–15). The influence of human activities on the environment resulted in a high ecological risk, thereby threatening human survival (16, 17). Therefore, quantifying human disturbances is of great significance to better understand the impacts of human activities on the ecosystem, which is essential for ensuring ecological protection, environmental management, and sustainable development of human society.

Human disturbances have been mainly reflected by various environmental indicators from different perspectives in the initial research stage. Some researchers have assessed the intensities of anthropogenic disturbance by investigating biological indicators and pollution discharges to the water bodies (18–22). However, others have used the species diversity to reflect the intensities of human disturbance in the forest ecosystem (23, 24). Hemeroby is a monitoring indicator, proposed for the first time by Jalas (25) to detect the intensity of human disturbance in forest ecosystems, then has been extensively applied by several researchers to evaluate the human disturbance in various types of ecosystems (10, 19, 26). In addition, numerous evaluation methods for assessing human disturbances have been proposed in recent years, shifting gradually the investigation of human disturbances from qualitative description to quantitative analysis. Indeed, with the development of Geographic Information System (GIS) and Remote Sensing (RS) technologies, data acquisition has become more diversified, rapid, and convenient, offering multi-source data and developing GIS-and RS-based quantitative evaluation methods for assessing human disturbances that integrate GIS and RS technologies (27–30). Many scholars have used land use data obtained from remote sensing images, as well as socio-economic and ground survey data, to analyze the intensity of one or multiple types of human disturbances in certain regions (26, 31–34). On the other hand, Brown and Vivas (3) developed Landscape Development Intensity (LDI) index using energy theory to measure the impact of human disturbances in wetlands. Whereas Sanderson et al. (2) used four types of variable data, namely population density, land transformation, accessibility, and electrical power infrastructure, to map the human footprint as an indicator of human disturbances. However, to date, quantitative research on human disturbances has been mostly based on biased single or multiple indicators using individual or partial components, which are not enough for comprehensively and accurately evaluating the intensities of human disturbances in the ecosystems. Besides the limited applicability of the developed evaluation methods in other areas due to spatial differences in environmental factors, the possibility that the same type of human disturbance source may exhibit different temporal intensities is not considered in the evaluation methods. Therefore, more effective evaluation methods of human disturbances need to be developed based on more comprehensive indicator systems that reflect human activities, taking into account the variability of indicators.

The Huaihe River Basin is an important region for the socioeconomic development of China due to its favorable environment and abundant natural resources, producing 1/6 of the country's agricultural production and serving as an important coal and electricity base in Eastern China (35, 36). In 2018, the Chinese government released the "Huaihe River Economic Belt Development Plan," which emphasized the excellent location and important status of the Huaihe River Basin, planning to accelerate the development of the Huaihe Ecological and Economic Belt to enhance ecological protection (15). However, the population density in the Huaihe River Basin is substantially higher than the national average population density, resulting in considerable pressure on the natural resources and serious water, air, and soil pollution from industrial pollutants. In general, human disturbances in the Huaihe River Basin are strong and frequent, resulting in severe constraints on its sustainable development.

In this study, multi-source data were used to develop a new method of human disturbances to achieve more convenient and comprehensive dynamic monitoring and evaluation of human disturbances. The human disturbances were classified into three types: land use naturalness transformation, resource consumption, and pollutant emissions. In this study, RS, GIS, and multi-source data were combined to establish the land use naturalness index (LNI), resource consumption index (RCI), and pollution emission index (PEI) to measure three types of human disturbances, taking into account the temporal variability of indicator parameters. Based on these three indicators, human disturbances index (HDI) was calculated to determine the intensities of human disturbances. The applicability and effectiveness of HDI, as well as the spatiotemporal changes in human disturbances, were assessed in the Huaihe River Basin.

2. Conceptual framework

Lands are used by humans to obtain produce material products and services through economic activities (3, 30). Different land use types are affected by human activities in different ways and to varying intensities, resulting in different ecological processes and environmental quality. Similar to

Ehrlich's classic IPAT formula (human impact, population, affluence, and technology), in which human impacts on Earth are equal population size times affluence (interpreted as energy available per person) times technology (37). The number of people in a given area is commonly considered the main factor affecting natural ecosystems, with higher population densities resulting in greater degrees of influence on natural ecosystems (38). Changes in energy source structure are responsible for many significant changes in human disturbances (2). Indeed, fossil fuels and electrical power affect substantially the environment (39). At the same time, air and water pollutant emissions from human production on the supra-regional scale and daily human activities can alter considerably the natural characteristics of the environment (3, 40, 41). In general, the ecosystem is under land conversion pressure, resource consumption, and pollutant emissions caused by human activities.

In this study, the factors of human disturbances on land units were classified into three types, namely land use naturalness transformation, resource consumption, and pollutants emission, then quantified using LNI, RCI, and PEI, respectively. Based on these three indicators, HDI was calculated to reflect the intensities of human disturbances on land units. Six variable data were selected in this study to calculate the intensities of three types of human disturbances according to their coverage, availability, and relevance. Land use naturalness dataset was used to calculate LNI; water and energy consumption datasets were used to calculate RCI; CO_2, N_2O, and non-point pollutant emission datasets were used to calculate PEI. The detailed HDI framework flowchart is shown in Figure 1.

3. Calculations of human disturbance indices

3.1. Land use naturalness index (LNI)

Naturalness is defined as the preservation of natural attributes of the ecosystem (28). Several studies have employed land use transformation to measure the impacts of human disturbances on land naturalness (42, 43) without appropriate classifications. Based on the concept of land use naturalness, Human Activity Intensity of Land Surface (HAILS) was proposed to measure the impacts of human activities on land surface (44), providing a clear scoring system. Therefore, the HAILS evaluation method was applied in this study to assign values to the naturalness of various land uses (Table 1) and calculate the LNI values according to the land use types of the study area. In addition, the subsequent RCI and PEI calculations were also based on this land use classification.

3.2. Resource consumption index

Previous studies have used DMSP-OLS night light data or calculated the consumption of non-renewable energy resources based on Energy Theory to measure the impacts of human disturbances on the environment (45, 46). However, these methods are limited by data availability and have poor comparability over long-term time scales. LDI considers water and non-renewable resource consumption, allowing for a comprehensive consideration of resource consumption (3). However, the calculations of energy consumption in different land use types and the attributions of hierarchical values of the LDI method are based on statistical methods to calculate energy consumption on different land use types without taking into account the temporal variation in the attributed hierarchical values, thereby restricting the applicability of the method in other regions worldwide.

In this study, the residents' consumption of non-renewable resources and the non-renewable resources consumption per unit area of each land use type were considered according to the calculation method of LDI, then water consumption and energy consumption were divided into two datasets for separate analysis. The non-renewable resource consumption per unit area of different land uses in the study area was calculated for each period based on energy and water consumption statistical data in different periods. In addition, electricity and fossil fuel consumption were converted into standard coal consumption to measure the non-renewable resource consumption. The consumption of residents was calculated using population density statistics and per capita consumption for urban and rural populations, respectively. The water and energy consumption datasets were obtained for different periods by overlay processing in ArcGIS.

3.3. Pollutant emission index

Several researchers have devoted considerable attention to point source pollution, resulting in effective control and management of this pollution type, while non-point source pollution still has negative impacts on the natural environment (47–49). Indeed, considerable amounts of airborne and non-point source pollutants have been released into the atmosphere and surface water bodies, respectively, making it challenging to measure their impacts on the natural environment due to the complexity of their dynamics (21, 50). Most studies have simulated non-point source pollution using semi-empirical and physically-based models, such as SWAT, EcoHAT, and HSPF. However, these models require large amounts of data for their calibration and validation (51–53), restricting their applicability in some regions.

In this study, the constantly updated global CO_2 and N_2O emission data, published by the Emissions Database for Global

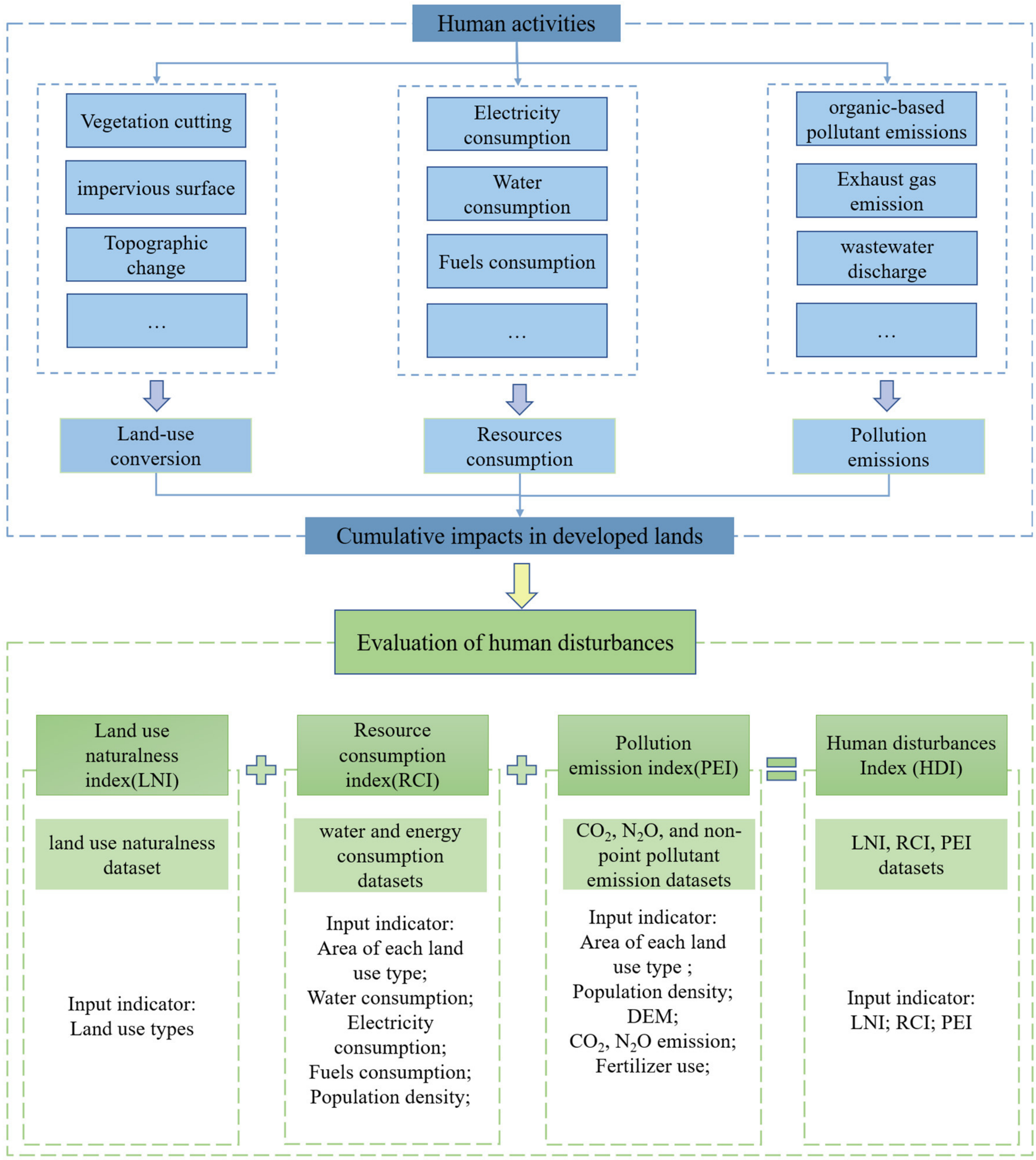

FIGURE 1
Conceptual framework of HDI.

Atmospheric Research (EDGAR), were used to measure the impacts of airborne pollutants, including all fossil CO_2 and N_2O sources (e.g., fossil fuel combustion, non-metallic mineral processes, agricultural liming, and solvent uses). The CO_2 and N_2O emission data were separated into two datasets for separate scoring and analysis.

The assessment of non-point pollution in water bodies is a complex and time-consuming task. The potential non-point pollution index (PNPI) is a GIS tool designed to assess the global pressure of different land uses on rivers and other surface water bodies using simple input data (47). The pollution emission per unit area of each land use type was calculated using statistical data, while the pollution emissions from residential areas were determined using population density and per capita emission data. Finally, the total pollution emission was calculated to determine the land cover indicator (LCI) of PNPI, then PNPI

TABLE 1 Classification of land use naturalness.

Levels	Categories	Classification signs	Scores
		Natural cover of the land surface does not change and is not used	0
Second level	CS1	Natural cover of land surface does not change but is used	0.67
	CS2	Natural cover of land surface changes and perennial crops are planted	1.33
	CS3	Natural cover of land surface changes and annual crops are planted	2
First level	FCS1	Natural cover of land surface changes	2
	FCS2	There are artificial insulation layers on the land surface. Water could be exchanged. The exchanges of nutrients, air, and heat are impeded	2
	FCS3	There are artificial insulation layers on the land surface. Nutrients could be exchanged. The exchanges of water, air, and heat are impeded	2
	FCS4	There are artificial insulation layers on the land surface. Air could be exchanged. The exchanges of water, nutrients, and heat are impeded	2
	FCS5	There are artificial insulation layers on the land surface. Heat could be exchanged. The exchanges of water, air, and nutrients are impeded	2
		There are artificial insulation layers on the land surface. The exchanges of water, nutrients, air, and heat are impeded	2

TABLE 2 Classification of HDI values.

Human disturbance levels	I	II	III	IV	V	VI	VII	VIII	IX	X
HDI	0–6	7–12	13–18	19–24	25–30	31–36	37–42	43–48	49–54	55–60

was determined according to Munafo et al. (47). The final obtained result is the non-point source pollution datasets.

3.4. Human disturbances index

In this study, the six datasets were overlayed in one map projection using ArcGIS, then standardized scores from 0 (low contribution) to 10 (high contribution) were attributed to reflect the estimated contribution to human disturbances. The natural breaks classification in ArcGIS was used to better classify similar values and maximize the variance between classes. Therefore, based on information from each data during the study period, the natural breaks classification was used to standardize the attributed values to resource consumption and pollutant emissions. The LNI, RCI, and PEI results were obtained by summing the human disturbance scores for each of the six datasets with the same weight. Afterward, stack the three disturbance layers with the same weight were stacked to compute the HDI. High and low HDI values indicate high and low levels of human disturbances, respectively. To further reflect the differences in human disturbances, the HDI values were classified into 10 levels using equal interval classification in ArcGIS (Table 2).

$$LNI + RCI + PEI = HDI \quad (1)$$

where *HDI* denotes the human disturbance index of the study area; *LNI* denotes the land use naturalness index of the study area; *RCI* denotes the resource consumption index of the study area; *PEI* denotes the pollution emission index of the study area.

4. Case study

4.1. Description of the study area

The Huaihe River Basin is located in Eastern China between 30°55′-37°50′ N and 111°55′-122°42′E, covering a total area of ∼3.3 × 10^5 km^2, including Henan, Hubei, Anhui, Jiangsu, and Shandong Provinces (Figure 2). The study area is separated into five secondary basins, namely upstream, midstream, downstream, Yishusihe, and Shandong Peninsula (15, 54). The mainstream of the Huaihe River is derived from Tongbaishan Mountain in Henan Province, China, flowing eastward into the Yellow Sea (55). On the other hand, the topography of the study area is dominated by low hills in the western and north-eastern parts of the basin and plains, accounting for 1/3 and 2/3 of the total area, respectively (56). The mean annual precipitation and mean annual temperature of Huaihe River Basin are 883 mm and 13.7°C, respectively (57), providing suitable environmental conditions. In addition, the Huaihe River Basin is an important industrial and agricultural production base in China, with a population density of 600 people/km^2, which is substantially

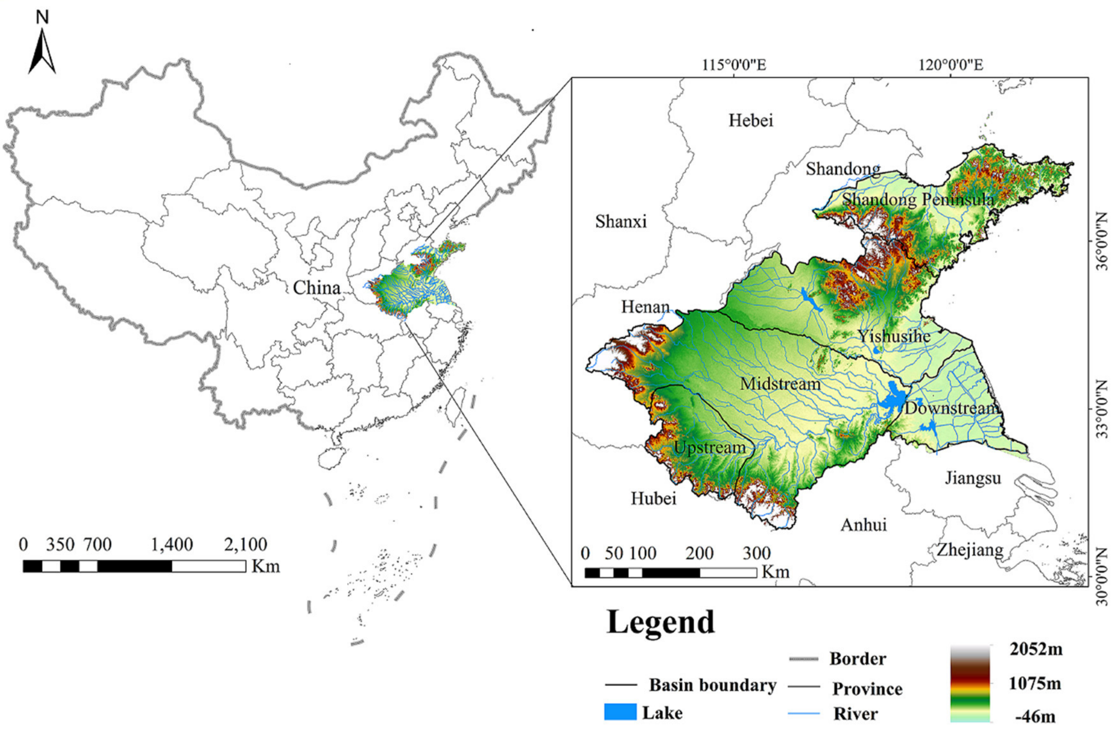

FIGURE 2
Geographic location of the Huaihe River Basin.

higher than the national population density (148 people/km^2) (36). Ecosystems in the study area have been under great pressure due to intensive resource exploitation (56).

4.2. Data sources and preprocessing

Land use data (spatial resolution of 1 km) for 1990, 1995, 2000, 2005, 2010, 2015, and 2018, and population density data (spatial resolution of 1 km) were obtained from the Resource and Environmental Science Data Center of the Chinese Academy of Sciences. The land use data were generated by processing Landsat remote sensing images, showing overall accuracies >90% (http://www.resdc.cn, accessed on 11 December 2021). We used ArcGIS 10.3 software to classify land use data into nine types, namely arable land, forest land, grassland, artificial water body, natural water body, urban land, rural land, industrial land, and unused land (Figure 3). In addition, soil texture data were obtained from the National Earth System Science Data Center, National Science & Technology Infrastructure of China (http://www.geodata.cn, accessed on 13 December 2021). While digital elevation model (DEM) data (spatial resolution of 1 km, accessed on 11 December 2021) were downloaded from the geospatial data cloud platform (http://www.gscloud.cn, accessed on 11 April 2022). Water consumption data were obtained from the water resources bulletin of the Huaihe River Basin and Shandong Peninsula (http://www.hrc.gov.cn, accessed on 11 April 2022). Electricity and fossil fuel consumption data were derived from the national and provincial statistical yearbook (https://data.cnki.net/Yearbook, accessed on 10 April 2022) of China. CO_2 and N_2O emission data were obtained from EDGAR (https://edgar.jrc.ec.europa.eu/, accessed on 11 April 2022).

4.2.1. Land use naturalness index of the Huaihe River Basin

The naturalness of the Huaihe River Basin was obtained in this study (Table 3) based on to the land use type and naturalness classification results (Figure 3 and Table 1).

4.2.2. Resource consumption index of the Huaihe River Basin

According to the Huaihe River Basin and Shandong Peninsula water resources bulletin, water consumption was classified into six main indicators, namely agriculture, industry, urban residents, rural residents, forestry and husbandry, and urban public. Water consumption per unit area of each land use type was computed independently using land use data, while that for forest land and grassland was calculated using forestry

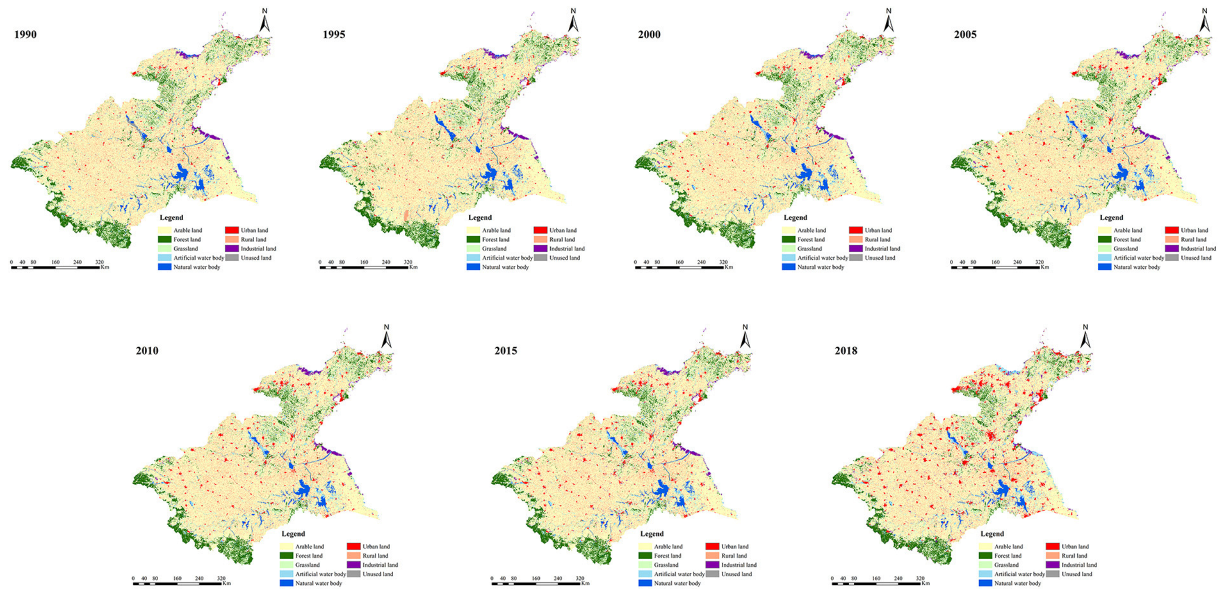

FIGURE 3
Temporal changes in land use types of the Huaihe River Basin over the 1990–2018 period.

TABLE 3 Land use naturalness index of the different land use types in the Huaihe River Basin.

Land use types	Classification signs	LNI
Arable land	Natural cover of land surface changes and annual crops are planted	2
Forest land	Natural cover of land surface does not change but is used	0.67
Grassland	Natural cover of land surface does not change but is used	1.33
Artificial water body	There are artificial insulation layers on the surface. Water could be exchanged. The exchanges of nutrients, air, and heat are impeded	6
Natural water body	Natural cover of the land surface does not change and is not used	0
Urban land	There are artificial insulation layers on the surface. Water could be exchanged. The exchanges of nutrients, air, water, and heat are impeded	10
Rural land	There are artificial insulation layers on the surface. Water could be exchanged. The exchanges of nutrients, air, water, and heat are impeded	10
Industrial land	There are artificial insulation layers on the surface. Water could be exchanged. The exchanges of nutrients, air, water, and heat are impeded	10
Unused land	Natural cover of the land surface does not change and is not used	0

and husbandry data. The water consumption by urban and rural residents was calculated using population density statistics and per capita consumption for urban and rural populations, respectively. The water consumption datasets were obtained for different periods using overlay processing in ArcGIS.

On the other hand, the energy consumption per unit of each land use type and per capita of urban and rural residents were calculated in this study based on the land use data and total energy consumption in different provinces. In addition, because energy consumption for transportation is not limited to roadways, the energy consumption per unit of transportation in urban, rural, and industrial lands was calculated. The temporal energy consumption datasets were obtained for different periods using overlay processing in ArcGIS.

Because of the small area of the Huaihe River Basin in Hubei Province, only Henan, Anhui, Jiangsu, and Shandong Provinces were considered in the calculation. All the resource consumption statistical data used were preprocessed to calculate the 5-year average consumption value, except those from 2016 to 2018, which were used to calculate the 3-year average consumption value.

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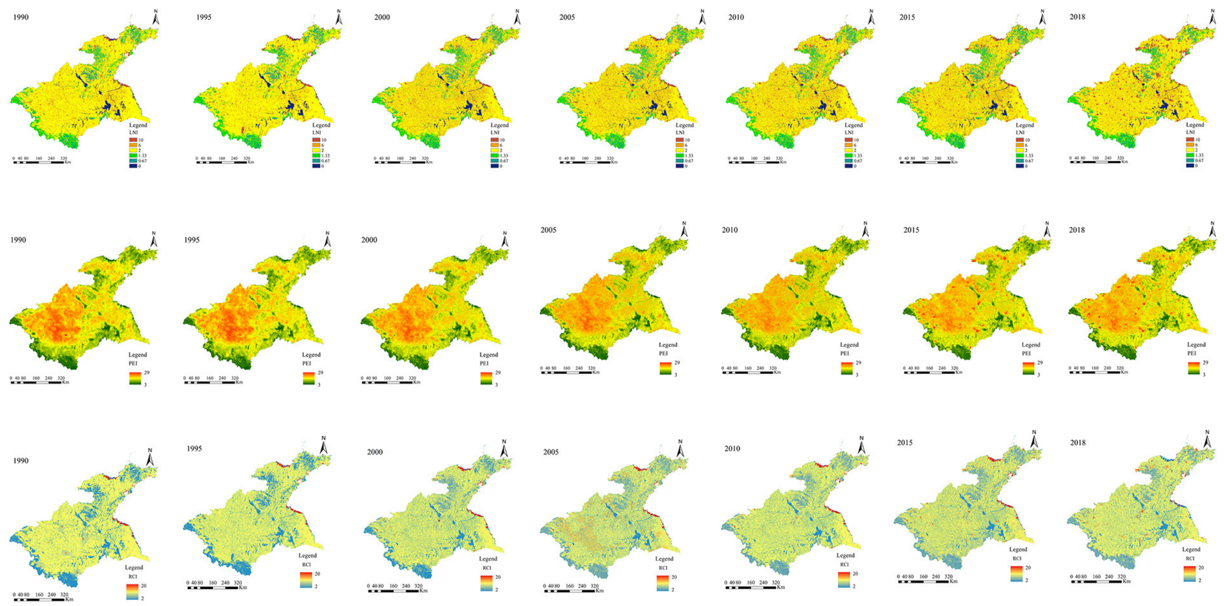

FIGURE 4
Spatiotemporal distribution of LNI, RCI, and PEI in the Huaihe River Basin over the 1990–2018 period.

4.2.3. Pollution emission index of the Huaihe River Basin

In this study, the CO_2 and N_2O emission data in the Huaihe River Basin were extracted using the extract by mask tool in ArcGIS software then the kriging interpolation was used to improve the spatial resolution to 1 km. The 5-year average CO_2 and N_2O emission values were calculated and considered in this study.

The National Water Environment Capacity Verification Manual, issued by the Chinese government, pointed out that non-point source pollution in China is primarily found in rural and arable areas, where high chemical oxygen demand (COD) and nitrogen oxides levels were observed. Therefore, the values of non-point source pollution were set to 0 for all land use types except for arable and rural lands. The nitrogen oxides emission was used instead of non-point source pollution due to the data availability. Based on the nitrogen oxides emission per rural person in the manual and the effective use rates of fertilizer in the yearbook, the distributions of temporal nitrogen oxides emission data over the study period. The nitrogen oxides emission data were used to obtain the land cover indicator (LCI) for the subsequent calculation of the PNPI. All processing was performed in ArcGIS and Matlab.

4.2.4. Summing the scores

The spatial distributions of LNI, RCI, and PEI in the Huaihe River Basin were obtained by summing the above-attributed values in ArcGIS 10.3 software (Figure 4), whereas the HDI values were obtained using Eq. 1 (Figure 5).

4.3. Spatiotemporal analysis of the human disturbances

4.3.1. Spatial centroid

The centroidal dynamics can reflect the spatial transformation characteristics and trends of regional elements (29). In this study, the centroid method was used to analyze the spatiotemporal distribution of the HDI values in the Huaihe River Basin according to the following equations:

$$X = \frac{\sum_{i=1}^{n}\sum_{j=1}^{m}\left(x_{ij} \times HDI_{ij}\right)}{\sum_{i=1}^{n}\sum_{j=1}^{m} HDI_{ij}}; \quad Y = \frac{\sum_{i=1}^{n}\sum_{j=1}^{m}\left(y_{ij} \times HDI_{ij}\right)}{\sum_{i=1}^{n}\sum_{j=1}^{m} HDI_{ij}} \backslash n \tag{2}$$

where X and Y denote the horizontal and vertical coordinates of the centroid, respectively; n and m denote the numbers of rows and columns of the raster map, respectively; x_{ij} and y_{ij} denote the latitude and longitude coordinates of row i and column j, respectively; HDI_{ij} denotes the value of HDI in row i and column j of the grid.

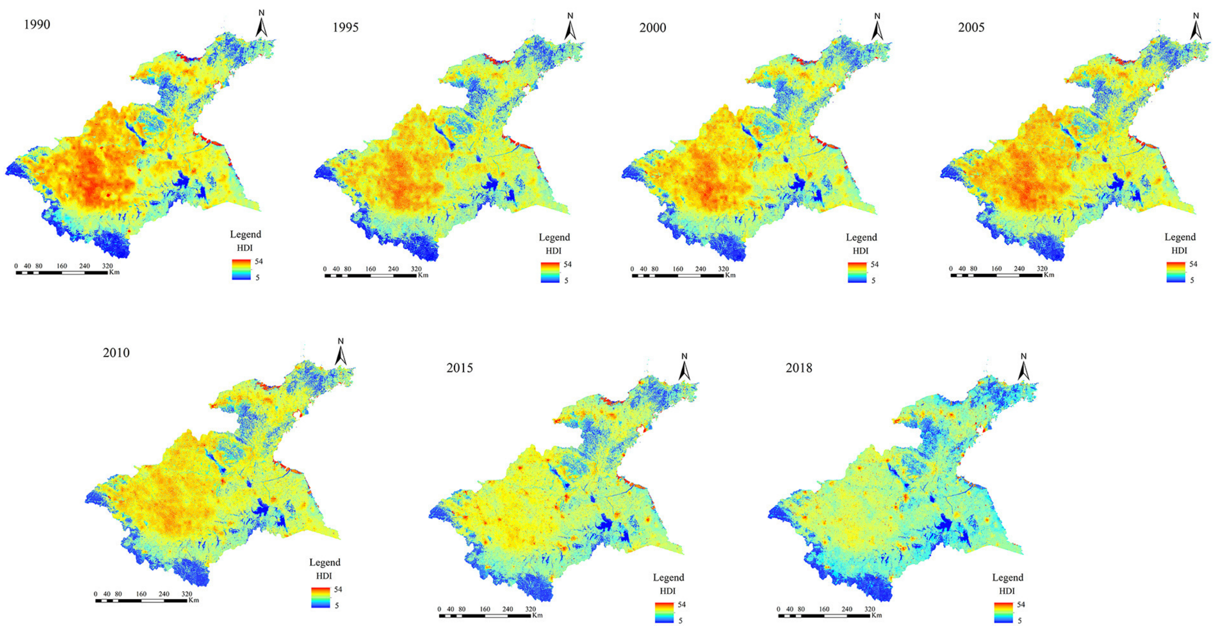

FIGURE 5
Spatiotemporal distribution of HDI in the Huaihe River Basin over the 1990–2018 period.

4.3.2. Spatial pattern analysis of HDI

In order to explore the spatial distribution of HDI in the Huaihe River Basin, the global Moran's I index was used to determine whether the HDI values are spatially clustered. In addition, the Getis-Ord Gi* index was used to further describe spatial distributions of human disturbances according to the following equations:

$$I = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} W_{ij}\left(x_i - \overline{x}\right)\left(x_j - \overline{x}\right)}{S^2 \sum_{i=1}^{n}\sum_{j=1}^{n} W_{ij}} \backslash n \tag{3}$$

$$G^* = \frac{\sum_{j=1}^{n} W_{ij}\left(d\right) x_j}{\sum_{j=1}^{n} x_j} \backslash n \tag{4}$$

where I denote the global Moran's I; n denotes the number of data; x_i and x_j denote the HDI values of the grid i and j, respectively; W_{ij} denotes the spatial weight matrix. In addition, the Z test was performed on Gi* to assess the reliability of the results. A positive Z (Gi*) value indicates a higher value around position i than the average value, suggesting a high-value spatial concentration (hot spot area). A negative Z (Gi*) value indicates a low-value spatial concentration (hot spot area).

5. Results

5.1. Spatiotemporal changes in LNI, RCI, and PEI

The three types of human disturbances showed different spatiotemporal changes in the Huaihe River Basin over the 1990–2018 period (Figure 4).

The areas with high naturalness were mainly located in the southwestern and western parts of the midstream, as well as in the Shandong Peninsula and northeastern parts of Yishusihe. These areas are mainly dominated by forestland, grassland, and water bodies. However, areas with high naturalness exhibited a certain spatiotemporal reduction trend. Regions with low naturalness values were observed in the midstream and Yishusihe, where urban, rural, and arable lands are the main land use types. Indeed, these areas tend to cluster gradually, resulting in a large combined area.

Areas with high resource consumption were mainly concentrated in the Jiangsu coastal zone and the northern part of the Shandong Peninsula, where urban land is the main land use type. In addition, relatively high resource consumption was observed from 2005 in the midstream and Yishusihe, while scattered point areas with high resource consumption were observed in the study area. Areas with low resource consumption were mainly found in forest land, grassland, and

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water bodies in the western and southwestern parts of the study area, showing a gradually decreasing spatiotemporal trend.

Pollutant emissions showed a downward trend over the study period. Before 2005, areas with high pollutant emissions are mainly concentrated in the arable land of the midstream, Shandong Peninsula, and Yishusihe, showing a slightly decreasing spatiotemporal trend. Areas with low pollutant emissions were mainly concentrated in the Jiangsu coastal zone, the southwestern, western, and southeastern parts of the midstream, and the northeastern part of the Shandong Peninsula, while no substantial spatiotemporal differences in the pollutant emissions were observed. It should be noted that there were increases in pollutant emissions in some parts of the study area from 2010, showing scattered areas.

5.2. Spatiotemporal changes in human disturbances

The spatial distributions of human disturbances and classification results in the study area are shown in Figures 5, 6, respectively. The results showed substantial spatiotemporal differences in human disturbance levels over the 1990–2018 period. These changes in human disturbances can be divided into two distinct phases, namely 1990–2005 and 2010–2018. The 1990–2005 period corresponded to the expansion period of high-level human disturbances. The levels of HDI in the coastal zones of Jiangsu and the northern part of the Shandong Peninsula were considerably higher than those in other regions. The spatial range of areas with levels V and VI expanded substantially to the central part of the midstream and Yishusihe, showing the highest areas with level VI in 2005. On the other hand, areas with low-level human disturbances began to expand in the 2010–2018 period. Indeed, an obvious reduction in areas with levels VI was observed in the midstream, while areas with level V gradually decreased, increasing areas with the HDI IV level. In addition, other areas with level V of the HDI were almost completely replaced by those with level IV of the HDI, while only some areas with levels V-IX of the HDI were observed mainly around the city areas in the study area.

The percentages of grids for different HDI levels in the study area were obtained from 1990 to 2018 (Table 4). According to the obtained results, levels IV and V of HDI exhibited the highest percentages of grids in the Huaihe River Basin over the study period. Areas with levels II to IV decreased first and then increased over the 1990–2018 period, while areas with levels V to VIII showed the opposite change. The highest intensity of human disturbances was observed in 2005. In addition, areas with levels II to IV and V to VIII accounted for 52.52 and 48.41% of the total surface of the study area, respectively, whereas the lowest intensity of human disturbances was observed in 2018. In this year, areas with levels II, III, and IV accounted for 89.76% of the total surface of the study area, while areas with levels V to VIII accounted for only 9.72% of the total surface of the study area. The obtained results showed an increasing-decreasing temporal trend in the intensity of human disturbances in the study area.

Areas with level V accounted for high proportions in the midstream and Yishusihe over the entire study period, while level IV was observed mainly in the upstream, downstream, and Shandong Peninsula. Overall, decreasing-increasing trends in levels II, III, and IV were observed in the five secondary basins of the study area, exhibiting the lowest areas in 2005 and 2010 and the highest in 2018. Levels II, III, and IV were observed mainly in the upstream, downstream, and Shandong peninsula, accounting for more than 60% of the total surface of the study area, as well as in the Yishusihe and Midstream, covering 40% of the total surface of the study area, while the areas above levels V were the opposite. These results indicated that the intensities of human disturbances in the upstream, downstream, and Shandong Peninsula were lower than those observed in the midstream and Yishusihe.

The spatial centroid variations of human disturbances in the Huaihe River Basin from 1990 to 2018 were determined using ArcGIS 10.3 based on the spatial centroid migration model (Figure 6). During the study period, the centroids of human disturbances were distributed in the junction of the midstream and Yishusihe, showing spatiotemporal migration direction. The centroid migration showed a 45° shift trend from southwest to northeast, with fluctuations in the speed of the centroid migration. The lowest speed of centroid migration was observed from 2010 to 2015. The space centroid shifted 602.80 m to the southwest, with an offset speed of 120.56 m/year. Whereas the highest speed of centroid was observed from 2015 to 2018. In this period, the space centroid shifted 3692.56 m to the northeast, with an offset speed of 738.51 m/year.

5.3. Cold and hot spots changes of human disturbances

To quantitatively analyze the spatiotemporal changes in human disturbances in the Huaihe River Basin over the 1990–2018 period, the global Moran's I index was calculated in this study using the spatial autocorrelation model in ArcGIS 10.3 (Table 5). The results showed significant and positive spatial autocorrelation ($p < 0.01$) in human disturbances in the Huaihe River Basin. Therefore, the Getis-Ord Gi* index can be used to further investigate the evolution characteristics of the local spatial concentration of human disturbances in the study area (Figure 7). Overall, the cold and hot spots of human disturbances in the study area exhibited similar patterns during the study period. Most of the hot spots were observed in the midstream, Yishusihe Peninsula, and central part of

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TABLE 4 Different levels of HDI in the Huaihe River Basin over the 1990–2018 period (%).

Study area	Year	I	II	III	IV	V	VI	VII	VIII
The Huaihe River Basin	1990	0.59	11.11	13.98	45.59	27.43	1.18	0.10	0.01
	1995	0.48	11.45	8.46	45.39	31.46	2.51	0.22	0.02
	2000	0.42	9.74	8.44	43.70	34.19	3.23	0.23	0.05
	2005	0.42	9.72	7.93	33.44	41.62	6.45	0.34	0.07
	2010	0.57	10.27	7.33	32.92	45.47	2.89	0.47	0.07
	2015	0.68	10.84	9.50	57.22	19.73	1.60	0.39	0.04
	2018	0.50	10.60	14.59	64.57	8.28	0.93	0.45	0.06
The Upstream	1990	0.03	18.41	22.80	38.26	20.39	0.12	0.01	0.00
	1995	0.02	20.28	9.31	44.97	24.85	0.50	0.07	0.00
	2000	0.02	17.07	9.86	46.36	26.27	0.37	0.05	0.00
	2005	0.04	16.79	7.66	40.71	33.14	1.54	0.11	0.01
	2010	0.13	17.49	5.91	43.52	32.14	0.71	0.10	0.02
	2015	0.13	17.03	12.24	58.50	11.43	0.54	0.12	0.02
	2018	0.07	18.99	20.86	55.71	3.73	0.39	0.22	0.03
Midstream	1990	0.85	11.17	9.58	34.70	42.12	1.50	0.07	0.01
	1995	0.79	11.11	5.58	34.83	43.19	4.27	0.21	0.03
	2000	0.59	10.43	4.77	32.33	45.64	5.92	0.23	0.07
	2005	0.68	10.28	4.80	25.15	46.10	12.54	0.37	0.08
	2010	0.81	10.63	4.63	25.48	53.83	4.19	0.36	0.06
	2015	1.03	10.74	6.69	49.05	30.88	1.18	0.37	0.05
	2018	0.95	10.73	9.97	65.16	12.05	0.70	0.36	0.08
Downstream	1990	1.60	5.86	18.24	69.81	3.57	0.88	0.04	0.00
	1995	1.17	6.96	6.98	76.60	7.30	0.83	0.16	0.00
	2000	1.38	5.85	8.33	73.64	9.57	1.15	0.09	0.00
	2005	1.28	5.62	7.49	60.55	23.38	1.58	0.10	0.00
	2010	1.88	5.56	6.57	58.03	25.98	1.66	0.25	0.07
	2015	1.95	6.12	11.80	74.82	3.77	1.27	0.23	0.04
	2018	0.73	7.05	20.96	67.80	2.94	0.41	0.10	0.01
Yishusihe	1990	0.10	6.63	11.53	49.91	30.61	1.06	0.14	0.02
	1995	0.01	6.79	11.38	41.44	38.44	1.69	0.22	0.02
	2000	0.10	4.98	11.03	41.10	40.70	1.77	0.26	0.05
	2005	0.02	4.91	11.16	25.88	54.34	3.23	0.38	0.08
	2010	0.18	5.96	10.75	26.40	54.02	2.05	0.56	0.09
	2015	0.19	7.27	10.99	60.16	19.17	1.83	0.38	0.01
	2018	0.10	6.49	12.61	71.21	7.96	1.21	0.37	0.05
Shandong Peninsula	1990	0.43	15.17	19.72	55.26	7.83	1.39	0.18	0.01
	1995	0.33	15.60	11.29	57.66	13.03	1.73	0.33	0.04
	2000	0.17	12.40	12.27	54.72	18.16	1.90	0.34	0.05
	2005	0.15	12.91	10.69	43.40	29.67	2.64	0.47	0.07
	2010	0.14	13.52	9.75	39.08	33.56	2.95	0.88	0.11
	2015	0.18	14.62	11.08	61.31	9.16	2.91	0.68	0.04
	2018	0.18	12.58	20.70	57.92	5.86	1.63	1.07	0.05

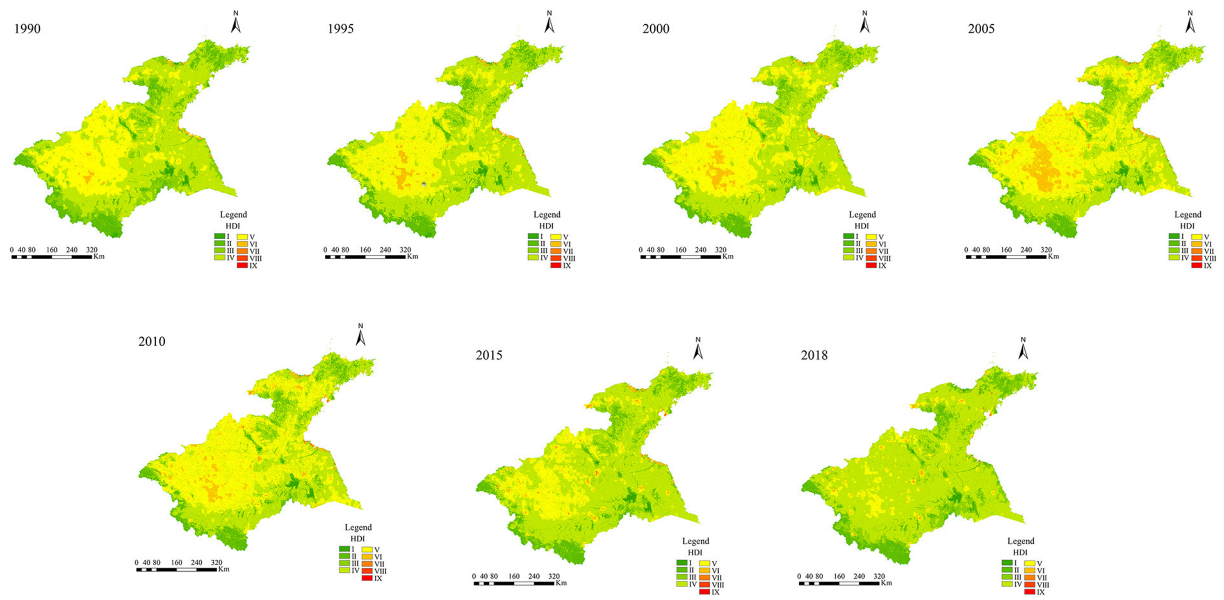

FIGURE 6
Spatiotemporal distribution of different levels of the HDI in the Huaihe River Basin over the 1990–2018 period.

TABLE 5 Spatial autocorrelation indices of the HDI in the Huaihe River Basin.

	1990	1995	2000	2005	2010	2015	2018
Moran's I	0.25	0.23	0.27	0.33	0.25	0.26	0.21
Z	46.92	53.89	62.37	75.86	71.67	67.31	53.87
P-level	0.00	0.00	0.00	0.00	0.00	0.00	0.00

the Shandong Peninsula, where urban, rural, and arable lands are dominant. In addition, areas with hot spots of human disturbances showed a decreasing temporal trend. Most cold spot areas were found in the upstream, western, southwestern, and southeastern of the midstream, as well as in the western and northeastern parts of the Shandong Peninsula. These areas are dominated by forest land, grassland, and water bodies. The distribution of cold spot areas was relatively stable without significant changes.

6. Discussion

6.1. Benefits of the HDI

Human disturbances have caused serious environmental problems, threatening sustainable human development (4, 16). Human disturbances affect ecosystems mainly through direct anthropogenic activities, such as the conversion of natural land into artificial land for economic development and urbanization, resulting in substantial consumption of resources and, consequently, serious pollution and climate change (2, 3, 58). The investigation of these human disturbances is an essential step for environmental protection and restoration. The HDI method can be used to classify the possible disturbances into three main types, namely land use naturalness transformation, resource consumption, and pollutant emissions. These three human disturbance types can be effectively quantified based on the literature (2, 3, 44, 47). Indeed, the required RS, GIS-related, multisource data in the HDI method are easily accessible, making it possible to investigate temporal changes in the HDI in several study areas with the data. Moreover, the HDI method can be applied at different scales by selecting appropriate data according to the specific characteristics of the study area, demonstrating stronger universal applicability than that of other traditional methods (e.g., biological indicators and pollution discharges). The results of the HDI calculation can support the analysis of the spatiotemporal changes in the regional human disturbances by considering the ecological and physical-geographic processes, thereby providing further insights into the relationships between humans and land, as well as the interactions between human activities and ecosystems. Therefore, the HDI method is of great importance for policy development and implementation

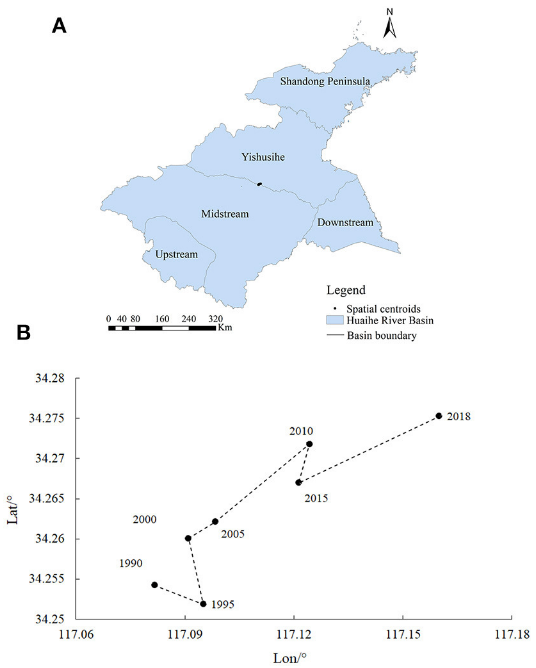

FIGURE 7
(A, B) Spatial distributions of cold and hot spots of the human disturbances in the study area.

of protective measures in the region. For areas with serious human disturbances, it is crucial to identify first the dominant human disturbances source types, then formulate corresponding policies to mitigate and control them, thereby reducing the cost, time, and difficulty of environmental protection and restoration.

6.2. Dynamics of human disturbances

Agriculture and industry were consistently the main types of human activities in the Huaihe River Basin over the 1995–2018 period because of the differences in levels of economic development and regional development policies. The results of this study showed spatiotemporal variations in the intensities of human disturbances in the secondary basins of the Huaihe River Basin as a result of the different levels of regional economic and policy development. The HDI results suggested two distinct periods during which considerable changes in the intensities of human disturbances in the Huaihe River Basin were observed, namely 1990–2005 and 2010–2020. The overall human disturbances in the study area showed an increasing trend over the 1990–2005 period due to the increasing economic development that marked this period. Indeed, a large area of arable land was converted to urban land, resulting in a substantial reduction of the land use naturalness in many areas (Figure 4). Moreover, considerable pollutant emissions and resource consumption were observed during the 1990–2005 period. In terms of spatial distributions, areas with high levels of HDI were mainly found in the arable and industrial lands (Figures 2, 6), providing evidence of the greater impacts of agricultural and industrial activities on the ecosystem than those of other human activities (33). On the other hand, positive effects of the environmental policies (e.g., Returning Farmland to Forest Program, Energy Saving and Emission Reduction, and Interim Regulations on the Prevention and Control of Water Pollution in the Huaihe River Basin) on reducing human disturbances were observed in the 2010–2018 period (15, 59). In addition, agricultural and industrial activities have changed from extensive to refined management, improving pesticide, fertilizer, and energy use efficiencies, while the consumption of resources and energy per unit area has been significantly reduced (28, 60). However, the increase in the urbanization level and urban population resulted in structural changes in human activities (61). In general, the levels of human disturbances in agricultural and industrial areas decreased to a certain extent, while those in urban areas of the inland plain increased substantially (Figure 6). The intensity of human disturbances decreased in the Huaihe river Basin (Figure 8), which might be due to the overall influences of improved management efficiency and pollution control capacity in the study area (12, 17). The intensities and spatial distributions of human disturbances are closely related to the urbanization process, as well as to the intensity of resource exploitation and utilization in the Huaihe river Basin. Therefore, government strategies and programs play a crucial role in the spatiotemporal changes of human disturbances (10, 62, 63).

6.3. Future research

The results of the present study demonstrated the effectiveness of the HDI method in investigating human disturbances in the Huaihe River Basin. However, due to our limited understanding of the complexity of human disturbances, all the types of human activities were not considered in the HDI method, while the combined effects of human disturbances were not demonstrated in the present study. Besides analyzing human disturbances gradients, policymakers and scholars can also combine the natural environmental characteristics, natural resource endowment, and the regional political and economic context to determine the thresholds of human disturbances that the study area can tolerate (58, 64). These suggestions may contribute to formulating and optimizing policies to effectively reduce the intensities of human disturbances and maintain the sustainable development of human society. In the future, dynamic modules, such as the conversion process of land use, consumption of natural resources and energy, and migration and transformation processes of pollutants, need to be considered in the HDI

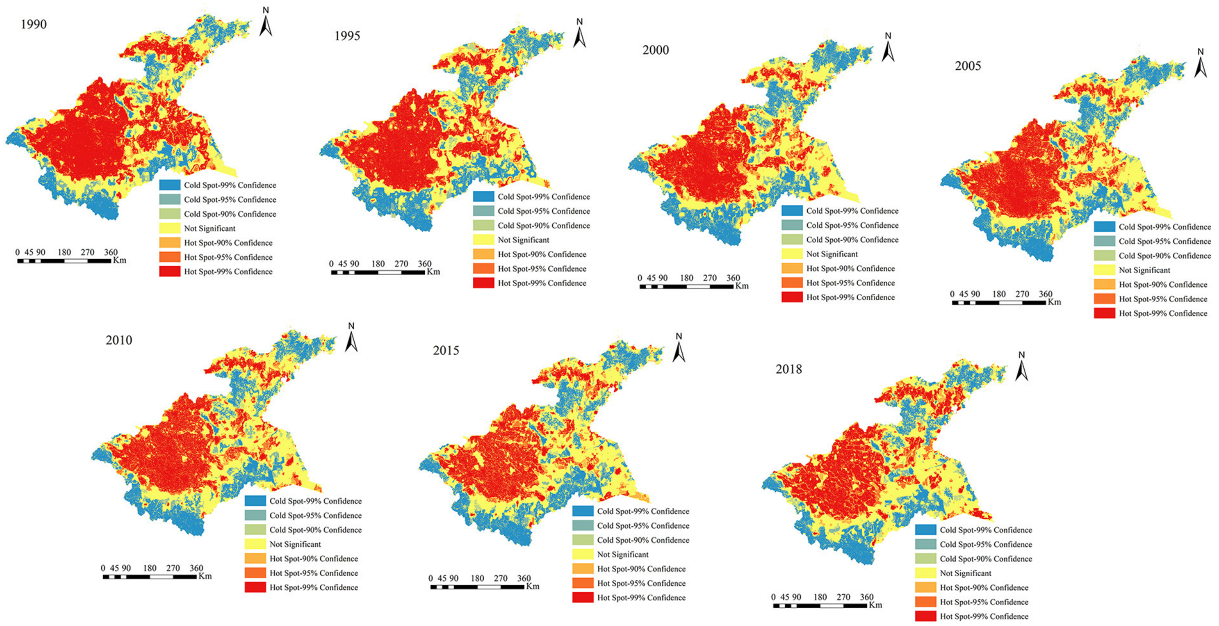

FIGURE 8
Migration of centroids of human disturbances over the 1990–2018 period.

method, with the support of big data, to more accurately quantify and monitor human disturbances, thereby providing some degree of prediction capability for the future change of human disturbances.

7. Conclusions

In this study, three components of human disturbances were quantified, namely land use naturalness transformation, natural resource consumption, and pollutant emissions, using the land use naturalness index (LNI), resource consumption index (RCI), and pollution emission index (PEI). The intensities of human disturbances were calculated using the HDI method by combining RS, GIS, and multisource data. The HDI method is based on the spatiotemporal variabilities of input parameters, achieving more convenient and comprehensive dynamic monitoring and evaluation of human disturbances. Moreover, this method is applicable to research areas of different scales. The results of this demonstrated the effectiveness and applicability of the HDI method to quantify human disturbances in the Huaihe River Basin, showing good results. The results of this study showed gradual increases and decreases in human disturbances in the Huaihe River Basin in the 1990–2005 and 2010–2018 periods, respectively. The intensity and spatial distribution of human disturbances were closely related to the urbanization process and intensities of resource exploitation and utilization, which are mainly determined through government strategies and economic development. In the early period (1990–2005), agricultural and industrial activities were the main causes of the higher intensity of regional human disturbances in the midstream and Yishusihe and Shandong Peninsula than that in other areas. Whereas the results showed decreases in the intensity of human disturbances in arable and industrial lands in the 2010–2018 period as a result of the implementation of several regional programs, such as Returning Farmland to Forest and Energy Saving and Emission Reduction programs. However, rapid population growth and accelerated urbanization resulted in changes in the structure of human activities, substantially increasing the intensity of human disturbances in urban areas. In general, the intensity of regional human disturbances can be effectively reduced by improving the energy structure and utilization, as well as minimizing pollutant emissions. In addition, maintaining grassland, forest land, and water body areas plays an important role in sustaining ecosystem naturalness and reducing the intensity of regional human disturbances. The results of the present study provide a scientific basis for ensuring effective environmental protection of the Huaihe River Basin, as well as a novel method for quantifying human disturbances.

Data availability statement

The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding authors.

Author contributions

HW and YZ designed the research. HW drafted the manuscript. MZ, CW, and KW analyzed the data and prepared figures. YZ and WS discussed the results and revised the manuscript. All authors contributed to the article and approved the submitted version.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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Evaluating the accessibility of public service facilities to tourists and residents in island destinations: Evidence from the Changhai County

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With the increasing diversity of social groups, public service facilities need to meet the diverse needs of different groups. However, there is still a lack of in-depth research evaluating urban public service facilities for diverse groups. Therefore, this paper use Kernel density spatial analysis method to delimits the research area based on data on the temporal and spatial behavior of islanders and tourists, and use urban network analysis (UNA) method to evaluates the public service facilities of the spatially overlapping area from the aspects of facility accessibility and availability. The study shows that (1) the spatial dislocation between facilities and residential places is serious, which leads to redundant construction or a lack of configuration of facilities in some areas. (2) The public service facilities in some areas can be used by tourists and residents to a similar degree, the number of facilities accessible to residents and tourists within a certain distance is not much different, and the configuration of facilities is relatively reasonable. (3) The overall configuration of infrastructure is biased toward residents, but the configuration of facilities in some areas can also reflect group fairness. The results indicate that the public facilities have a tendency to serve residents, and the results can give some suggestions for public facilities configuration to build a human-oriented island.

KEYWORDS

island tourism, public service facilities, tourists and residents, urban network analysis (UNA), Changhai County

1. Introduction

As a carrier of public services for residents' daily lives (1), public service facilities should be guided by the principle of fairness so that all residents within the scope of facility services can enjoy public services equally.

Public service facilities include education, medical care, culture and sports, commercial services, municipal public utilities and other facilities (2), and they are the material guarantee for improving the quality of life of residents and have strong external effects. In the context of the transformation of the main social contradictions in the new era of China, residents' demand for public service facilities is no longer limited to survival needs. Rather, it has gradually turned to development and enjoyment needs (3). Therefore, meeting the diverse needs of residents and realizing the equalization and precise allocation of public service facilities are one of the requirements of new urbanization construction (4). Furthermore, with the development of cities or tourist destinations, the heterogeneity of social groups increases, and societies become more diverse. The configuration of public service facilities should be more in line with individual needs and should gradually be realized from regional equality to spatial equality and social equality, rooted in the people-oriented planning concept of new urbanization construction.

In recent years, with the development of tourism, islands or other place have gradually become the consumption space of urban society (5). Many scholars attach importance to island tourism (6), ice-snow tourism (7), rural tourism (8) and ecotourism research (9). The island tourism research, on the one hand, scholars at home and abroad focuses on tourism product development and marketing (10, 11). On the other hand, pay attention to the relationship between island tourism and ecological environment, society, economy, etc. Including the impact of economic development on tourism (12), and also include the impact of island tourism on the ecological environment (13), society and economy (14–16), such as the impact of tourists' behavior on the island environment (17), and the impact of island facilities on tourism activities. For example, the authors analyze that the improvement of island public service facilities can significantly increase the number of tourists (18). In general, there are relatively few studies on island public facilities at present, but from the existing studies, improving public service facilities is more important for island tourism, and many islands in the world are almost facing the same problem, that is, tourists are far higher than local residents in the peak tourism season, leading to the island infrastructure can not meet the actual needs. For example, scholars have analyzed analyzed the problems of sewage facilities and proposal sustainable segment management strategies on the islands in Croatia (19). In fact, in tourism destinations, as the tourism space conflict between local residents and tourists about the possession of resources with the nature of public goods often occurs (20), island public service facilities also belong to resources with strong public attributes, so the research on the allocation of public service facilities for island tourism destinations is of great significance to alleviate tourism space conflict.

In fact, the research on public service facilities began as early as the second half of the 19th century. With the proposal of the location theory of public service facilities (21), scholars outside China carried out in-depth research on the location selection of public service facilities (22), facility accessibility (23), and spatial fairness and its social and economic benefits (24, 25). At the end of the 20th century, research on the configuration of public service facilities that was oriented toward determining the actual layout of a city became a research hot spot in China. Scholars first paid attention to the spatial layout and location of public service facilities (26) and then carried out research on the characteristics of the spatial layout and the accessibility of public service facilities (27–29), social differentiation and satisfaction with public service facilities (30, 31). With the development of geographic information system technology and attention to social equity, research on the accessibility of public service facilities has become a hot topic. Scholars outside China have carried out empirical research on the accessibility of schools and hospitals, the concept of accessibility (32, 33) and the influencing factors of accessibility (34, 35). Chinese scholars have mostly focused on cities, counties and other regions and conducted accessibility evaluation research on parks, green spaces, educational facilities, or medical facilities (36, 37). Based on existing studies, current research outside China has entered the stage of social equity, and most Chinese research is still in the stage of spatial equity. Scholars in China and elsewhere have conducted research on the accessibility of public service facilities and the fairness of facility allocation.

There have been many research results, but there are still shortcomings: ① From the perspective of research objects there are few studies on evaluating the accessibility of different types of public service facilities, such as shopping and catering facilities, and the research objects are mostly urban or rural residents. That is, the research objects are a single group or are based only on age, occupation, or income to divide people into different categories. The utilization of public service facilities in existing research changes little over the course of a year. There are few comparative studies on the fairness of different activity groups in tourist destinations. ② From the perspective of the research area studies take cities, counties, and streets as homogeneous units. However, the optimal allocation of public service facilities is affected by factors such as the area type, grade and population, and it needs to undergo different stages to achieve social equity and universal sharing. Therefore, under the guidance of the people-oriented principle, the optimal configuration of public service facilities should start from common needs and rigid needs with a high degree of urgency, then the local optimization of elastic needs, and finally individual needs (38). The existing research does not consider the priority of public service facilities configuration, which is inappropriate.

In summary, with the heterogeneity of social groups increasing, society become more diverse. This paper takes island tourism destination as the research object, because the tourist destinations have obvious slow and peak seasons, and there are obvious differences in the main activity groups during the year. Different from cities or villages, in tourist destinations, the configuration of public service facilities needs to not only consider the daily needs of local residents but also meet the needs of tourists. In addition, the large difference in the number of residents and tourists in tourist destinations has led to a surge in the demand for facilities during the peak tourist season. With the departure of tourists, the idleness of facilities has also become a problem that urgently needs to be solved. Therefore, for tourist destinations, the allocation of public service facilities needs to consider group fairness and allocation efficiency (39). Hence, assessing the allocation of infrastructure is conducive to meeting the needs of diverse activity groups, effectively responding to the daily needs of residents as well as the needs of tourists and improving the group equity and the efficiency of facility allocation as much as possible. Therefore, choosing the island tourism destination as the research area can better reveal the fairness and efficiency problems reflected in the public service facility configuration under the background of social group diversification, which is the first innovation of this paper. At the same time, this study can make suggestions on the allocation of public service facilities through the study of infrastructure evaluation, and will also provide experience for other regions similar to island tourism destinations. On the other hand, different from the existing research, this paper based on judging the overlapping area of the behavioral spaces of tourists and residents, take facilities with high common demand as the research object and evaluates facility accessibility, which is the configuration process of public service facilities from common needs to personalized needs, and this is the second innovation of this paper. The questions of interest are as follows: (1) What is the current spatial configuration of public service facilities in the study area? (2) What is the availability of catering and shopping facilities for residents and tourists? (3) What is the accessibility of shopping and catering facilities to residents and tourists? What is the difference? This study expects to propose suggestions on spatial optimization for this area.

2. Research materials and methodologies

2.1. Study area

The area of this study is Changhai County (38°55′-39°18′N, 122°13′-123°17′E), which is situated in northeastern China. It is a typical tourist destination with a clear off-peak season. The tourist season is from May to October every year. The main activity groups on the island include residents and tourists. November to April of the following year is the tourist off-season, tourists and related practitioners leave, and residents constitute the main activity group on the island. There is a large gap between the number of tourists and residents. According to the 2019 "Changhai Statistical Yearbook," the total number of tourists in Changhai County reached 1.34 million, which was 19 times the total number of local residents in that year. There are obvious differences in the main activity groups in the case area over the course of a year, and the allocation of public service facilities should take into account the issue of group fairness and the issue of allocation efficiency.

This paper uses activity log survey data from island residents and tourists in January and July 2019 and ArcGIS 10.2 software to perform kernel density estimation of the temporal and spatial behavioral activities of residents and tourists to show the spatial range of their behaviors. The behavioral space of residents represents the area where public service facilities may be used in the tourist off-season, and the behavioral space of tourists represents where public service facilities may be used in the peak season. The reason is that the peak season is from May to October every year, and the number of tourists far exceeds the number of residents. Therefore, the behavior space generated by tourist activities can represent the area where the public service facilities can be used during the peak season, while the tourism off-season is from November to April of the next year, and almost no tourists appear. The behavior space formed by residents' activities is the area where the public service facilities can be used during the off-season. As shown in Figure 1, most of the behavioral spaces of residents and tourists are scattered, and only two parts of the area overlap. Therefore, the overlapping area of the behavioral spaces of residents and tourists is the research area, and priority should be given to the optimal configuration of public service facilities in this area.

2.2. Data source and processing

2.2.1. Questionnaire survey data

From January 24 to 27 and from July 27 to August 1, 2019, the research team conducted a questionnaire survey on the residents and tourists of Dachangshan Island, Xiaochangshan Island and Guanglu Island. The survey content included personal socioeconomic attributes, activity itineraries and other information. A total of 310 and 315 questionnaires were distributed to residents and tourists, respectively, and 285 and 303 were recovered, respectively.

2.2.2. Data on public service facilities

The overlapping area of the behavioral spaces of residents and tourists is the space shared by the two groups. The degree of infrastructure sharing in the region is higher than that in other regions, but not all public service facilities in the region have the same degree of sharing. The degree of sharing of facilities that can meet some of the common needs of tourists and residents is the highest. In existing research on the degree of sharing, Ta and other scholars conducted research on the spatial isolation of Shanghai suburban residents by constructing the spatial sharing degree index (40). Sun and other scholars took

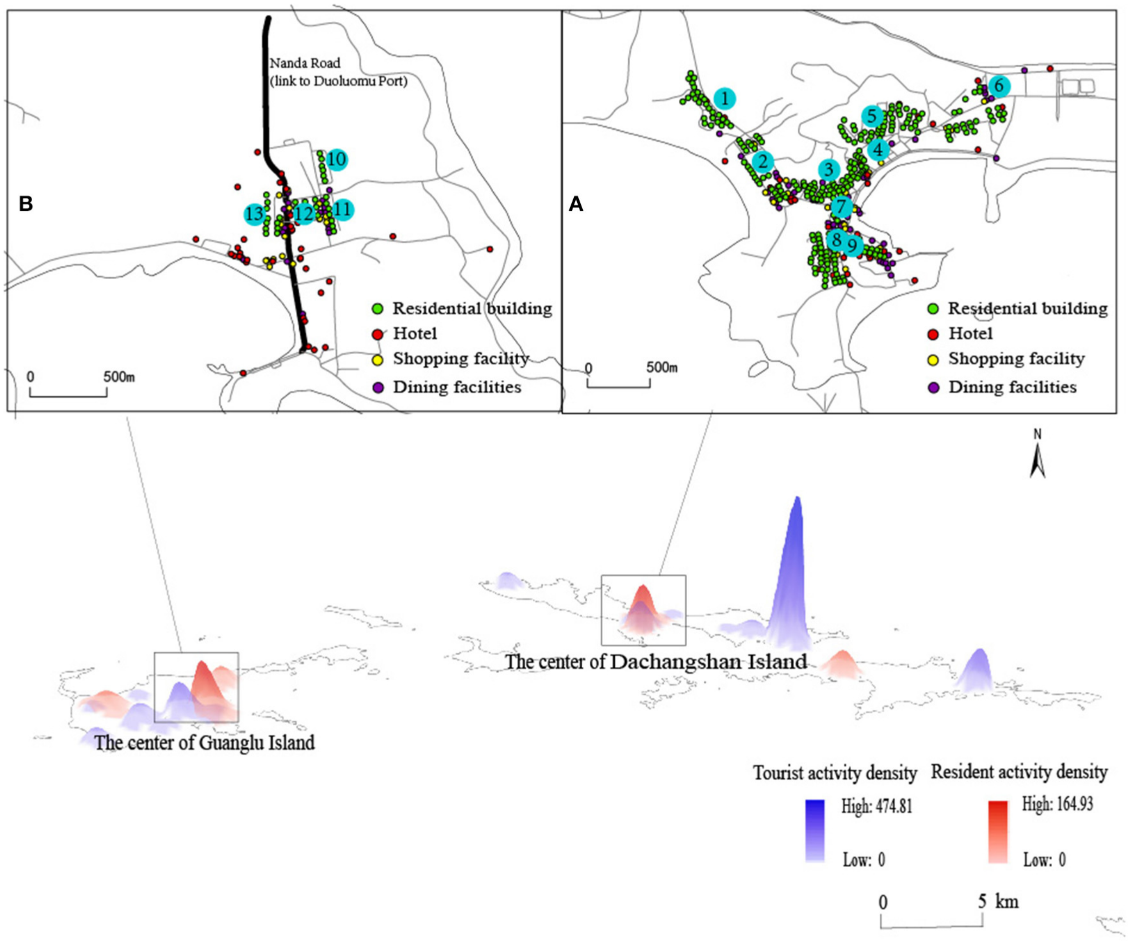

FIGURE 1
Location of the study area. **(A)** The center of the Dachangshan island. **(B)** The center of the Guanglu island. The numbers 1-13 represent the mainly places in the study area.

the social life circle division as an example (41). In the former, the sharing index was determined by the number of different groups existing in the research area. The higher the number of groups is, the higher the sharing degree. In the latter, the research area was jointly utilized by multiple communities. Both studies conducted research from the perspective of spatial sharing but ignored the situation of facility sharing in the same space, that is, a situation where the same infrastructure is used by different groups. Tourists and residents are part of the unity of society and are natural persons. The tourism process includes activities such as eating, lodging, traveling, playing, shopping, etc. Eating is one of the common activities of tourists and residents. In addition, shopping facilities such as shops and convenience stores are shared infrastructures for residents and tourists. Then this paper selects catering facilities and shopping facilities with a high degree of sharing in the overlapping area as the research objects. Through the open platforms of Baidu Map and AutoNavi Map, the catering facilities, shopping facilities, tourist accommodation facilities such as fishing village restaurants and hotels, residential buildings and road network data of the study area were obtained. A total of 76 fishing village restaurants, 61 shopping facilities such as shops or supermarkets, 140 catering facilities, and 269 residential buildings were obtained. The distribution of facilities is shown in Figure 2. Area A is the center of Dachangshan Island, and area B is the center of Guanglu Island.

2.3. Methodologies

This paper installs the urban network analysis tool (Urban Network Analysis (UNA) Toolbox plug) in Rhino 6.13 software and uses the reach function of the tool for analysis. The advantage of this analysis tool is that actual roads are regarded as a network, a facility is regarded as a node, and, rather than

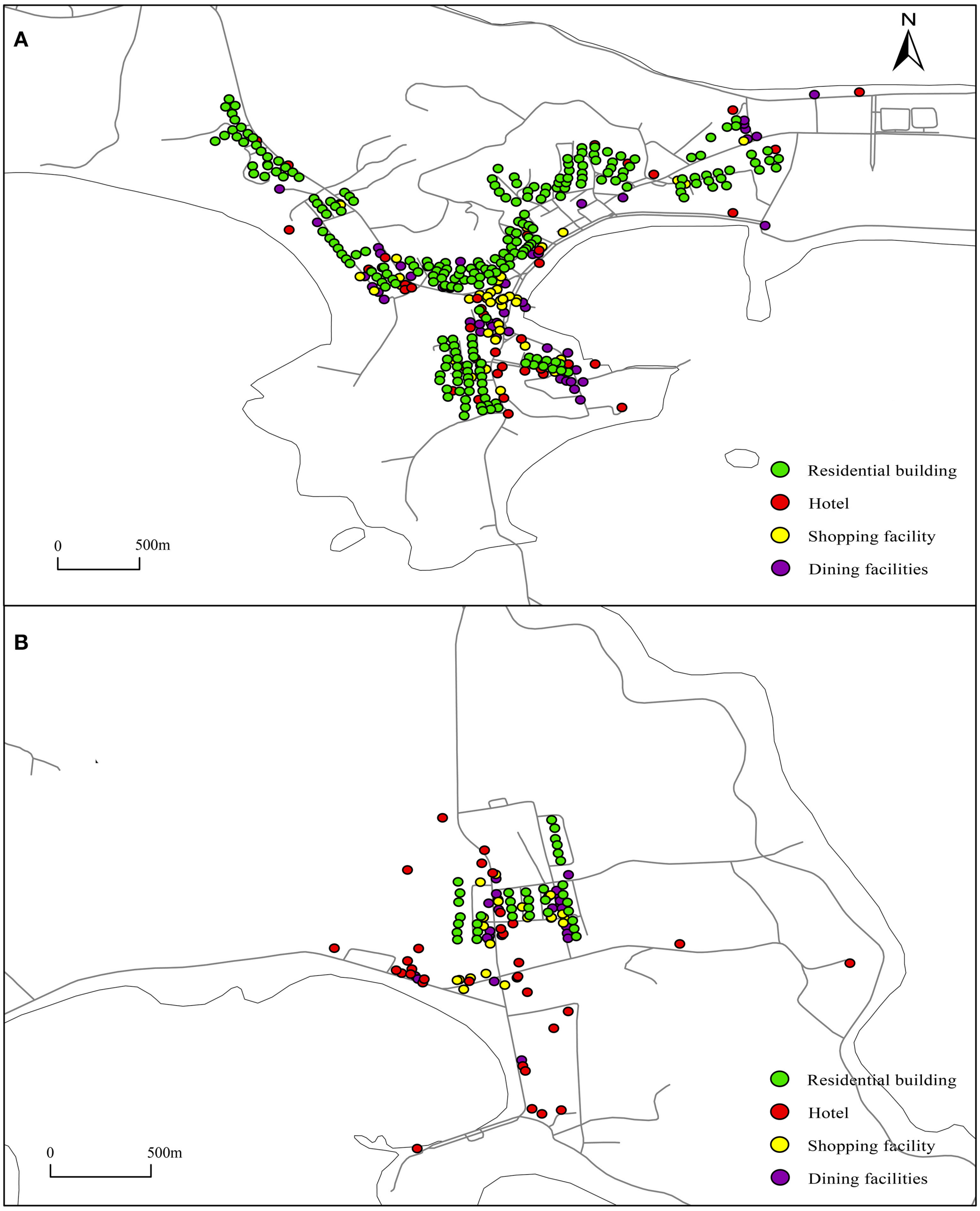

FIGURE 2
Distribution of facilities in the study area. **(A, B)** The results are counted according to the number of the facilities, including catering and shopping facilities, hotel and residential buildings.

using the activity radius as a circle to calculate the travel distance, the distance of the road network is used as the actual activity distance of an individual, which is closer to reality (42, 43). Through the reach index (Reach) in the UNA tool, the number of target points reachable from the starting point under the condition of the shortest path is calculated. In other words, the number of accessible facilities within a certain distance is calculated using residential building as the starting point. Additionally, the number of accessible residential buildings is calculated using the facilities as a starting point. The number of reachable target points is assigned as a weight to the starting point and exported to ArcGIS for spatial display. The specific formula is as follows:

$$R[i]^r = \sum\nolimits_{j \in G-\{i\}, d[i,j] \leq r} w[j] \ldots\ldots \quad (1)$$

In the formula, $R[i]^r$ represents the number from starting point i to destination j within distance r and G is the transportation network in the study area. $d[i,j]$ represents the shortest distance from origin i to destination j. $w[j]$ represents the weight of destination point j. Referring to existing research, the range of the community living circle is usually set as the range within 15 min that residents can reach by walking, that is, the range of 800 m from their homes (44). Meanwhile, 800 m corresponding to 10 min of walking is considered as an acceptable walking distance (45).Therefore, this paper sets distance r to 800 m. By using the Reach function, the needs and accessibility of residents and tourists to share public service facilities are evaluated based on two aspects, facility availability and facility accessibility. Taking catering facilities as an example, the availability of facilities refers to calculating the number of residential areas, fishing village restaurants or hotels that can be served by catering facilities within a certain range. It reflects the supply of catering facilities. Considering the distribution and agglomeration of catering facilities, if the distribution of catering facilities is sparse and there are residential buildings that can serve residential buildings or fishing village restaurants and hotels, the value is extremely large. This indicates that the configuration of catering facilities in this area is lacking and should be increased. Suppose that certain catering facilities are concentrated and that there are few residential buildings or fishing village restaurants and hotels that can serve them. This indicates that there is redundant construction of catering facilities in the place and that the number of catering facilities should be reduced. Facility accessibility refers to the calculation of the number of catering facilities that can be reached within a certain range in residential areas, fishing village restaurants and hotels. It reflects the availability of catering facilities. The number of catering and shopping facilities that tourists and residents can reach within a certain range from the accommodation point is calculated, and whether the catering and shopping facilities in the study area focus on residents or tourists is evaluated in terms of the number of facilities that can be reached, reflecting group fairness. In addition, comparing the number of accessible facilities between regions can reflect the spatial fairness of facilities in different regions, making it possible to propose suggestions for the optimization of the facility space in the region.

3. Results

3.1. Spatial patterns of service facilities

The reach function of the UNA tool is used to analyze the agglomeration of facilities. Both catering and shopping facilities are set as the starting and ending points, road data are imported, and the number of facilities that can be reached from other facilities within 800 m is calculated. The greater the number of accessible facilities is, the higher the concentration of facilities. As shown in Figure 3A, the facilities in area A have a T-shaped distribution, and the facilities in area B have three clusters (3B). In general, the degree of agglomeration of facilities in area B is higher than that in area A (Figure 3). Dachangshan Island has areas with a lower degree of agglomeration of facilities, while the degree of agglomeration of facilities in the center of Guanglu Island is not much different.

3.2. Degree of facility availability

To analyze the utilization of dining facilities and shopping facilities in the overlapping area of visitor and resident activity spaces, catering facilities and shopping facilities were set as the starting point, tourist accommodation facilities such as fishing village restaurants and hotels and residential buildings were set as the ending point, the road network was imported, the reach index was calculated, and weights were assigned to each catering facility and shopping facility. The results are shown in Figures 4, 5.

3.2.1. Degree to which catering facilities can be used by tourists

As shown in Figure 4A, within a range of 800 m, the catering facilities in area A that can be used by tourists from high to low: The People's Hospital of Changhai (about 19), the area from the south of Changhai Mall to the north of Changhai Market (within 6–15), the Sanpanian Community(within 5–6), the area from the People's Government of Dachangshan Island to Bilang Street (<5), The latter two areas are considered to be unreasonably configured due to the large distribution of catering facilities but low availability. The area with the highest degree of utilization of catering facilities by other tourists' accommodation facilities in Guanglu Island Town Center is located between the Hongzhi Community and Jinhai Garden, with ∼20 catering facilities (Figure 4B). The Nanda Line is a north-south main road that runs through the center of Guanglu Island town. The north side is mainly connected to Duoluomu Port. It is the main transportation line for tourists to enter and leave the island. There are many accommodation facilities along the line. Therefore, this area serves a small number of residents but a large number of tourists.

3.2.2. Degree to which catering facilities can be used by residents

As shown in Figure 4A, the catering facilities can be used by residents within 800 m from high to low: the People's Government of Dachangshan Island (Labaichuan Store, can serve for 88 residential building), the People's Hospital of Changhai County (about 35), the Sanpanian Community, (within 14–28), the area between Changhai Mall and Changhai Market (within 9–19), the area from the People's Government of Dachangshan Island to Bilang Street (<9). First, the point with the highest degree of utilization is Dongshan District on the north side. The number of residential buildings near the

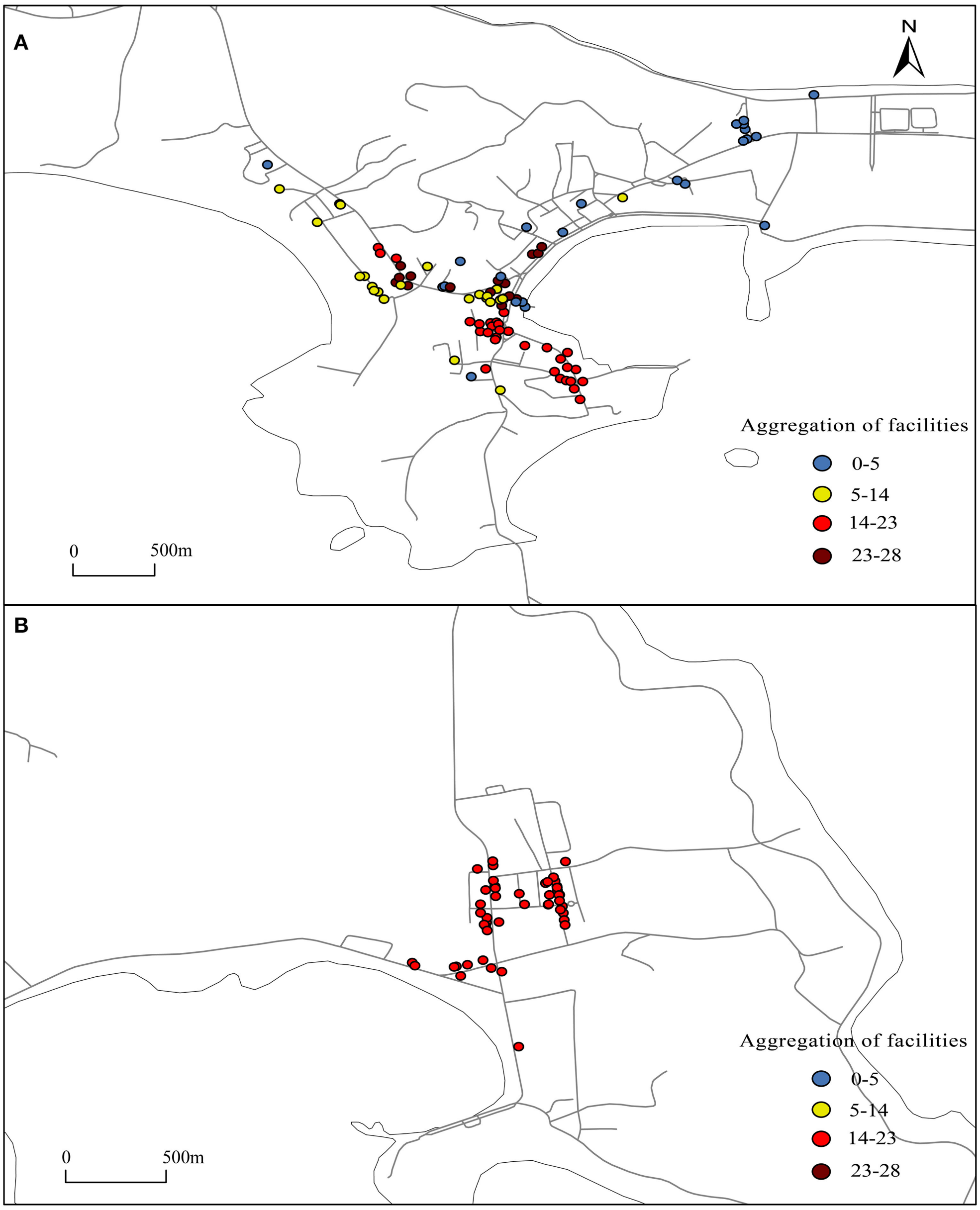

FIGURE 3
Facility agglomeration in the study area. **(A, B)** Setting both catering and shopping facilities as the starting and ending points, import the road data, and calculate the number of facilities that can be reached from other facilities within 800 meters. The greater the number of accessible facilities is, the higher the concentration of facilities.

store is high, but the number of dining facilities is minimal. This finding indicates that the area where the point located is a catering facility demand area and that catering facilities can be appropriately configured to provide services for residents and relieve the pressure of catering demand at this point. Secondly, the area with the highest degree of utilization, that is, the area where catering facilities can be utilized by tourists. The catering facilities in this area, whether for tourists or residents, are the highest degree of utilization, indicating that catering facilities are reasonably configured. Finally, there are two areas where catering facilities are constructed repeatedly, that is, the number of catering facilities is large, but the degree of serving tourists and residents is low. There are ∼35 catering facilities in the center of Guanglu Island that can serve tourists. The catering facilities between residential buildings can be highly utilized by residents; the catering facilities along the road can be highly utilized by tourists (Figure 4B).

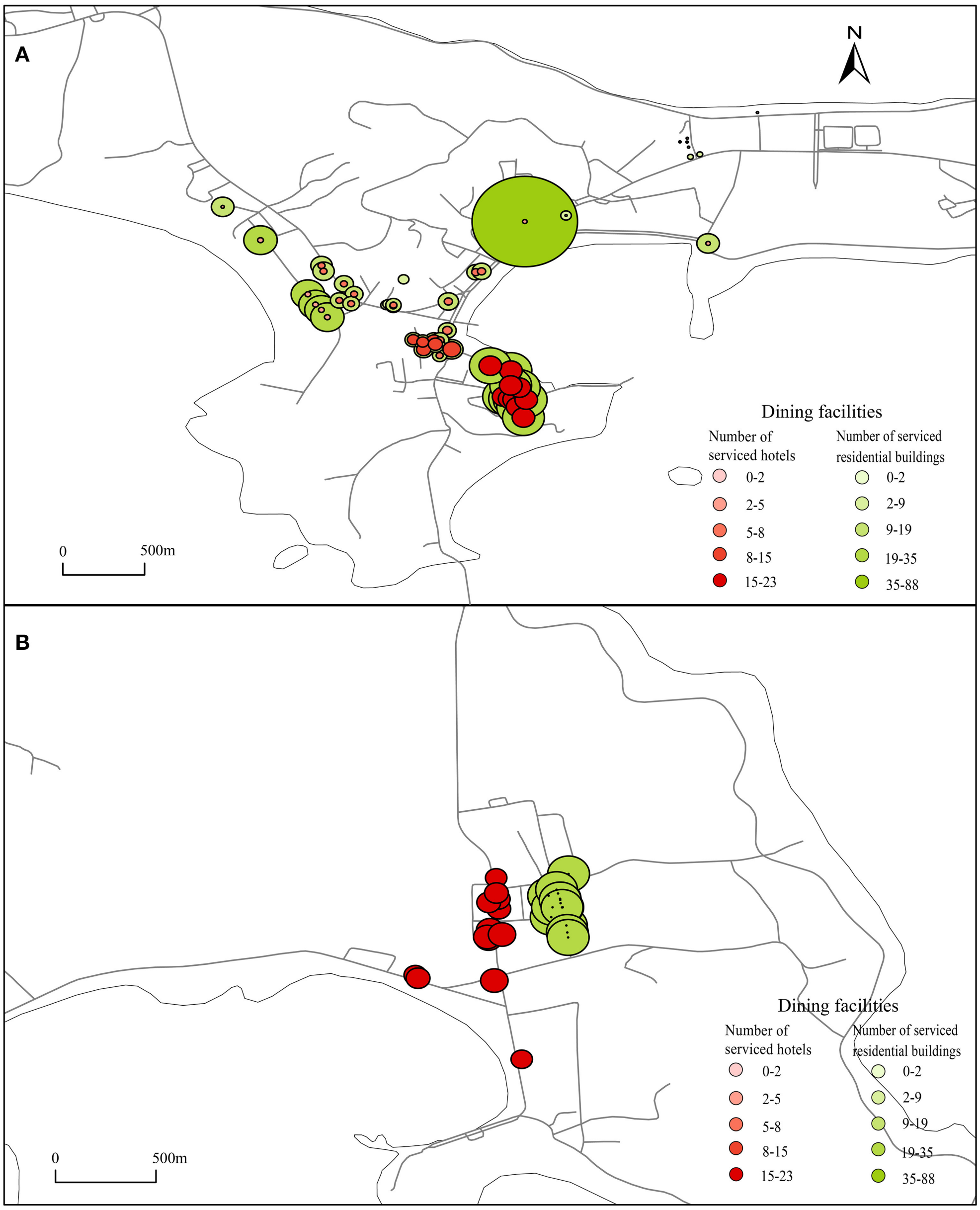

FIGURE 4
Dining facilities serving tourists. **(A, B)** Dining facilities were set as the starting point, fishing village restaurants, hotels and residential buildings were set as the ending point, import the road network, and calculate the reach index, then the reach index were assigned to each dining facilities.

3.2.3. Degree to which shopping facilities can be used by tourists

As shown in Figure 5A, the shopping facilities in the area southeast of the People's Hospital of Changhai have the highest level of service for tourists. Additionally, this area is also the area with the highest level of catering facilities serving tourists. This finding shows that tourists can easily get catering services and shopping services here. Secondly, the Changhai Mall is the area with the most concentrated shopping facilities in Dachangshan Island, but the availability of facilities is low, have redundant construction of shopping facilities when only serving tourists. Finally, the shopping facilities in the areas east, west and north of Changhai Mall serve tourists less well, because there are fewer shopping facilities. The area with the highest degree of utilization of shopping facilities in Guanglu Island Center is located near the intersection of the Nanda Line and Dongxu Line (Figure 5B). This area can serve 23 hotels, while a single shopping facility on Dachangshan Island can serve up to 19 hotels.

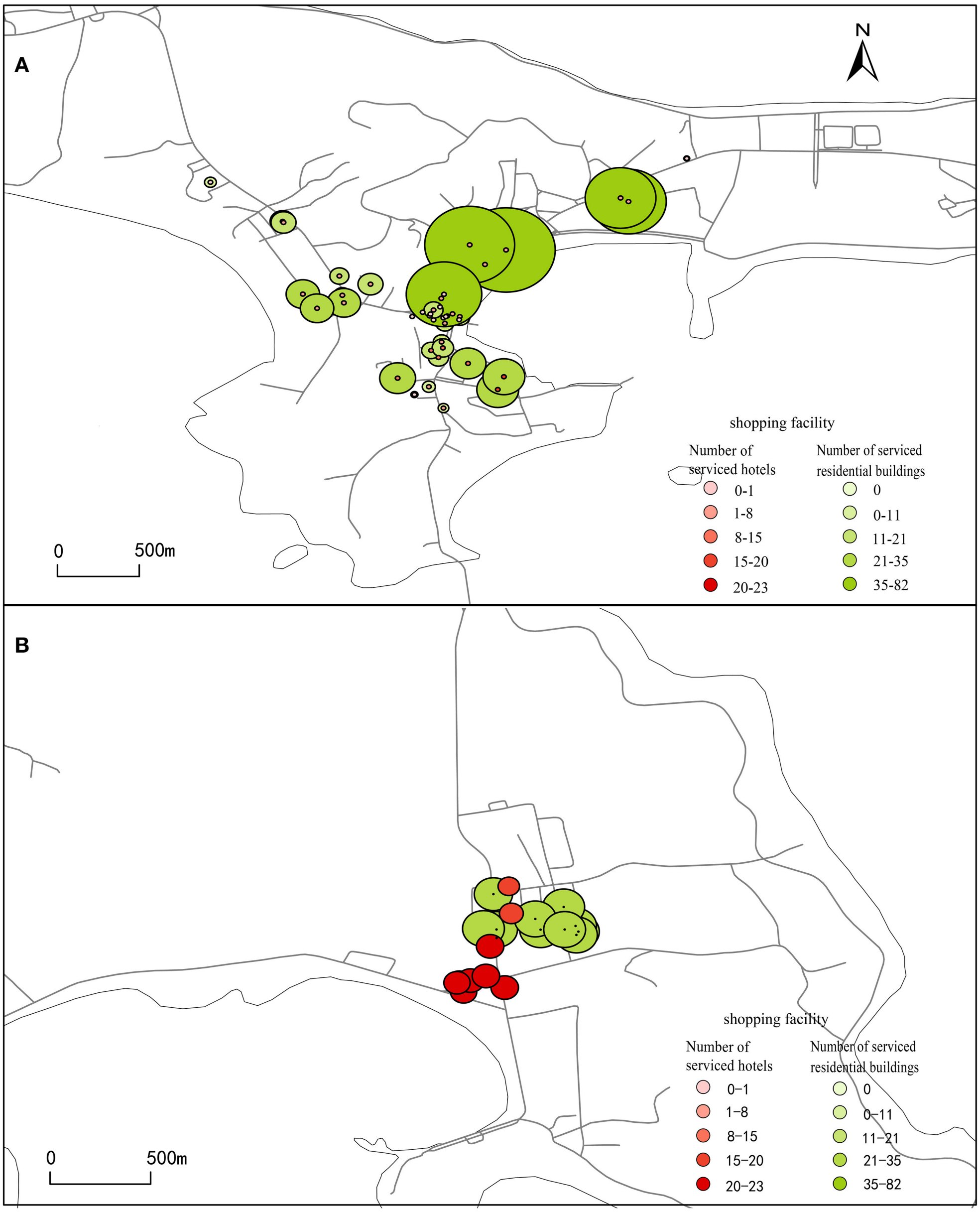

FIGURE 5
Shopping facilities serving tourists. **(A, B)** Shopping facilities were set as the starting point, fishing village restaurants, hotels and residential buildings were set as the ending point, import the road network, and calculate the reach index, then the reach index were assigned to each shopping facilities.

3.2.4. Degree to which shopping facilities can be used by residents

Through the analysis of Figure 5A: First, the public service facilities in two regions are unreasonable. One region has too many facilities and is idle, while the other region has insufficient facilities. Second, there is still an area with reasonable allocation of public service facilities. he shopping facilities in area A can serve up to 82 residential buildings, which is close to the maximum number of residential buildings served by catering facilities. Additionally, It is also located near the People's Government of Changhai County. It means that there is a greater demand for dining facilities and shopping facilities. The shopping facilities in the Changhai Mall are not highly usable by tourists and residents, and there is redundant construction of catering facilities and shopping facilities. However, the People's Government of Changhai County have high demand for catering facilities and shopping facilities. Thus, the shopping and catering facilities near Changhai Mall can be transferred to this area. The vicinity of the People's Hospital of Changhai is an area with a large number of catering and shopping facilities serving residents and tourists. Not only can provide catering and shopping services for tourists during the tourist season but also can service residents during the tourist off-season. It has become an area with a reasonable configuration of facilities in the center of Dachangshan Island. Figure 5B shows that the shopping facilities in Guangludao Center can be most utilized by residents is located between the buildings.

3.3. Facilities accessible to residents and tourists

Using the UNA analysis tool, tourist accommodation facilities and residential buildings were set as the starting point, dining facilities and shopping facilities were set as the ending point, and then, the road network was imported. The number of shopping and dining facilities that can be reached from residential buildings and tourist accommodations within a range of 800 m was calculated, and the results are shown in Figures 6–9.

3.3.1. Catering facilities accessible to tourists

As shown in Figure 6A, the areas where tourists in area A can reach the highest number of catering facilities are the area between the Changhai Shopping Center and Changhai Market as well as the area southeast of the People's Hospital of Changhai. The number of accessible catering facilities is ∼16, which is the same as the number of catering facilities accessible to residents in this area. This finding indicates that the configuration of catering facilities in this area can reflect group fairness. The points where tourists can reach the most catering facilities within 800 m of Guanglu Island Town Center are located along the Nanda Line and Dongxu Line, and the number of accessible catering facilities is between 11 and 14 (Figure 6B). Combined with the facilities accessible to residents in Figure 7B, the number of catering facilities accessible to residential buildings is 14. This finding indicates that the layout of catering facilities in the center of Guangludao town is relatively fair and slightly biased toward residents.

3.3.2. Catering facilities accessible to residents

As shown in Figure 7A, on the east side of the People's Hospital of Changhai, there are a large number of catering facilities accessible to residential buildings, and the catering facilities can be used by residential buildings to a high degree. For residential buildings such as Sanpanian Community, the number of catering facilities available within 800 m is lower, but there are more residential buildings. Within 800 m, the number of catering facilities that residents can reach is small, the number of services that a single facility can serve is as high as 88, and facilities are in short supply. From the Figure 7B, the number of catering facilities within 800 m of each residential building on Guanglu Island is 14, indicating that the layout of catering facilities in the center of Guanglu Island is fair for each residential building.

3.3.3. Shopping facilities accessible to tourists

Figure 9A shows that the configuration of shopping facilities in the center of Dachangshan Island is strongly biased toward residents. The maximum number of shopping facilities that residents can walk to and reach is 16, but the maximum number of shopping facilities that tourists can reach is only 12 (Figure 8A), located in Sanpanian Community. In addition, the number of accessible shopping facilities in the area south of Changhai Mall is ∼7. That means there is some kind of obstacle in the area that hinders passage, resulting in a decrease in the number of accessible facilities. Visitors to Guanglu Island have fewer accessible shopping facilities than dining facilities. The number of accessible dining facilities is ∼14 (Figure 6B), and the number of accessible shopping facilities is ∼9 (Figure 8B). These findings indicate that there is little difference in the number of dining and shopping facilities available to tourists.

3.3.4. Shopping facilities accessible to residents

As shown in Figure 9A, some residential buildings in the Sanpanian Community have 24-26 shopping facilities within 800 m. At the same time, the centralized distribution of shopping facilities also affects the number of shopping facilities accessible to residential buildings in the area south of Changhai Mall, reaching between 8 and 20. There is a large difference in the number of accessible dining facilities and shopping facilities in the Dongshan Community. The number of catering facilities accessible to the residential buildings in this area is ∼1, but the number of accessible shopping facilities is between 6 and 14, indicating that there are redundant shopping and catering facilities on the east and west sides that should be appropriately transferred to this area to meet the needs of residents. As shown in Figure 9B, a single residential building in the center of Guanglu Island has 14 accessible catering facilities and ∼20 accessible shopping facilities. The number of accessible shopping facilities is higher than the number of accessible catering facilities. The reason is residents mainly eat at home; thus, their daily shopping needs are slightly higher than their catering needs, indicating that in terms of the configuration, the ratio of catering facilities to shopping facilities in the study area is in line with the actual situation.

4. Discussion and conclusion

4.1. Discussion

In this paper, the spatial and temporal behavior of differentiated groups is used to delineate the overlapping

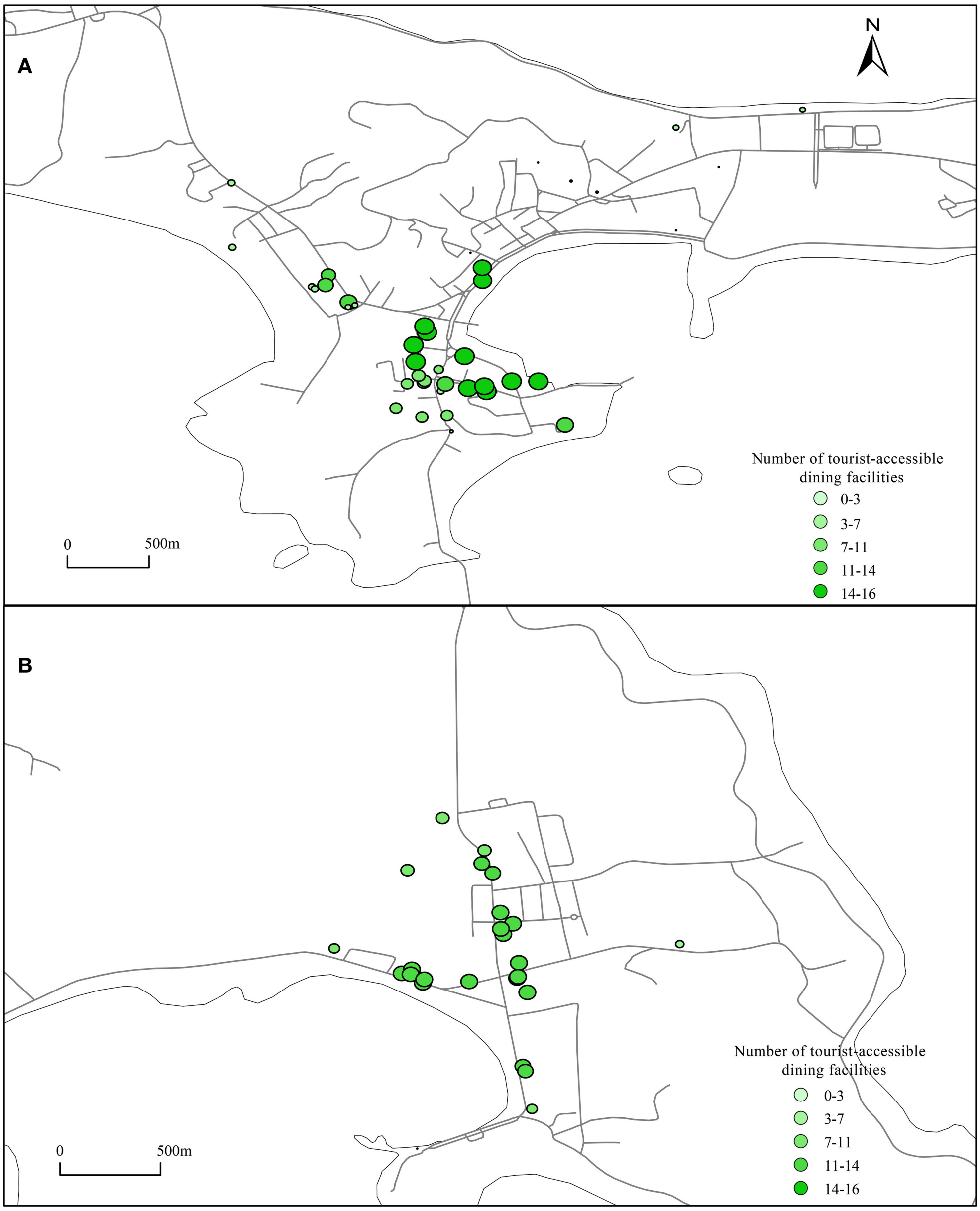

FIGURE 6
Catering facilities accessible to tourists. **(A, B)** Using the UNA analysis tool, set the tourist accommodation facilities as the starting point, catering facilities as the ending point, import the road network, and calculate the number of catering facilities that can be reached from the tourist accommodations within a range of 800 meters.

area of the behavioral space. Selecting catering and shopping facilities with a high degree of sharing and evaluating the configuration of facilities from the perspective of accessibility and availability hold practical significance for the optimal configuration of island public service facilities. In the tourist off-season, residents constitute the main activity group, and in the peak tourist season, there are a large number of tourists. The facility configuration in the overlapping area of the behavioral space needs to consider not only the issue of group fairness but also the issue of configuration efficiency. This paper analyzes the accessibility of public service facilities in the context of multiple groups of tourist destinations.

(1) Based on the availability of facilities (Table 1), there is a serious mismatch between the spatial distribution of facilities and residential places in the study area. This mismatch includes not only the mismatch in the spatial distribution of shopping and dining facilities and tourist residential places but also the dislocation in the spatial distribution of residential buildings. Due to the locationally inappropriate distribution

FIGURE 7
Catering facilities accessible to residents. **(A, B)** Using the UNA analysis tool, set the residential buildings as the starting point, catering facilities as the ending point, import the road network, and calculate the number of catering facilities that can be reached from residential buildings within a range of 800 meters.

of facilities and accommodation, some areas have redundant construction of facilities or a lack of configuration. Differently, there are few catering and shopping facilities near the People's Government of Changhai County, but the availability of catering and shopping facilities for residents is high. These findings indicate that the configuration of shopping and catering facilities here is unreasonable for residents and should be increased. At the same time, the degree of utilization by tourists is low, which shows that the configuration of catering and shopping facilities has little impact on tourists and that the configuration of facilities here can consider only the needs of residents.

(2) Based on the accessibility of facilities, the configuration of catering and shopping facilities in the study area generally shows a tendency to serve residents, with more facilities accessible to residents than to tourists. The main reason is that these facilities serve residents over the course of the whole year and serve tourists only in the peak tourist season. However, in some areas, the configuration of catering facilities is fair to tourists and residents and can reflect group equity. These facilities are mainly

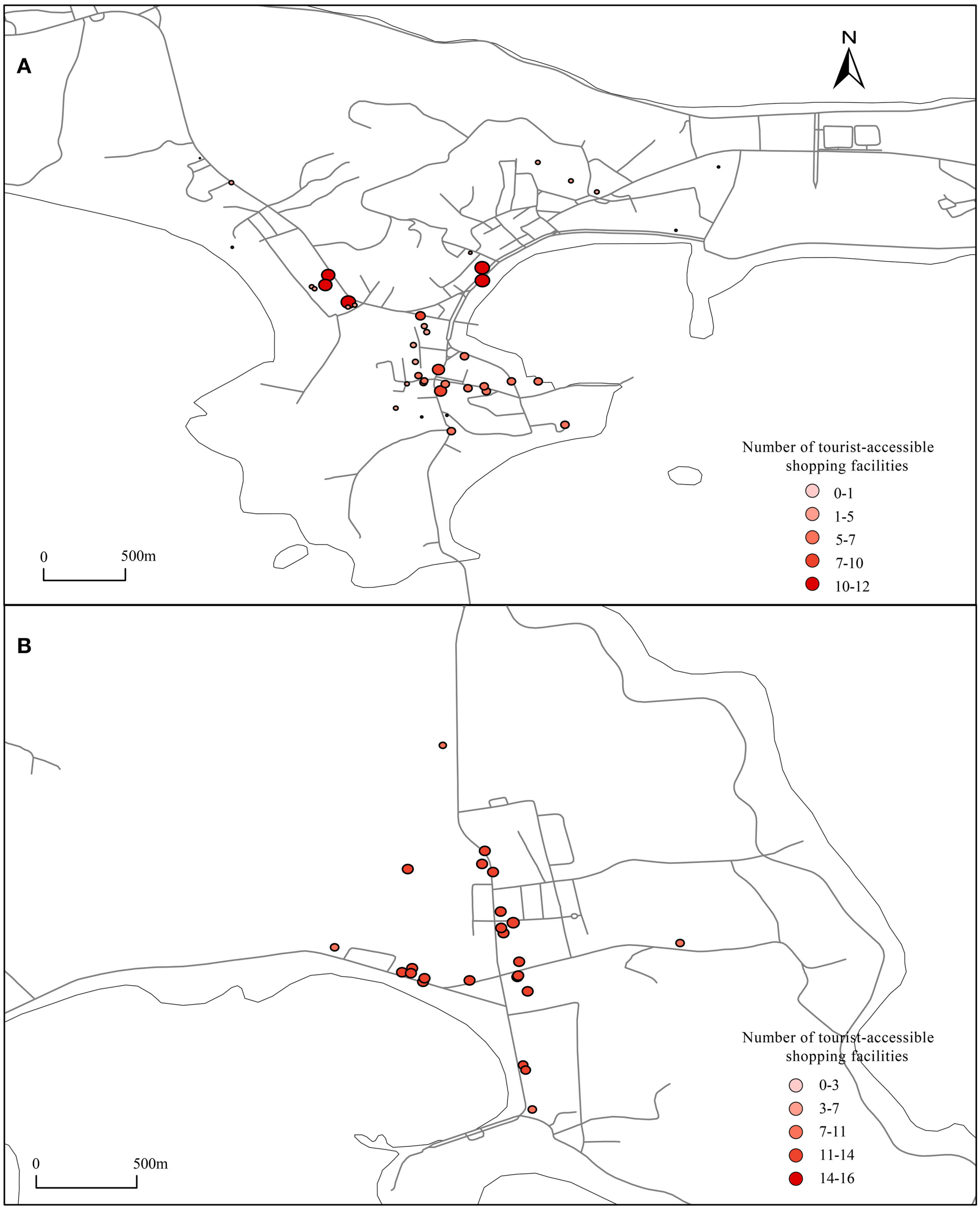

FIGURE 8
Shopping facilities accessible to tourists. **(A, B)** Using the UNA analysis tool, set the tourist accommodation facilities as the starting point, shopping facilities as the ending point, import the road network, and calculate the number of shopping facilities that can be reached from tourist accommodations within a range of 800 meters.

distributed in the area southeast of the People's Hospital of Changhai. The number of catering facilities accessible to tourists and residents is ∼16, and the degree of sharing of catering facilities is high.

Except for those areas with a reasonable configuration of catering and shopping facilities, the facilities in other areas should be configured in areas with high accessibility for residents and tourists as much as possible to reduce the spatial dislocation between facilities and residential areas for residents and tourists, improve the degree of sharing and accessibility of facilities, avoid the waste of facilities in the tourist off-season, and improve the efficiency of facility configuration. Taking areas with excessive facility construction as an example, their catering or shopping facilities should be transferred to areas with few facilities as much as possible to improve the utilization efficiency of facilities. In addition, if there are few catering and shopping facilities accessible to residents and tourists in a certain area but there are many residential buildings and there are few hotels, then even though the configuration of facilities does not conform to the principle of a high degree of sharing, since the configuration of

FIGURE 9
Shopping facilities accessible to residents. **(A, B)** Using the UNA analysis tool, set the residential buildings as the starting point, shopping facilities as the ending point, import the road network, and calculate the number of shopping facilities that can be reached from residential buildings within a range of 800 meters.

facilities is of little significance to tourists, the needs of residents should mainly be considered, and appropriate new facilities should be added.

Carrying out an evaluation of the facility configuration from the microlevel perspective of individuals' spatiotemporal behavior is meaningful for exploring human-oriented spatial planning under the background of changing activity groups in the future space. However, this paper has the following shortcomings: Firstly, the public service facilities studied only include catering and shopping facilities, without considering other types of public service facilities, due to the limitations of the data acquired, the public service facility data that can be obtained is greatly limited. Secondly, this paper only considers the number of facilities, not the scale of facilities. In the future, we can obtain more detailed public service facility data and population data for in-depth research. Finally, the accessibility of facilities only considers the spatial accessibility, while the time accessibility is not considered in this manuscript. In fact, since public service facilities are not open all day, accessibility will be affected by the opening time of public service facilities, resulting in space accessibility but time unreachability.

TABLE 1 Facility configuration in the study area.

Facilities	Utilization by tourists	Utilization by residents	Number	Evaluation	Location
Catering facilities	High		Many	Reasonable	The area southeast of the People's Hospital of Changhai Qingfeng Street, Sanpanian Community
	Low		Many	Too much	The area southeast of the People's Hospital of Changhai Qingfeng Street, Sanpanian Community
		High	Many	Reasonable	The area southeast of the People's Hospital of Changhai
		High	Few	Not enough	The area near the the People's Government of Changhai
		Low	Many	Too much	Qingfeng Street, Sanpanian Community, etc.
Shopping facilities	High		Many	Reasonable	The area southeast of the People's Hospital of Changhai
	Low		Many	Too much	The Changhai Mall, Sanpanian Community
		High	Many	Reasonable	The area southeast of the People's Hospital of Changhai
		High	Few	Not enough	The area near the the People's Government of Changhai
		Low	Many	Too much	The Changhai Mall

4.2. Conclusion

The theory of temporal geography holds that the existence of individuals in spatial places involves the consumption of time and space. Differences in the purpose of the temporal and spatial behavior of different groups lead to differences in their utilization of the same space. The infrastructure in a space is required to provide diversified services to meet the needs of different groups. Due to the development of tourism, destinations no longer are defined by a single main activity. At the same time, meeting the tourism needs of tourists and the living needs of residents has posed new challenges to the optimization of the space of public service facilities. However, to achieve group equity as much as possible, the allocation of public service facilities needs to undergo through different stages. Therefore, this paper takes a tourist island with obvious differences in the main active groups in the same space as an example and delimits the study area by the characteristics of the temporal and spatial behavior of different groups, that is, the overlapping area of the behavioral space of different groups. Based on the two aspects of facility accessibility and availability, research evaluating the configuration of catering facilities and shopping facilities in the study area is conducted, and the results of the study are as follows.

(1)The "dislocation" of spatial distribution between public service facilities and residential areas is serious, and only one regional facility configuration is reasonable. It is suggested that the public service facilities that can be used at a low level should be moved to the areas with large demand for facilities, so as to improve the utilization efficiency of public service facilities and reduce the "dislocation" of space between residential areas and facilities.

(2)The number of facilities accessible to residents on Dachangshan Island and Guanglu Island is generally greater than that accessible to tourists. The public facilities serve for residents more than the tourists is a right choose. Because the residents are the foundation of the island development, but the tourists just an important outside factors, it's a driving force to the development of the island, it is also important, but not the first important. Guaranteeing the daily needs of islanders and meeting the diverse tourism needs of tourists are the basis for the sustainable development of island tourism.

This paper analyzes the accessibility of public service facilities in the context of multiple groups of tourist destinations and is an active exploration of the configuration of public service facilities under the background of changing activity groups in the future space.

Data availability statement

The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding author.

Author contributions

XZ was responsible for the writing of the manuscript. DZ provided the writing ideas of the paper and gave guidance in the writing process. All authors contributed to the article and approved the submitted version.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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Assessment of changes in environmental factors in a tourism-oriented Island

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Tourism development has influenced industrial structure changes and has become a major driving force for China's new urbanization. However, the development will negatively impact natural resources and the ecological environment and will become an essential driving factor for land use change. Therefore, understanding the impact of tourism urbanization is crucial for sustainable local development. This study selected the Dachangshan Island in the Changhai County, Dalian, China, as the study area, because it is the only coastal island-type border county in China. During the study period, changes in local environmental factors were analyzed based on land use data, Landsat 5 and Landsat 8 data of 2009, 2014, and 2019. The results showed that: (1) the overall land surface temperature (LST) in the research region shows an increasing trend; the LST in 2014 and 2019 increased by 6.10 and 5.94 °C, respectively, compared with 2009. With respect to specific land types, impervious surfaces maintained a high land surface temperature (25.44, 32.38, and 31.86); however, surface temperatures for cropland, forest, grassland, and water bodies remained stable. (2) The land use land cover (LULC) change analysis from 2009–2019 indicates that impervious surfaces and cropland increased by 0.5653 km^2 and 0.9941 km^2, while the areas of forest, grassland, and water bodies decreased. The results also showed that forests (−1.3703 km^2) are most affected by urbanization. (3) The results of the landscape index calculation showed that the variation at the patch scale is different for different LULC types. The patch density of impervious surfaces decreased, but the aggregation index increased over time, while the patch density of the forest increased continuously. At the landscape scale, overall patch type and distribution remained stable. The purpose of this study is to explore the environmental changes of islands and provide a reference for the sustainable development of islands.

KEYWORDS

tourism urbanization, land cover transformation, land surface temperature, landscape index, Dachangshan Island

1. Introduction

According to the National Bureau of Statistics, China's urbanization rate increased from 36.2 in 2000 to 60.6% in 2019. With the acceleration of urbanization, tourism has also seen rapid development, with statistics from the Ministry of Culture and Tourism in 2019 showing that tourism accounted for 11.05 percent of Gross Domestic Product (GDP). It can be seen that the tourism is an integral part of economic development. Previous studies show that the tourism industry is an essential driver of urbanization and that cities are the basis for developing the tourism industry; these two impact and constrain each other (1). It is therefore imperative that the role of tourism is brought into the context of sustainable development and that urbanization and tourism are integrated to promote co-development.

The tourism boom has not only contributed to the transformation of the local industrial structure, but also to the morphology and social evolution of rural communities, thus contributing to local economic development (2–5). Mullins first proposed the concept of tocapurism urbanization in 1991 (6). However, the process of tourism urbanization tourism is usually accompanied by an influx of tourists and an increase in traffic pressure, which affects residents' quality of life in tourist destinations (7–9). Adedoyin and Bekun (10) showed that tourism had become a more significant source of pollution than construction, further contributing to global carbon emissions. Recently, creating perfect urban facilities and services that guarantee smooth tourism activities has gathered increased attention, and an excellent tourism environment can enhance tourists' satisfaction and loyalty to the destination (11–13). However, rapid urbanization has also caused noticeable negative impacts, such as reduction of marine biodiversity, increased urban heat island effect, destruction of the ecological environment, and a decline in air quality (14–18). Furthermore, some studies have shown that the efficacy of tourism urbanization is affected by spatial planning (19). Therefore, when formulating relevant developmental policies, local governments should pay attention to balancing tourism and urbanization as much as possible while maintaining good economic development.

Recent studies on tourism urbanization are usually combined with air quality change, land use transfer, ecological, and environmental damage, and carbon emissions (20–23). These studies showed that factors such as the tourism industry, urbanization, ecological environment, and carbon emissions are mainly quantified, and a coupling analysis of these factors is carried out to analyze their evolution and spatial differences (10, 24, 25). For example, Li et al. (26) constructed a multi-indicator system to study the relationship between tourism urbanization and ecological and environmental elements in Chongqing, and the results show that the degree of coordination between the three increases over time. From the perspective of the research scale, it is mainly carried out from regions, urban agglomerations and tourism city scales (27–29), Gan et al. (30) used the gravity model of tourism economy to study the spatial characteristics of tourism economy in urban agglomeration in the middle reaches of the Yangtze River, in order to promote the cooperation and spatial integration of tourism economy in urban agglomeration. Foreign studies are mainly concentrated in tourism-oriented countries, while domestic studies are mainly distributed in eastern provinces and developed urban areas. However, correlation studies usually use longer time series of correlation data to analyze the interaction between factors.

The sudden outbreak of COVID-19 dealt a severe blow to tourism worldwide (31–33). Research on Spanish tourism by academics such as Arbulu showed that domestic travel dropped by 42.64% during the pandemic compared to 2019 (34). To rebuild and meet the needs of tourism and related development post-COVID-19 pandemic, land types often change and lead to changes in the local thermal environment (35–37). Among them, the most intuitive is an increase in impervious surfaces. Cities can divide the urban functional areas and relocate relevant industries to specific areas to improve the urban environment. However, the development of coastal cities is limited by land use to a certain extent (38). In addition, high temperatures and sea-level rise caused by high temperatures are obstacles to enhancing the economic potential of coastal tourist cities. Studies have shown that tourism-induced pollution and land-use change can also lead to changes in the carbon cycle and carbon sequestration capacity of vegetation, thereby exacerbating the impacts of climate change (15, 23). Recent studies have shown that climate change increase the vulnerability index of islands to climate change in developing countries (39–41). Therefore, it is imperative to analyze the changes in environmental factors in coastal tourism cities and islands.

Against the background of continuously practicing the strategy of building maritime power (a strategy proposed by the 18th National Congress of the Communist Party of China), islands have attracted many tourists with their unique natural conditions and fishing customs, which has promoted island tourism development (42–44). However, unlike land tourism cities, their unique geographical location and limited area have hindered such development to a certain extent. Cyffka et al. (45) found in their study, on the Elba Island and Malta, that the more tourism grew, the more serious the urban sprawl became, leading to the loss of the rural population. Hence, the interaction between tourism and urbanization will unavoidably cause alterations in the environmental elements of the islands. Therefore, the study of the changes in environmental factors on islands is not only conducive to environmental protection but also to the sustainable development of islands (46).

In summary, this study focused mainly on analyzing the changes in island environmental factors under tourism urbanization, including land surface temperature (LST), land cover, and landscape index-related factors. We chose the

Changhai County, Dalian City, Liaoning Province, China, as the research area, which has formed a tourism industry with resource characteristics and folk characteristics based on natural and human resources. Therefore, the research contents of this paper mainly include three aspects: (1) analyzing the land surface temperature changes of islands during the period (2009–2019); (2) analyzing the land use changes during this period; and (3) using the land use data to calculate and analyze the corresponding landscape index and pattern change in the study area. We then provide suggestions for sustainable island tourism and island development.

2. Data and methods

2.1. Study area

Dachangshan Island (122°57′ E, 39°27′ N) is located in the southeast of the Liaodong Peninsula and north of the Changshan Archipelago, and it's part of the Changhai County. The island is narrow from east to west and has a warm, temperate, and semi-humid climate characterized by four distinct seasons. The study area mainly includes the Lijia, Xiaopaozi, Sannomiya Temple, Xiaoyanchang, Chengling, and Four Stone Villages (Figure 1).

2.2. Data sources

This study analyzed tourism income and population data from the statistical bulletin of the Changhai County from 2009–2020 (Figure 2). Overall, tourism income and population showed an increasing trend year by year. In 2020, owing to the impact of COVID-19, the number of tourists and tourism income showed a sharp decline. The tourist population and income declined in 2014 but picked up afterwards. China Tourism Statistics Bulletin, suggests that overseas tourism was a potential factor that may have led to the decrease in tourist numbers and income in the study area. Meanwhile, 2020 was excluded owing to the impact of COVID-19. The purpose of this paper is to analyse the changes in environmental factors on the island during the summer months and, combined with the availability of remote sensing image data, we have finally chosen the land surface temperature and land cover data from 2009, 2014, and 2019, (Details of the data are shown in Table 1), and calculated the landscape index of each period.

2.3. Methods

2.3.1. Land surface temperature inversion

LST inversion methods include the single-window algorithm, single-channel algorithm, radiative transfer equation algorithm and so on. Among which, the radiative transfer equation method has high inversion accuracy owing to a large number of input parameters and has been most widely used by scholars (44, 45). The mono-window algorithm is also widely used owing to its simplicity and universality. The single-window algorithm was adopted for this study because it has the strongest universality to retrieve the land surface temperature (47, 48). This method can convert the image DN value into the corresponding radiation intensity and then radiation brightness. The equations used are as follows:

$$L_\lambda = Gain \times DN + Offset \tag{2.1}$$

$$T_a = \frac{K_2}{\ln\left(1 + \frac{K_1}{L_\lambda}\right)} \tag{2.2}$$

The inversion equation of land surface temperature is as follows:

$$T\_s = (a(1 - C - D) + (b(1 - C - D) + C + D)$$

$$T\_10 - DT\_a)/(C - 273.15) \tag{2.3}$$

$$C = \varepsilon\tau \tag{2.4}$$

$$D = (1 - \tau)[1 + (1 - \varepsilon)\tau] \tag{2.5}$$

In Equation (2.1), L_λ is the radiation intensity, Gain is the gain factor, and Offset is the offset function (both of which can be obtained from image metadata). According to the data sources K_1 and K_2, Equation (2.2) the different data correspond to different parameters. In Equation (2.3), T_s is the surface temperature value (K), where T_a is the average temperature of the atmosphere (K), T_10 is the luminance temperature (K) of the sensor, a and b are reference coefficients (when the surface temperature is between 0 and −70 °C, a = −67.355351, b = 0.458606), τ is the propagation of the atmosphere, and ε is the surface emissivity.

2.3.2. Land use data

To understand land cover change in the research region, we used the land cover data generated by Yang et al. (49) based on the Google Earth Engine (GEE), which covers the land use dynamics in China from 1990–2019. It is divided into ten land cover types, and the verification results show that the overall accuracy is as high as 79.31%. In this article, the land cover data for 2009, 2014, and 2019 were extracted, and the land transfer matrix was drawn for the land change in these two periods to analyze the land cover change of islands in different periods.

2.3.3. Calculation of landscape index

The landscape index can indicate information about the landscape pattern of land use types in a specific region. The scale of the study can be classified into patch level indices, patch type

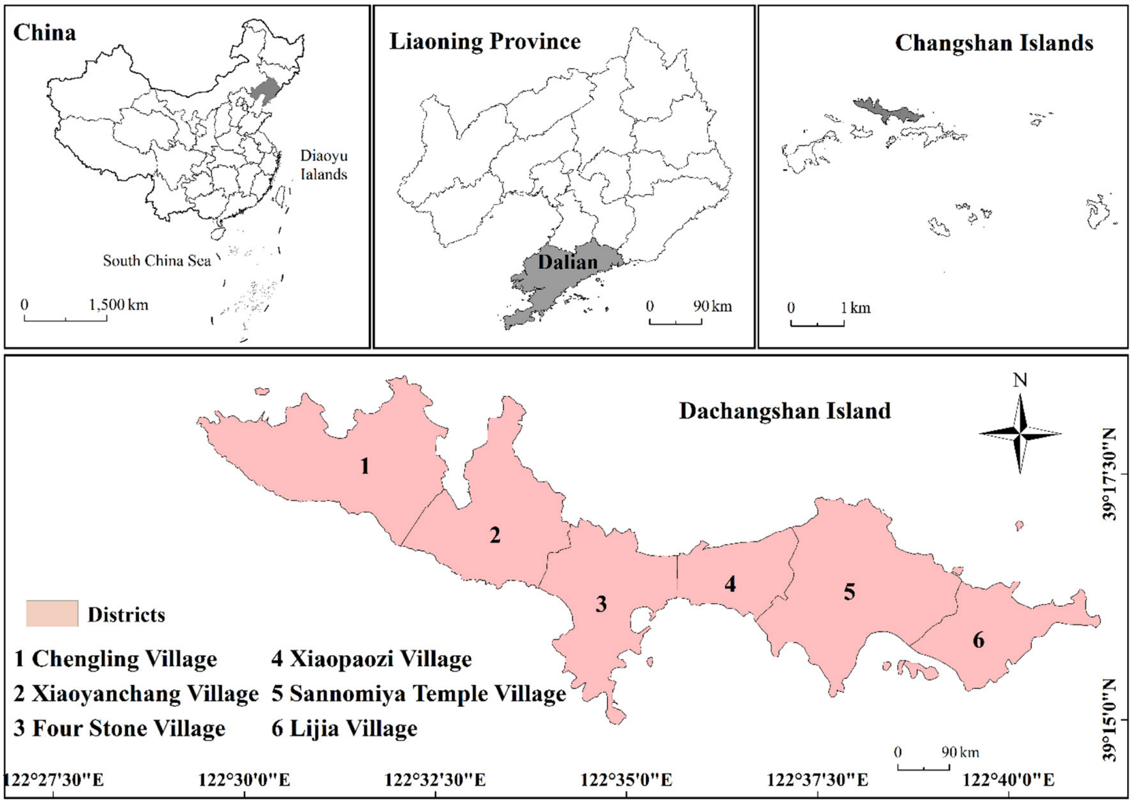

FIGURE 1
Location of the study area.

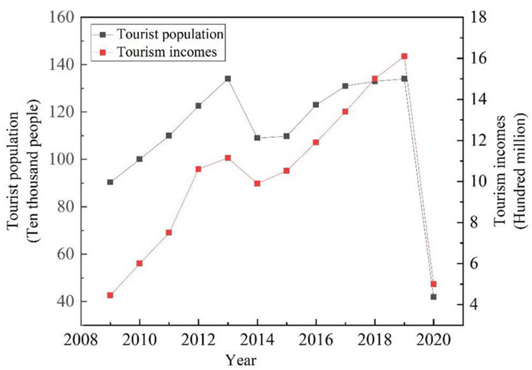

FIGURE 2
Tourism incomes and tourism population, 2009–2020.

level indices and landscape level indices (50). The study area was examined from the patch-type and landscape levels for this study. Finally, we selected the patch density, aggregation index, landscape shape index, and Shannon diversity index to analyze the landscape changes of the Dachangshan Island. Table 2 presents the meaning of each index and the calculation method. The entire process was performed using Fragstats v4.2.1.

TABLE 1 Data types and sources.

Data types	Time	Resolution	Sources
Landsat-5	2009.7.11	30 m	https://search.earthdata.nasa.gov/search/
Landsat-8	2014.7.6, 2019.7.4	30 m	http://www.gscloud.cn/
Land use data	2009, 2014, 2019	30 m	https://doi.org/10.5281/zenodo.4417810
Statistical yearbook data	2009-2020		http://www.dlch.gov.cn

3. Results

3.1. Land surface temperature change

The LST is a critical indicator that reflects the urban thermal environment. Figure 3 shows the land surface temperature distribution on the Dachangshan Island in 2009, 2014, and 2019, respectively. As only one meteorological station exists

TABLE 2 Calculation method and description of landscape index.

Landscape index	Equation	Unit and value range	Explain
Patch density	$PD = (10000)(100)$	Num/100 ha(0,+∞)	The larger the number of plaques per unit area, the finer the segmentation of plaques
Aggregation index	$AI = \left[\frac{g_{ii}}{max \rightarrow g_{ii}}\right](100)$	Percent (0,100]	Degree of patch aggregation in landscape
Landscape shape index	$LSI = \frac{.25\ E^{*}}{\sqrt{A}}$	None [1, +∞)	Describe the characteristics of patch shape in the whole landscape, the larger the value, the more isolated the patch
Shannon's diversity index	$SHDI = -\sum_{i=1}^{m}(P_i \times InP_i)$	[0,100)	The larger the value, the more abundant the patch types and distribution in the landscape

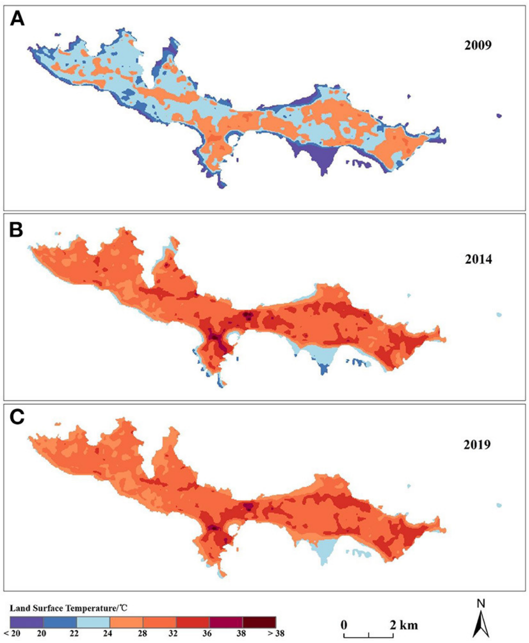

FIGURE 3
(A–C) Show the land surface temperature in 2009, 2014, and 2019, respectively.

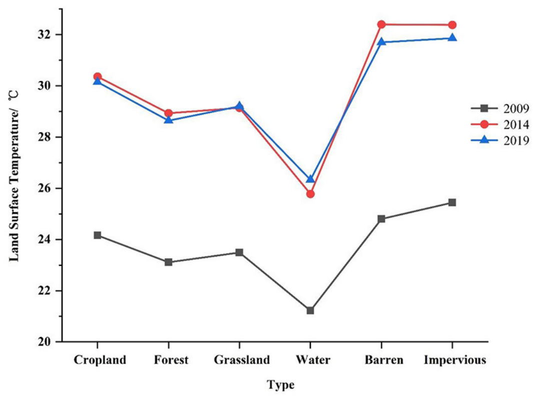

FIGURE 4
Land mean surface temperature changes in 2009, 2014, and 2019 by local table types.

in the study area, we chose to use ASTER__08 LST data for accuracy validation, and due to data quality limitations, we only validated the temperature accuracy for 2014 as well as 2019. We extracted the corresponding temperature values separately by creating random points in Arcgis 10.5 software and performed regression analysis on both. The results showed that the inverse surface temperature Pearson correlation coefficients were 0.816 and 0.808 for 2014 and 2019. Where the surface temperature increased by 6.10°C and 5.94°C in 2014 and 2019 respectively compared to 2009. The high-temperature areas were mostly located in the central and eastern parts of the island, while the western part usually had low temperatures. Figure 5 shows that the central and eastern parts of the island consist mainly of impervious areas. Also, in conjunction with Figure 6, it was found that the increase or decrease in impervious surface was mainly concentrated in the eastern part of the island during the two time periods 2009–2014 and 2014–2019. Vegetation was mainly found in the western part of the island, and the 2019 statistical bulletin of Changhai County indicates that the local forest cover reached 47.78% at the end of the year. In the context of global warming, there are also differences in surface temperature between different land covers, so this paper also analyses the changes in surface temperature over three time periods under different land cover types (Figure 4); the results show that:the average land surface temperature of each land type during the study period generally showed an increasing trend. For instance, barren and impervious surfaces show higher LST values than of the others in any period, with the highest variation and continuous increase in the range from 2009–2014. The higher LST values for these two surfaces can be attributed to the nature of their surface cover and characteristics (low specific heat capacities, and high reflectivity) (51). However, although cropland, forest, grassland, and water also showed significant increases, the overall values were lower than those of the barren and impervious categories. This is because vegetation

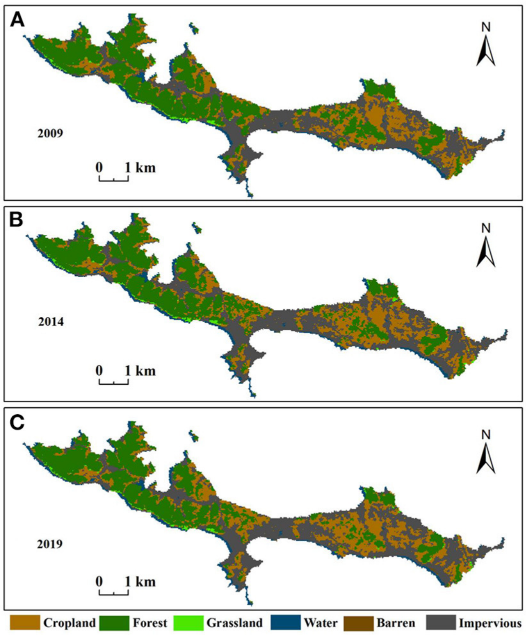

FIGURE 5
(A–C) Shows the different land use in 2009, 2014, and 2019, respectively.

can usually alleviate the temperature rise through transpiration, whereas water has a higher specific heat capacity, so it usually has a lower temperature (49, 50).

3.2. Land use change

To reflect land cover change in the study area, land use maps were created for each period (Figure 5). In general, the land cover of the research area had minor changes. The western part was still dominated by forest, while the central and eastern parts were dominated by mainly impervious, cropland, and other land types. The land use transfers during the study are presented in Figure 6. Significant increased in cropland and impervious surfaces during this period. Cropland increased throughout the island, whereas the changes to impervious surfaces was predominantly concentrated in the eastern part of the island. The land use change from 2009 to 2014 is shown in Table 3; cropland and impervious areas increased by 0.3511 km^2 and 0.5673 km^2, respectively. The areas of barren forest, grassland, and water were reduced, with forest being the most affected (0.8378 km^2). From 2014–2019 (Table 4), cropland (0.2141 km^2) and impervious (0.4269 km^2) areas increased, while forest (0.5326 km^2), grassland (0.0382 km^2), and water (0.0702 km^2) decreased. Combined with Figure 1, it was found that impervious area increased mainly in Xiaobaozi Village, Sanguangmiao Village and Lijia Village from 2009-2014, while impervious area increased mainly in Sanguangmiao Village from 2014-2019, while the increase in cultivated land was mainly concentrated in Sishi Village, but it tended to be surrounded by large areas of forest land and was therefore more dispersed.

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3.3. Landscape index results

The landscape index was used to analyze the landscape characteristics in 2009, 2014, and 2019, and and the results of the calculations are shown in Table 5. The land use change analysis results using the patch type scale for 2009–2019 indicate that cropland, grassland, and impervious type patch density exhibited decreasing trends, demonstrating that patch attributes gradually tend to be homogeneous in per unit area. In contrast, the aggregation index of impervious increased during the same period. The patch density of water and forest showed a gradual increase, indicating that the fragmentation degree of these two landscapes continuously increased. The fragmentation of the forest is mainly evident in Four Stone Village, where forest and corpland are interspersed. However, the change in the aggregation index of water was greater than that of the forest, and the aggregation index of water was as high as 85.0641 in 2019. In addition, the barren patch density and aggregation index reached their highest levels in 2014. From the overall landscape scale, it was found that the landscape shape index first increased and then decreased from 2009–2019, with 2014 as the cut-off point, indicating that the patches in the whole study area had experienced a transition from separation to integration. With the development of the island, different functional land uses gradually concentrated with each other to rationalize the use of resources and improve land use efficiency. However, the Shannon diversity index was stable (0.9195) in 2009 and 2014, but slightly decreased (0.9180) in 2019. This result suggests that the patch types and distribution in the study area did not change significantly during this period.

4. Discussion

To meet the development of tourism, the land use and land cover of islands have changed because of anthropogenic factors. In 2014, the website of the Central People's Government of the PRC issued several opinions on promoting the reform and development of tourism, pointing out that tourism is an essential component of the modern service industry, and accelerating the reform and development of tourism is an inevitable requirement to adapt to the upgrade in people's consumption and the industry's structure. Moreover, according to the National Bureau of Tourism Statistics, the number of outbound tourists exceeded 100 million for the first time in 2014, which is also a potential

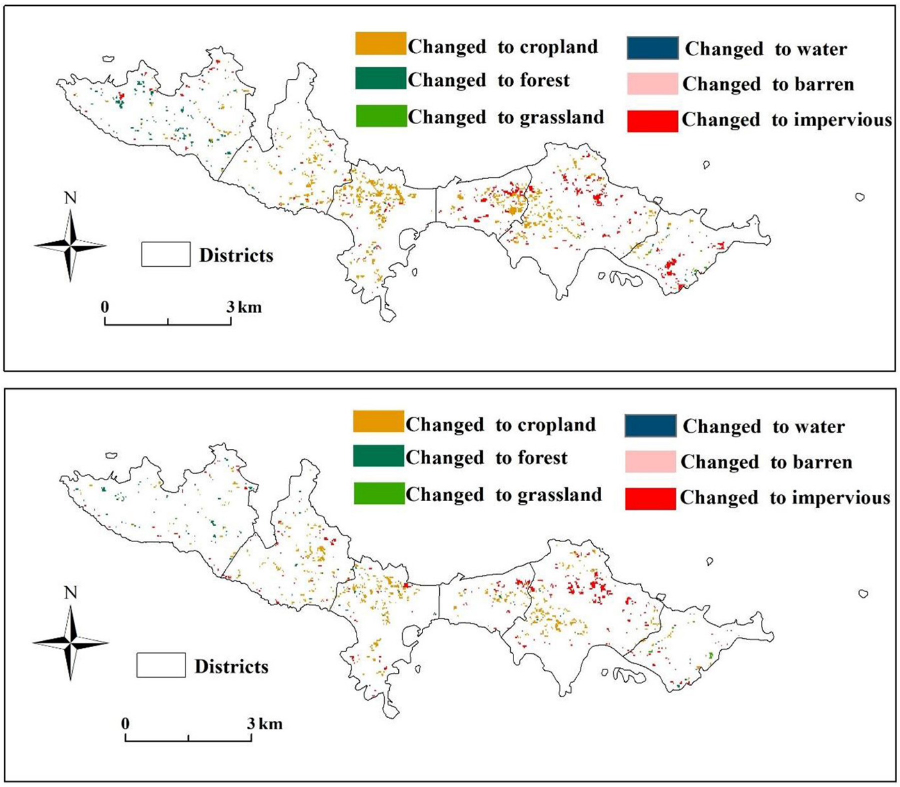

FIGURE 6
Land use transfer and change from 2009–2014 and from 2014–2019.

TABLE 3 Land use change from 2009–2014 (km^2).

		Land cover 2014						
Land cover		Barren	Cropland	Forest	Grassland	Impervious	Water	Sum
2009	Barren	0.0146	0	0	0	0.0049	0	0.0195
	Cropland	0	5.1168	0.1460	0.0188	0.4568	0	5.7384
	Forest	0	0.9295	8.7053	0	0.0688	0	9.7036
	Grassland	0.0014	0.0389	0.0146	0.2537	0.0146	0	0.3233
	Impervious	0	0	0	0	7.6025	0.0049	7.6074
	Water	0	0.0042	0	0	0.0271	1.2333	1.2646
	Sum	0.0160	6.0895	8.8659	0.2725	8.1747	1.2382	24.6567
	Change	−0.0035	0.3511	−0.8378	−0.0507	0.5673	−0.0264	

factor that may have caused decrease in visitor numbers and revenue in 2014. However, the decrease in the number of tourists creates a peculiar opportunity for the restoration of the local ecological environment. Previous studies on tourism have used statistical data to analyse the impact of tourism on the local economy, population and other aspects, while statistical data is often only available until the relevant agencies can obtain it at a specific time, this paper uses remote sensing data to evaluate the environmental factors of the island in a number of ways that are more timely and objective than statistical data. Table 6 shows that from 2009–2019, the impervious area increased the most (0.9941 km^2), followed by cropland (0.5653 km^2). Barren land, forest, grassland, and water tended to decrease. Among them, forests decreased the most (−1.3703 km^2), and an analysis of land use change shows that forests are the most vulnerable land cover type on islands of limited size

TABLE 4 Land use change from 2014–2019 (km^2).

	Land cover 2019							
	Land cover	**Barren**	**Cropland**	**Forest**	**Grassland**	**Impervious**	**Water**	**Sum**
2014	Barren	0.0146	0	0	0	0.0014	0	0.0160
	Cropland	0	5.6571	0.1098	0.0195	0.3031	0	6.0895
	Forest	0	0.6132	8.2151	0.0028	0.0348	0	8.8659
	Grassland	0.0014	0.0306	0.0063	0.2120	0.0222	0	0.2725
	Impervious	0	0	0	0	8.1726	0.0021	8.1747
	Water	0	0.0028	0.0021	0	0.0674	1.1659	1.2382
	Sum	0.0160	6.3036	8.3333	0.2343	8.6016	1.1679	24.6567
	Change	0.0000	0.2141	−0.5326	−0.0382	0.4269	−0.0702	

TABLE 5 Landscape index calculation for 2009, 2014, and 2019.

	2009		**2014**		**2019**	
	PD	**AI**	**PD**	**AI**	**PD**	**AI**
Cropland	1.9094	72.9598	1.8173	72.6306	1.5336	74.8115
Forest	0.4524	89.9972	0.6288	88.3603	0.6595	88.7919
Grassland	0.7131	41.1765	0.6441	42.0593	0.5828	38.2143
Water	0.4754	65.6355	0.4831	65.4198	0.5138	85.0641
Barren	0.0613	31.2500	0.0383	37.0370	0.0537	33.3333
Impervious	1.3266	81.9858	1.2346	82.9733	1.1962	83.7299
LSI	10.5997		10.8255		10.5453	
SHDI	0.9195		0.9195		0.9180	

compared to other land covers. Especially in Four Stone Village, where Cropland and Forest are interspersed, it is important to meet the sustainable development of the island Corpland while protecting the ecological environment. In addition, related studies have shown that vegetation can cool cities through transpiration and provide shade (51, 52). Furthermore, other studies have found that the configuration of green spaces has different effects on temperature mitigation (53–55), implying that for islands with minimal land area, more focus should be given to rational planning of local land types while promoting tourism development.

The change of land cover and the difference in land properties led to the corresponding change in LST. When Ara et al. (56) analyzed the correlation between the tourist pressure index and land use and surface temperature, they found that with an increase in the tourist pressure index, land use changes became more frequent, further aggravating surface temperature changes. Under the background of global warming, the island's overall land surface temperature is rising, the Impervious and Barren most obvious (Figure 4), with a simultaneous temperature rise in Cropland, Forest, Grassland, and Water. Safarrad et al. (57) analyzed the impact of tourism on LST and found that the LST between tourist areas and other regions was significantly different. In addition to the changes in natural elements, tourism is usually accompanied by a large inflow of people into the designated islands, during which, a large amount of anthropogenic heat will also be generated, resulting in heat discomfort, which will negatively impact the physiology and psychology of tourists (28, 58). Whereas, tourists usually stay in tourist areas for a specific period of time, the state of the environment is critical to the sustainability of the local area for those living on the island for long periods of time, and it is shown in chapter 3.2 that forests are the most vulnerable surface type, and that forests have a significant effect on cooling. This requires the local government to plan the island's land use in a way that meets the needs of tourism development and maintains the balance of the island's environment in the process of developing tourism.

The related landscape pattern indices can quantitatively reflect landscape characteristics (59). However, it must be screened according to the actual situation. The results indicated that the landscape diversity in the research area was stable, and the landscape types were gradually integrated. In addition, some scholars have divided the research area into tourism and non-tourism land based on the data of interest, analyzed the changes in LST, normalized index, and land use between them,

TABLE 6 Land use change from 2009–2019 (km^2).

	Land cover	Barren	Cropland	Forest	Grassland	Impervious	Water	Sum
		Land cover 2019						
2009	Barren	0.0132	0	0	0	0.0063	0	0.0195
	Cropland	0	4.7588	0.2044	0.0271	0.7481	0	5.7384
	Forest	0	1.4753	8.1074	0.0063	0.1147	0	9.7036
	Grassland	0.0028	0.0626	0.0195	0.2009	0.0375	0	0.3233
	Impervious	0	0	0	0	7.6025	0.0049	7.6074
	Water	0	0.0070	0.0021	0	0.0925	1.1631	1.2646
	Sum	0.0160	6.3036	8.3333	0.2343	8.6016	1.1679	24.6567
	Change	−0.0035	0.5653	−1.3703	−0.0889	0.9941	−0.1015	

and provided suggestions for sustainable development of local tourism (60, 61). However, this method is suitable mainly for tourism in cities, where, unlike on islands with limited land areas, life and tourism intersect, making it difficult to define tourism and non-tourism.

4.1.Limitations

This study analyzed the impact of tourism on the environmental factors of the Dachangshan Island from 2009–2019. However, due to the limitation of image quality and time, remote sensing data of the same day could not be obtained; thus, there were certain deficiencies in the analysis of land surface temperature changes. In addition, because of the limited study area, we selected land use data with a resolution of 30 m to ensure data consistency. There may be an incomplete representation of the actual land cover in the study area. Therefore, higher-resolution data should be used for analysis when studying islands with limited areas.

5. Conclusions

To better understand the changes in the environmental factors of tourism-oriented islands, this study used multi-source data to analyze the environmental factors of the Dachangshan Island based on tourism income and the number of tourists. The key findings are as follows:

(1) The land surface temperature in the study area exhibited a rising trend during the periods considered, with impervious and barren areas having a higher LST. The cropland, forest, grassland, and water surface temperatures increased evenly; however, they were lower than those in impervious and barren areas.
(2) The western part of the research area is still mainly composed of forests, whereas the central and eastern parts of the research area are composed of impervious, cropland, and other land types. Land use changes during 2009–2019 showed that overall forest, grassland, water, and barren areas reduced, while cropland and impervious areas increased.
(3) The calculation results of the landscape index showed that from 2009–2019, land types show different trends of change. At the patch type scale, the most noticeable impervious patch decreased continuously, while the aggregation index increased continuously, indicating that imperviousness gradually integrated with increasing anthropogenic factors.

Data availability statement

The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding authors.

Author contributions

ZS wrote the main manuscript text. YJ, XZ, YZ, XX, and JX conducted the experiment and analyzed the data. All authors reviewed the manuscript. All authors contributed to the article and approved the submitted version.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Publisher's note

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Impacts of industrial agglomeration on industrial pollutant emissions: Evidence found in the Lanzhou–Xining urban agglomeration in western China

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Industrial agglomeration does not only promote economic and social prosperity of urban agglomeration, but also increases industrial pollution, which poses a health risk to the general public. The Lanzhou–Xining urban agglomeration in western China is characterized by industrial agglomeration and serious industrial pollution. Based on the county panel data of the Lanzhou–Xining urban agglomeration in western China from 2010 to 2018, a research of the impacts of industrial agglomeration on industrial pollutant emissions was conducted by using spatial analysis technology and spatial econometric analysis. The results indicate that industrial agglomeration is an important factor leading to an increase in industrial pollutant emissions. In addition, population density, economic level, and industrial structure are also important factors that lead to the increase in industrial pollutant emissions. However, technological level has led to the reduction in industrial pollutant emissions. Furthermore, industrial pollutant emissions are not only affected by the industrial agglomeration, population density, economic level, industrial structure, and technological level of the county but also by those same factors in the surrounding counties, owing to the spatial spillover effect. Joint development of green industries and control of industrial pollutant emissions is an inevitable result for the Lanzhou–Xining urban agglomeration in western China.

KEYWORDS

Lanzhou–Xining urban agglomeration, spatial econometric analysis, industrial agglomeration, industrial pollutant emissions, spatial effect

1. Introduction

Industrial agglomeration is the main spatial organization form of industrialization. Through the mechanisms of scale economy, industrial agglomeration promotes economic competitiveness, optimizes the resource allocation, and stimulates technological innovation, which at the same time has also led to an increase in industrial pollutant emissions (1). The increase in industrial pollutant emissions from China's industrialization not only affects public health but also affects the sustainable development of the economy and society (2). The pollution generated from China's industrial production is more serious than that which is generated in daily life, and preventing and controlling the discharge of industrial pollution have become an important goal of environmental pollution control in China (3).

During the past decades, urban agglomerations have seen rapid industrialization, and rapid economic growth along with sharply increasing industrial pollutant emissions (4). Therefore, the impact of industrial agglomeration on industrial pollutant emissions has received much attention in the research community. However, the results of such research have not always been in agreement, owing to the differences in research areas, methods, and objectives. This indicates that the impact of industrial agglomeration on industrial pollutant emissions is a complex issue (5). For instance, the elimination of polluting industries in the eastern and central provinces of China leads to the transfer of these industries to the western provinces of China (6). By acquiring these polluting industries, urban agglomerations in western China have promoted the level of industrial activity, causing environmental problems such as increasing industrial pollutant emissions (7).

Industrial agglomeration is an inevitable result of industrial development in urban agglomerations. Industrial agglomeration can reduce transaction costs, increase returns on scale, and reduce transportation costs, which together promote expansion of the industrial scale (8). Industrial agglomeration is more prone to rapid expansion of the industrial scale, resulting in growing energy consumption and industrial pollutant emissions (9). Therefore, areas with high levels of industrial agglomeration are also areas of significant industrial pollution. There seems to be a simple logic here: industrial agglomeration leads to an increase in industrial pollutant emissions (10). However, this conclusion seems to be contradictory to traditional agglomeration economic theory, which suggests that spatial agglomeration has economies of scale and spillover effects (11). Therefore, whether due to the spillover effect of pollution reduction technology or to the scale effect of environmental factors, industrial agglomeration has contributed to a reduction in pollutant emissions from industry. However, does industrial agglomeration lead to an increase or decrease in industrial pollutant emissions? The truth needs to be verified. With the presence of rapid industrial growth in urban agglomerations in western China, it is necessary and urgent to analyze the impact of industrial agglomeration on industrial pollutant emissions. Answering the above questions would provide an effective reference for improving the impact of industrial activity on urban agglomerations in western China.

2. Literature review

Upon reviewing the researches that have been conducted, we have come to the conclusion that industrial agglomeration has an impact on industrial pollutant emissions through the effects of pollution and self-purification. On the one hand, the pollution effect of industrial agglomeration leads to an increase in industrial pollutant emissions, and industrial agglomeration leads to the expansion of industrial production scale, which increases raw material consumption and industrial pollutant emissions through the scale effect (12). In the process of industrial agglomeration, some enterprises exhibit free-riding behavior in industrial pollution reduction, resulting in severe pollution of the industrial agglomeration area (13). In the process of industrial agglomeration, environmental regulations are regarded as a tool for promoting competition for resources. Local governments usually adopt environmental regulations in a race to the bottom, creating a refuge for pollution and promoting pollution agglomeration (14). Meanwhile, the self-purification effect of industrial agglomeration leads to a reduction in industrial pollutant emissions. The scale effect and spillover effect of industrial agglomeration reduce industrial pollutant emissions by sharing pollution treatment equipment and technology (15). Industrial agglomeration reduces industrial pollutant emissions by building symbiotic and mutually beneficial relationships between industries (16). Through industrial agglomeration, environmental regulations mobilize the enthusiasm of enterprises and, in turn, carry out industrial pollution reduction to curb industrial pollutant emissions (17).

In the process of industrial agglomeration, population density, economic level, technological level, and industrial structure impact industrial pollutant emissions. A thorough investigation was conducted on the impact of industrial pollutant emissions in light of the factors mentioned above.

Industrial agglomeration leads to changes in population size in the area. On the one hand, industrial agglomeration can provide more employment opportunities and effectively improve population density. With the increase in population density, more products are produced to meet the material needs of residents, resulting in an increase in industrial pollutant emissions (18). The population, on the other hand, may migrate geographically due to an increase in industrial pollutant emissions, resulting in a reduction in population density and industrial pollutant emissions (19).

Industrial agglomeration leads to changes in economic level in the area. On the one hand, industrial agglomeration promotes economic prosperity and social development, and such increase in economic level leads to an increase in raw material consumption and industrial pollutant emissions (20). On the other hand, when the economic level reaches a certain level, residents express greater demand for local environmental quality, forcing the government to adopt stricter environmental regulations, increase investment in industrial pollution prevention and control, and reduce industrial pollutant emissions. This is known as the Environmental Kuznets Curve (21).

Industrial agglomeration leads to changes in the technological level of the area. On the one hand, industrial agglomeration can promote technology sharing, matching, and learning by building symbiotic and mutually beneficial relationships between industries. Furthermore, enterprises can effectively reduce industrial pollutant emissions by sharing pollution treatment technologies and equipment (22). On the other hand, some studies have concluded that although technological progress has improved the production efficiency and expanded production scale, it has not made the production process more environmentally friendly. When technological level promotes the improvement of the production efficiency, it leads to an expansion in the scale of production. Although the pollutant emissions of a single product would have decreased, industrial pollutant emissions would have actually increased (23).

Industrial gatherings lead to changes in the industrial structure of the area. On the one hand, industrial agglomeration leads to adjustments in industrial structure, which can result in extension of the industrial chain, improvement in the efficiency of resource utilization, and reduction in the proportion of high-polluting industries in the national economic structure, reducing industrial pollutant emissions (24). On the other hand, industrial pollutant emissions will increase if resource utilization efficiency is ignored during the process of industrial structure adjustment and the proportion of high-polluting industries is increased (25).

According to previous studies, industrial agglomeration leads to an increase in industrial pollutant emissions through the pollution effect. It also effectively reduces industrial pollutant emissions through the self-purification effect. Both effects simultaneously play a role in the process of industrial agglomeration. Industrial agglomeration leads to changes in population size, economic level, technological level, industrial structure, and other factors, and these changes all have impacts on industrial pollutant emissions. The pollution effect and self-purification jointly effect determines the impact of industrial agglomeration on industrial pollutant emissions (26).

The spatial effect of industrial agglomeration affects the spatial distribution of industrial pollutant emissions. If spatial factors are ignored, the results of estimating the impact of industrial agglomeration on industrial pollutant emissions will be biased. An industrial pollutant emission is a derivative of industrial agglomeration which means it exceeds the environment's ability to purify itself. Therefore, due to the spatial spillover effect, industrial pollutant emissions in this region have an impact on industrial pollutant emissions in the surrounding areas (27). An increase in industrial pollutant emissions suggests that this region has lower environmental costs and is more likely to form a pollution refuge, attracting polluting industries to gather through pollution dividends, which affects industrial pollutant emissions in adjacent regions (28). Therefore, it is reasonable to include spatial factors in the analysis of the impact of industrial agglomeration on industrial pollutant emissions.

Therefore, the impact of industrial agglomeration on industrial pollutant emissions is not only a practical problem faced by regional socio-economic development, but also a scientific problem to be discussed in terms of environmental economic geography. Previous research has demonstrated that spatial factors play an indispensable role in the impact industrial agglomeration has on industrial pollutant emissions (29). As there are differences in levels of industrial development and industrial pollutant emissions at the provincial, municipal, and county scales, under the background of differentiated industrial developmental policies and industrial pollution control policies, the impact of industrial agglomeration on industrial pollutant emissions of urban agglomeration can be more accurately described based on county scale data (30). Only by integrating factors such as industrial agglomeration, population density, economic level, technological level, and industrial structure into a unified research framework and analyzing the pollution effect and self-purification effect created by these factors together, can the impacts of industrial agglomeration on industrial pollutant emissions be effectively described.

3. Materials and methods

3.1. Study area

The Lanzhou–Xining urban agglomeration is an important carrier for economic development and industrial agglomeration, located in the upper reaches of western China. It comprises 41 counties in Lanzhou, Xining, Baiyin, Dingxi, Linxia, and Haidong (Figure 1) (31). Lanzhou–Xining has the typical characteristics of a western China urban agglomeration: (1) Pollution-intensive industries account for a high proportion of the regional industrial structure; (2) Industrial pollutant emissions account for a high proportion of the total regional pollutant emissions. (3) There is a significant contradiction between industrial development and industrial pollution prevention (32). The Lanzhou–Xining urban agglomeration has absolute advantages in the support of pollution-intensive industries, such as the presence of a petrochemical industry, non-ferrous metallurgy, salt chemical industry, building

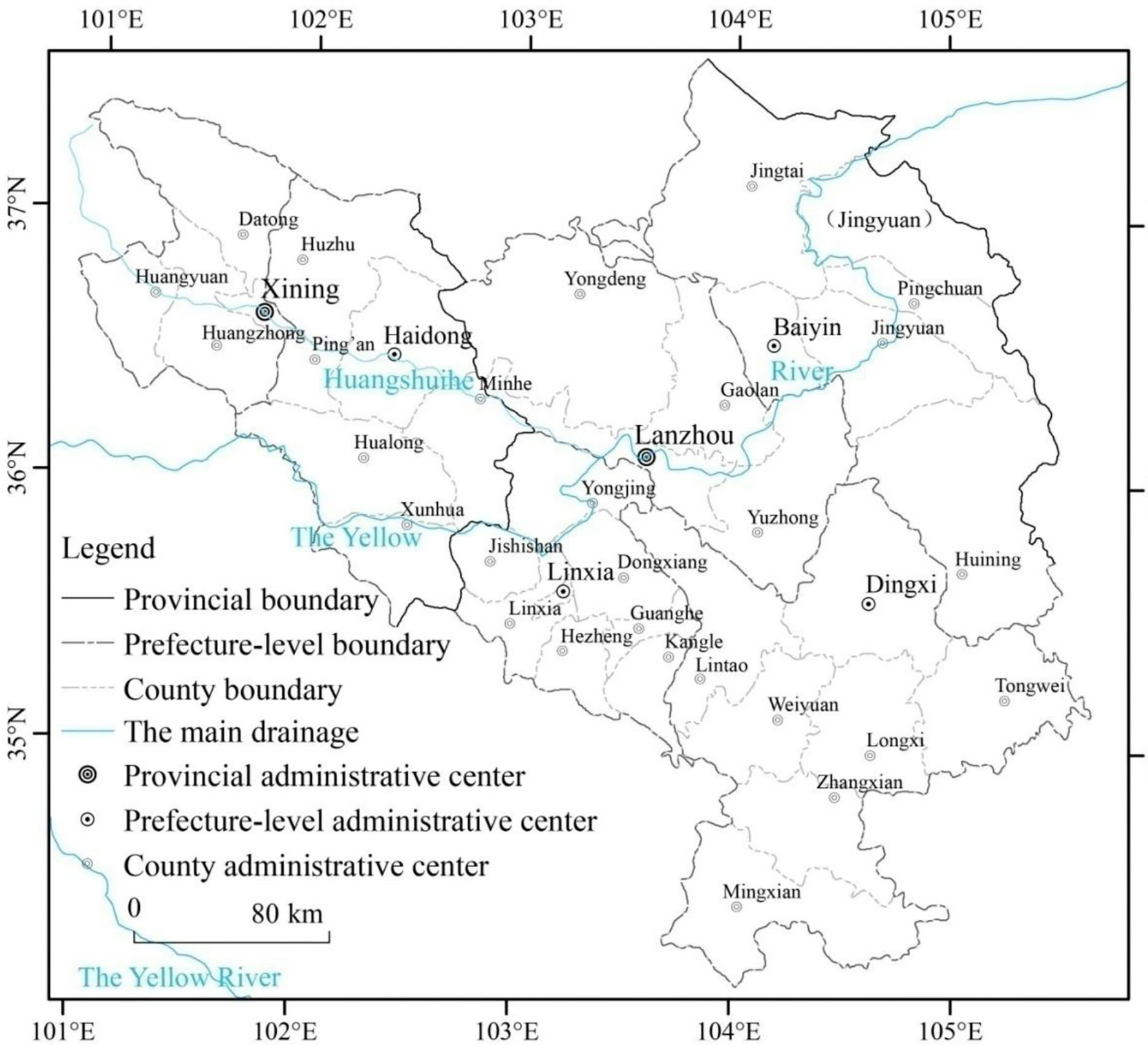

FIGURE 1
Geographical position and spatial extension of Lanzhou–Xining urban agglomeration in western China.

materials and energy supply. Thus, the environmental pressure brought on by pollution-intensive industries is increasingly severe (33). Based on data from 41 counties of the Lanzhou–Xining urban agglomeration in western China from 2010 to 2018, this study examines the spatial characteristics of industrial agglomeration and industrial pollution by using spatial analysis. Spatial factors are introduced into the classic STIRPAT model, and a spatial economic model is constructed to analyze the impact of industrial agglomeration, population density, economic level, technological level, industrial structure, and other factors on industrial pollutant emissions from a spatial perspective, investigating the impact of industrial agglomeration on industrial pollutant emissions in the Lanzhou–Xining urban agglomeration of western China.

3.2. Methodology

3.2.1. Calculation of industrial agglomeration

Geographic concentration index is an effective index that considers regional area factors to measure the spatial concentration of industrial activities. The industrial value added represents the outcome of the industrial production activities of industrial enterprises during the reporting period in monetary terms. Thus, industrial agglomeration is defined as the amount of industrial activity per unit area (34). This study calculates the industrial agglomeration level of each county in the Lanzhou–Xining urban agglomeration in western China by using the geographical concentration index. The model is defined as (35).

$$Agg_{it} = (x_{it}/\sum_{i=1}^{n} x_{it})/(TER_i/\sum_{i=1}^{n} TER_{it})(i = 1, 2, 3, \cdots, n) \quad (1)$$

Here, Agg_{it} is the industrial agglomeration level of county i at time t, x_{it} is the industrial added value of county i at time t, TER_i is the area of county i, and n represents the total number of counties (41) in the Lanzhou–Xining urban agglomeration in western China.

3.2.2. Analysis of spatial correlation

Global Moran's I was used to analyze the spatial correlation of industrial pollutant emissions in the Lanzhou–Xining urban agglomeration in western China (36). In case there may be differences in the effects of industrial agglomeration on industrial pollutant emissions of different physical forms, industrial wastewater, industrial SO_2, and industrial soot are used to represent three different physical forms of industrial pollution. The model is defined as (37).

$$\text{Global Moran's } I = \frac{n\sum_{i=1}^{n}\sum_{j=1}^{n} W_{ij}(x_i - \bar{x})(x_j - \bar{x})}{\sum_{i=1}^{n}\sum_{j=1}^{n} W_{ij}\sum_{i=1}^{n}(x_i - \bar{x})^2} \quad (2)$$

Here, x_i and x_j represent the industrial pollutant emissions of county I and county j, respectively. Variables $\bar{x}$ and W_{ij} are the mean value and geospatial weight matrix based on Queen's principle, respectively, and n is the total number of counties in the Lanzhou–Xining urban agglomeration in western China.

3.2.3. SPIRPAT model

The IPAT model divides the factors affecting environmental change into those involving population, economy, and technology (38). The IPAT model is widely used to analyze the impact of human factors on environmental change because of its concise and representative characteristics. The model is defined as (39).

$$I = P \times A \times T. \quad (3)$$

Based on the original variables of the IPAT model, the STIRPAT model is constructed by adding random variables. The standard form of the STIRPAT model is (40).

$$I = \alpha P^b A^c T^d e \quad (4)$$

Here, I is the environmental impact, P is the population size, A is the affluence, T is the technical level, α is a constant, and e is the random error. In addition, b, c, and d are indexes of population size, affluence, and technical level, respectively. Model (4) can be logarithmically processed to obtain an empirical model (41).

$$\ln I = \ln \alpha + b \ln P + c \ln A + d \ln T + \ln e. \quad (5)$$

Here, b, c, and d are explanatory variable coefficients. The STIRPAT model allows the inclusion of other explanatory variables in the application process (42). Based on the representative studies that have been carried out, industrial agglomeration and industrial structure are added to the empirical form of STIRPAT model, and STIRPAT is updated to the following model (43).

$$\ln POL_{it} = \beta_0 + \beta_1 \ln Agg_{it} + \beta_2 \ln P_{it} + \beta_3 \ln A_{it} + \beta_4 \ln T_{it} + \beta_5 \ln G_{it} + \varepsilon_{it} \quad (6)$$

Here, POL_{it} is the industrial pollutant emissions of county i at time t. Industrial pollutant emissions are expressed by the industrial wastewater, industrial SO_2, and industrial soot. Agg_{it} is the level of industrial agglomeration, expressed by the geographical concentration of industrial added value of county i at time t (44). P_{it} is the population density, expressed by the population per unit area of county i at time t (45). A_{it} is the economic level, expressed by the per capita GDP of county i at time t (46). T_{it} is the technical level, expressed by the industrial energy consumption intensity of county i at time t (47). G_{it} is the industrial structure and is expressed by the ratio of the added value of the secondary industry in the regional GDP of county i at time t (48). β_1, β_2, β_3, β_4, and β_5 are explanatory variable coefficients. β_0 is the constant term, and ε_{it} is the random error.

3.2.4. Spatial econometric models

It is more effective to solve the problem of spatial dependence by using spatial econometric models, which cannot be handled by linear regression analysis. By adding the spatial term of explanatory variables and the spatial term of explained variables to the STIRPAT model, the spatial impact of industrial agglomeration on industrial pollutant emissions can be examined effectively (49). Based on the improved SPIRTAT model, a spatial econometric model is established. Spatial econometric models mainly include spatial lag panel data model (SLM), spatial error panel data model (SEM), and spatial Durbin panel data model (SDM). This study offers three alternative models (50).

(1) Spatial lag panel data model (SLM):

$$\ln POL_{it} = \rho \sum_{j=1}^{n} W_{ij} \ln POL_{jt} + \beta_1 \ln Agg_{it} + \beta_2 \ln P_{it} + \beta_3 \ln A_{it} + \beta_4 \ln T_{it} + \beta_5 \ln G_{it} + \mu_i + \lambda_i + \varepsilon_{it}. \quad (7)$$

Here, POL_{it} is the industrial pollutant emissions of county i at time t. Agg_{it}, P_{it}, A_{it}, T_{it}, and G_{it} represent the industrial agglomeration level, population density, economic level, technical level, and industrial structure, respectively, of county i at time t. Additionally, ρ represents the spatial lag coefficient, and W_{ij} is the geospatial weight matrix based on Queen's principle. β_1, β_2, β_3, β_4, and β_5 are explanatory variable coefficients, μ_i represents the space fixed effect, λ_i represents the time fixed effect, and ε_{it} is the random error.

(2) Spatial error panel data model (SEM):

$$\ln POL_{it} = \beta_0 + \beta_1 \ln Agg_{it} + \beta_2 \ln P_{it} + \beta_3 \ln A_{it} + \beta_4 \ln T_{it} + \beta_5 \ln G_{it} + \mu_i + \lambda_i + \delta \sum_{j=1}^{n} W_{ij}\phi_{it} + \varepsilon_{it}. \quad (8)$$

Here, POL_{it} is the industrial pollutant emissions of county i at time t. Agg_{it}, P_{it}, A_{it}, T_{it}, and G_{it} represent the industrial agglomeration level, population density, economic level, technical level, and industrial structure, respectively, of county i at time t. β_0 is the constant term. β_1, β_2, β_3, β_4, and β_5 are explanatory variable coefficients, δ is the spatial error coefficient, and W_{ij} is the geospatial weight matrix based on Queen's principle. $W_{ij}\varphi_{it}$ is the spatial error term, μ_i is the space fixed effect, λ_i is the time fixed effect, and ε_{it} is the random error.

(3) Spatial Durbin panel data model (SDM):

$$\ln POL_{it} = \rho \sum_{j=1}^{n} W_{ij} \ln POL_{it} + \beta_1 \ln Agg_{it} + \beta_2 \ln P_{it} + \beta_3 \ln A_{it} + \beta_4 \ln T_{it} + \beta_5 \ln G_{it} + \theta_1 \sum_{j=1}^{n} W_{ij}\beta_1 \ln Agg_{it} + \theta_2 \sum_{j=1}^{n} W_{ij} \ln P_{jt} + \theta_3 \sum_{j=1}^{n} W_{ij} \ln A_{jt} + \theta_4 \sum_{j=1}^{n} W_{ij} \ln T_{jt} + \theta_5 \sum_{j=1}^{n} W_{ij} \ln G_{jt} + \mu_i + \lambda_i + \varepsilon_{it}. \quad (9)$$

Here, POL_{it} is the industrial pollutant emissions of county i at time t. Agg_{it}, P_{it}, A_{it}, T_{it}, and G_{it} represent the industrial agglomeration level, population density, economic level, technical level, and industrial structure, respectively, of county i at time t. β_1, β_2, β_3, β_4, and β_5 are explanatory variable coefficients. θ_1, θ_2, θ_3, θ_4, and θ_5 are spatial autocorrelation coefficients of the explanatory variables, ρ represents the spatial lag coefficient, W_{ij} is the geospatial weight matrix based on Queen's principle, μ_i is the space fixed effect, λ_i is the time fixed effect, and ε_{it} is the random error.

3.3. Data source

Based on the availability and statistical consistency of the data, this study used the county-based data from the Lanzhou–Xining urban agglomeration in western China from 2010 to 2018 (Table 1). To make the empirical data more consistent with the normal distribution and eliminate heteroscedasticity in the model, the economic and social data, industrial pollutant emission data, and energy consumption data were processed logarithmically before the model estimation. ① Economic and social data. The economic and social data of the 41 counties in the Lanzhou–Xining urban agglomeration from 2010 to 2018, which included the resident population, industrial added value, added value of the secondary industry, and regional GDP, were derived from the 2011–2019 Gansu Development Yearbook, 2011–2019 Qinghai Statistical Yearbook, and Statistical Yearbooks of Lanzhou, Xining, Baiyin, Dingxi, Linxia, and Haidong over the years, adjusting the economic data to the price in 2010, according to the GDP deflator. ② Industrial pollutant emission data and energy consumption data. Data of industrial pollutant emissions and energy consumption from the 41 counties in the Lanzhou–Xining urban agglomeration from 2010 to 2018 were taken from the Environmental Statistical Systems of Lanzhou, Xining, Baiyin, Dingxi, Linxia, and Haidong. ③ Geospatial data. From 2010 to 2018, the administrative divisions of the 41 counties in the Lanzhou–Xining urban agglomeration were slightly adjusted in general. To show the comparison, the geospatial data are based on the 2015 China county administrative boundary data, provided by the resource and environment science and data center of the Chinese Academy of Sciences.

4. Results

4.1. Spatial pattern of industrial agglomeration

According to Formula 1, the industrial agglomeration of the Lanzhou–Xining urban agglomeration was calculated, and spatial visualization was carried out through ArcGIS10.2 (Figure 2). The spatial pattern of industrial agglomeration of the Lanzhou–Xining urban agglomeration in western China has the following characteristics. ① Spatial imbalance. In the 1950s and 1970s, Lanzhou, Xining, and Baiyin were regarded as important industrial and energy bases in western China and won key construction projects in China. Owing to the inertia of industrial development, Lanzhou, Xining, and Baiyin have become the high-level areas of industrial agglomeration in the Lanzhou–Xining urban agglomeration. Meanwhile, cities with relatively slow industrial development, such as Dingxi, Linxia, and Haidong, have become the low-level areas of industrial agglomeration in the Lanzhou–Xining urban agglomeration. ② Matthew effect. On the one hand, population, capital, technology, and other factors continue to flow from the low-level areas of industrial agglomeration to the high-level areas through the siphon effect. On the other hand, the high-level areas of industrial agglomeration prioritize becoming the geographical space to assume the transferred industries from the eastern

TABLE 1 Definition and explanation of variables.

Variables	Definition	Sample size	Std.Dev	Min	Max
Water	Industrial wastewater emission (10,000 tons)	9*41 = 369	4.29	0.20	3,245
SO_2	Industrial SO_2 emission (tons)	9*41 = 369	8.52	10.00	46,126
SOOT	Industrial SOOT emission (tons)	9*41 = 369	4.15	5.00	25,000
Agg	Geographical concentration of industrial added value	9*41 = 369	10.57	0.02	67.23
P	Population density (10,000 people/km^2)	9*41 = 369	3.12	0.41	0.59
A	Economic level (10,000 Yuan/person)	9*41 = 369	1.22	1.35	7.15
T	Industrial energy consumption intensity (standard coal/10,000 Yuan)	9*41 = 369	3.15	2.30	10.27
G	Percentage secondary industries in GDP (%)	9*41 = 369	2.37	0.34	0.78

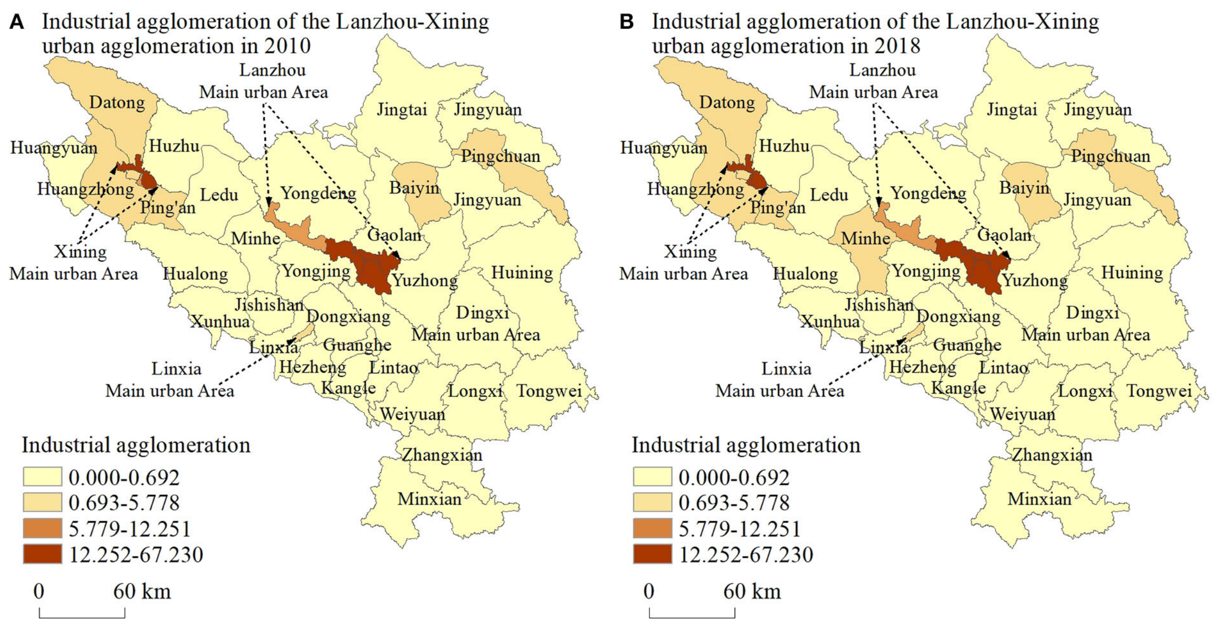

FIGURE 2
Spatial pattern of industrial agglomeration of Lanzhou–Xining urban agglomeration in western China.

and central regions. Consequently, the industrial agglomeration level difference among the counties under the jurisdiction of the urban agglomeration has gradually increased. In 2010, the industrial agglomeration level was between 0.02 and 42.64, while in 2018, the industrial agglomeration level was between 0.03 and 67.23. The ratio of the highest value to the lowest value increased from 1888.15 to 2389.93.

4.2. Spatial pattern of industrial pollutant emissions

ArcGIS10.2 was used to visualize the industrial pollutant emissions of the Lanzhou–Xining urban agglomeration in western China in 2010 and 2018 (Figure 3). The spatial pattern of the industrial pollutant emissions of the Lanzhou–Xining urban agglomeration in western China has the following characteristics. ① Spatial patterns of industrial pollutant emissions and industrial agglomeration have spatial convergence. High-level areas of industrial pollutant emissions are concentrated in Lanzhou, Xining, and Baiyin, whereas low-level areas of industrial pollutant emissions are concentrated in Dingxi, Linxia, and Haidong. ② Industrial pollutant emissions have generally declined. Industrial pollutant emissions have been effectively controlled as a result of the continuous implementation of the concept of ecological civilization and the deepening of pollution prevention and management. From 2010 to 2018, the gap between the high-level areas and low-level areas of industrial pollutant emissions among the 41 counties

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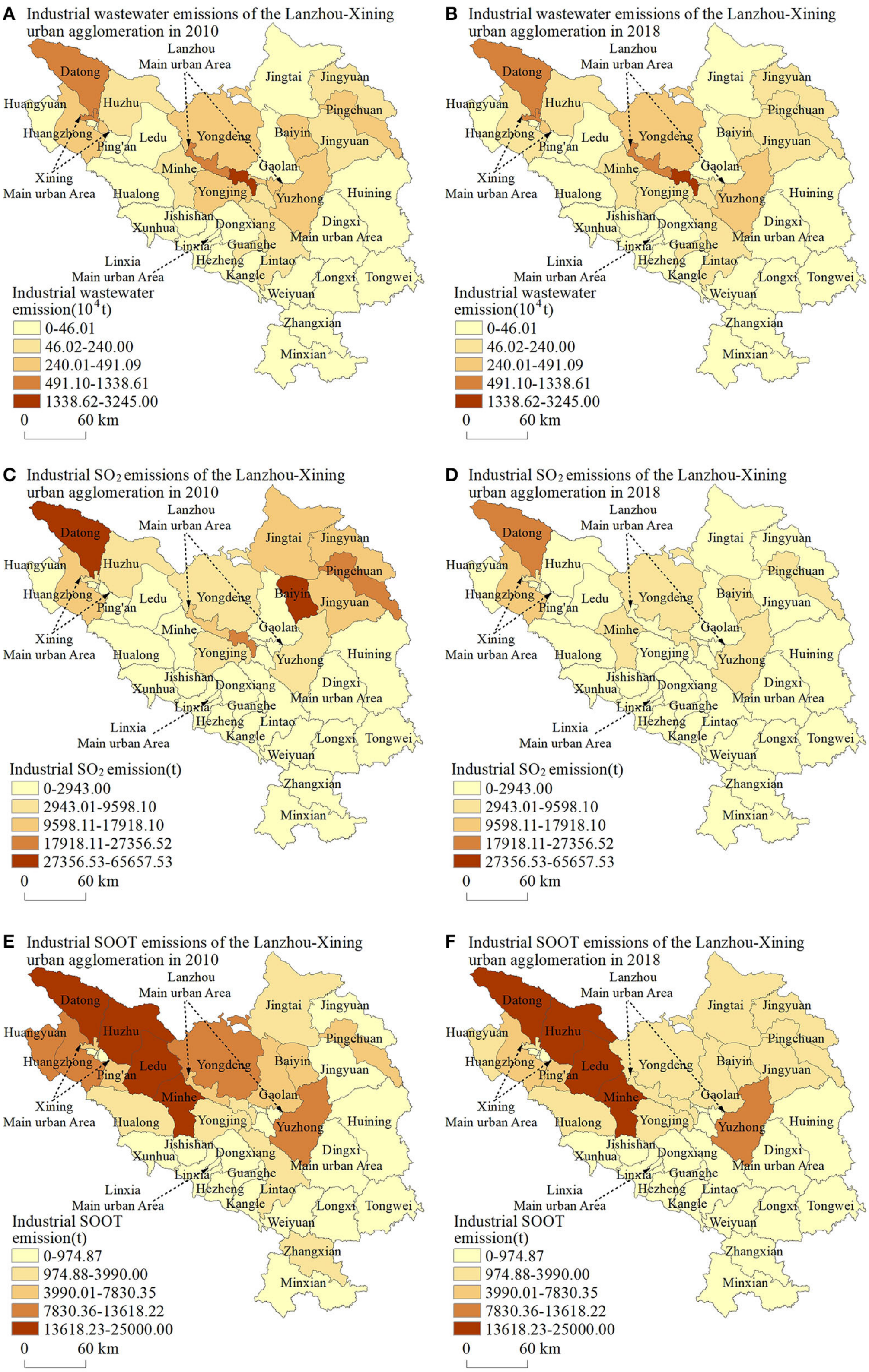

FIGURE 3
Spatial pattern of industrial pollutant emissions of Lanzhou–Xining urban agglomeration in western China.

of the Lanzhou–Xining urban agglomeration in China has been narrowing. In 2010, the county with the highest industrial wastewater emissions had 3,245 $\times$ 10^4 tons of emissions, and the county with the lowest industrial wastewater emissions had 0.2 $\times$ 10^4 tons; meanwhile, in 2018, the county with the highest industrial wastewater emissions had 2,258 $\times 10^4$ tons of emissions, and the county with the lowest industrial wastewater emissions had 0.2 $\times$ 10^4 tons. In 2010, the county with the highest industrial SO_2 emissions emitted 65,658 tons, and the county with the lowest industrial SO_2 emissions emitted 24 tons; in 2018, the county with the highest industrial SO_2 emissions accounted for 23,000 tons, and the county with the lowest industrial SO_2 emissions accounted 10 tons. In 2010, the county with the highest industrial soot emissions yielded 25,000 tons, and the county with the lowest industrial soot emissions yielded 7 tons; meanwhile, in 2018, the county with the highest industrial soot emissions yielded 24,477 tons, and the county with the lowest industrial soot emissions yielded 5 tons.

4.3. Estimation results of traditional panel data model

This linear regression model is commonly estimated by OLS. Tables 2–4 show the impact of industrial agglomeration on industrial wastewater emissions, industrial SO_2 emissions, and industrial soot emissions, respectively, by OLS. It can be seen from the estimation results in Tables 2–4 that the regression coefficient of industrial agglomeration is significantly positive when the spatial effect is not considered, indicating that the improvement in industrial agglomeration leads to an increase in industrial pollutant emissions. Meanwhile, the impact of industrial agglomeration on industrial wastewater emissions, industrial SO_2 emissions, and industrial soot emissions is different. The impact of industrial agglomeration on industrial SO_2 emissions is the most significant, whereas the impact on industrial wastewater emissions is the weakest. Meanwhile, the impact of industrial agglomeration on industrial soot emissions is at the intermediate level. The regression coefficients of economic level, population density, and industrial structure are all significantly positive, indicating that economic level, population density, and industrial structure have a promoting effect on industrial pollutant emissions. The regression coefficients of the technical level are significantly negative, indicating that the technical level has an inhibitory effect on the industrial pollutant emissions.

4.4. Spatial autocorrelation test

Based on GeoDa 1.14, global Moran's I was used to analyze the spatial correlation of industrial wastewater emissions, industrial SO_2 emissions, and industrial soot emissions of the Lanzhou–Xining urban agglomeration in western China. It can be seen from Table 5 that Moran's I of industrial wastewater emissions, industrial SO_2 emissions, and industrial soot emissions from 2010 to 2018 are all positive, and the p-value has passed the 5% significance level test. Areas with high levels of industrial pollutant emissions are adjacent to areas with high levels of industrial pollutant emissions, whereas areas with low levels of industrial pollutant emissions are adjacent to areas with low levels of industrial pollutant emissions (51). This means that the industrial wastewater emissions, industrial SO_2 emissions, and industrial soot emissions all have spatial positive correlation. According to the analysis of global Moran's I for industrial wastewater emissions, SO_2 emissions, and industrial soot emissions, the spatial positive correlation of industrial wastewater emissions is the weakest, and the global Moran's I is between 0.101 and 0.151. The spatial positive correlation of industrial soot emissions is the most significant, and the global Moran's I is between 0.219 and 0.297. The spatial positive correlation of industrial SO_2 emission is at the intermediate degree, and the global Moran's I is between 0.115 and 0.177. Based on GeoDa 1.14, Global Moran's I was used to analyze the spatial correlation of industrial agglomeration level, population density, economic level, technical level, and industrial structure of the Lanzhou–Xining urban agglomeration in western China (52). It can be seen from Table 5 that Moran's I of industrial agglomeration level, population density, economic level, technical level, and industrial structure from 2010 to 2018 are all positive, and the p-value has passed the 5% significance level test.

4.5. Model selection

As the industrial wastewater emissions, industrial SO_2 emissions, and industrial soot emissions of the Lanzhou–Xining urban agglomeration in western China are all positively correlated in space, a spatial econometric model should be built when analyzing the impact of industrial agglomeration on the emission types. As far as model selection is concerned, the spatial panel model should be constructed in such a way that it can be further evaluated through comparison with non-spatial panel models. This research utilizes the LM test for the derived spatial panel data (53). If the results of both the LM-ERR and LM-LAG are not statistically significant, the traditional panel model is chosen; if any of them is significant, then the spatial econometric model is utilized to capture the spatiality.

Our LM test results are presented in Table 6. According to the results, LM-ERR and LM-LAG of industrial wastewater emissions are significant at the 5% level. LM-ERR and LM-LAG of industrial SO_2 emissions are significant at the 1% level. LM-ERR and LM-LAG of industrial soot emissions are significant at the 5% level. As the LM test rejected the original

TABLE 2 OLS estimation results of industrial agglomeration impact on industrial wastewater emissions.

Determinants	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)
ln Agg_{it}	0.213**(3.21)	0.241**(3.45)	0.225* (3.09)	0.217**(3.07)	0.205**(2.95)
ln P_{it}	-	0.119*(2.45)	0.203*(2.78)	0.117*(2.76)	0.122*(2.46)
ln A_{it}	-	-	0.175*(2.56)	0.154*(2.34)	0.134*(2.32)
ln T_{it}	-	-	-	−0.107* (2.08)	−0.121*(2.03)
ln G_{it}	-	-	-	-	0.251***(3.27)
R^2	0.256	0.267	0.264	0.252	0.283
Obs	369	369	369	369	369

In parentheses the *t*-values are given. ***, **, or * indicates significance at the 1, 5, and 10% levels, respectively.

TABLE 3 OLS estimation results of industrial agglomeration impact on industrial SO_2 emissions.

Determinants	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)
ln Agg_{it}	0.281* (3.89)	0.254* (3.63)	0.237* (3.32)	0.243** (3.41)	0.261* (3.52)
ln P_{it}		0.101* (2.02)	0.190* (2.38)	0.182* (2.29)	0.131* (2.17)
ln A_{it}		-	0.106* (2.26)	0.117* (2.42)	0.115* (2.36)
ln T_{it}		-	-	−0.119 (2.28)	−0.106* (2.14)
ln G_{it}				-	0.270** (3.89)
R^2	0.297	0.294	0.301	0.322	0.341
Obs	369	369	369	369	369

In parentheses the *t*-values are given. ***, **, or * indicates significance at the 1, 5, and 10% levels, respectively.

TABLE 4 OLS estimation results of industrial agglomeration impact on industrial soot emissions.

Determinants	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)
ln Agg_{it}	0.203* (2.35)	0.216* (3.10)	0.276* (3.52)	0.217*** (3.09)	0.223* (2.65)
ln P_{it}		0.142* (2.54)	0.174* (2.96)	0.155* (2.94)	0.120* (2.33)
ln A_{it}		-	0.107* (2.31)	0.138* (2.73)	0.124* (2.51)
ln T_{it}		-	-	−0.131 (2.11)	−0.141* ((2.36)
ln G_{it}				-	0.171** (2.73)
R^2	0.224	0.245	0.256	0.278	0.287
Obs	369	369	369	369	369

In parentheses the *t*-values are given. ***, **, or * indicates significance at the 1, 5, and 10% levels, respectively.

hypothesis, it shows that the spatial effect should be considered when analyzing the impact of industrial agglomeration on industrial wastewater emissions, industrial SO_2 emissions, and industrial soot emissions. This spatial effect shows that spatial autocorrelation and spatial error correlation coexist in the model. Thus, it is more appropriate to analyze and select the SDM with the dual effects of spatial lag and spatial error autocorrelation at the preliminary stage (54).

The Wald test and LR test were used to determine whether SDM would degenerate into SLM or SEM. As shown in Table 6, the Wald test spatial lag, Wald test spatial error, LR test spatial lag, and LR test spatial error of industrial wastewater emissions are all significant at the 1% level. The Wald test spatial lag, Wald test spatial error, LR test spatial lag, and LR test spatial error of industrial SO_2 emissions are all significant at the 5% level. The Wald test spatial lag, Wald test spatial error, LR test spatial lag, and LR test spatial error of industrial soot emissions are all significant at the 5% level. Since the Wald test and LR test reject the original hypothesis, it indicates that SDM will not degenerate into SLM or SEM. Therefore, the SDM including the spatial lag dependent variable and spatial autocorrelation error term should be used to analyze the impact of industrial agglomeration on industrial wastewater emissions, industrial SO_2 emissions, and industrial soot emissions (55).

TABLE 5 Global Moran's *I* statistics of and industrial pollutant emissions, industrial agglomeration level, population density, economic level, technical level, and industrial structure.

Years	Water	SO_2	SOOT	Agg	*P*	A	T	G
2010	0.131***	0.156**	0.297***	0.250***	0.269***	0.235***	0.117**	0.175***
2011	0.101**	0.126**	0.223***	0.236***	0.252***	0.257***	0.121**	0.165***
2012	0.120**	0.117**	0.249***	0.247***	0.249***	0.243***	0.125**	0.160***
2013	0.151***	0.132**	0.233***	0.255***	0.243***	0.242***	0.127**	0.121**
2014	0.140***	0.115**	0.273***	0.285***	0.248***	0.267***	0.128**	0.112**
2015	0.146***	0.154***	0.270***	0.275***	0.266***	0.270***	0.114**	0.124**
2016	0.145**	0.177***	0.246***	0.278***	0.267***	0.269***	0.119**	0.157***
2017	0.151***	0.157***	0.224***	0.279***	0.269***	0.271***	0.121**	0.160***
2018	0.143***	0.163***	0.219***	0.281***	0.270***	0.274***	0.125**	0.162***

***, **, or * indicates significance at the 1, 5, and 10% levels, respectively.

TABLE 6 Spatial econometric model selection test.

Determinants	Water		SO_2		Soot	
	Statistics	*P*-value	Statistics	*P*-value	Statistics	*P*-value
LM spatial lag	7.362	0.022	8.639	0.005	9.638	0.035
LM spatial error	5.638	0.037	6.397	0.004	5.875	0.040
Wald test spatial lag	45.862	0.001	52.364	0.000	63.214	0.023
Wald test spatial error	37.661	0.007	36.530	0.000	55.638	0.025
LR test spatial lag	32.255	0.003	26.326	0.001	28.351	0.023
LR test spatial error	41.261	0.001	35.612	0.000	33.652	0.032
Hausman test	86.231	0.002	72.585	0.032	82.657	0.017

TABLE 7 Estimation results of spatial Durbin model of industrial agglomeration and industrial pollutant emissions.

Determinants	Spatial fixed effects			Time fixed effects			Spatial–time fixed effects		
	Water	SO_2	Soot	Water	SO_2	Soot	Water	SO_2	Soot
$W \times POL_{it}$	0.202***	0.244***	0.230***	0.211***	0.275***	0.254***	0.217***	0.251***	0.235***
$\ln Agg_{it}$	0.254***	0.262***	0.233***	0.263***	0.274***	0.251**	0.277***	0.285***	0.254**
$\ln P_{it}$	0.178***	0.227***	0.165**	0.172**	0.219**	0.173**	0.145**	0.272**	0.170**
$\ln A_{it}$	0.132**	0.145**	0.127**	0.131**	0.178**	0.146**	0.151**	0.162**	0.164**
$\ln T_{it}$	−0.117**	−0.102**	−0.132	−0.074*	−0.135**	−0.147	−0.165**	−0.149**	−0.158
$\ln G_{it}$	0.204***	0.221***	0.218***	0.242***	0.203***	0.279***	0.254***	0.262***	0.214***
$W \times \ln Agg_{it}$	0.120***	0.112***	0.139***	0.110***	0.182***	0.169***	0.140***	0.182***	0.134***
$W \times \ln P_{it}$	0.043**	0.057**	0.031**	0.067***	0.097***	0.055***	0.063***	0.089***	0.074***
$W \times \ln T_{it}$	0.050**	0.082**	0.069**	0.098**	0.054**	0.088**	0.074**	0.056**	0.073**
$W \times \ln \mathrm{T}_{\mathrm{it}}$	−0.093**	−0.077**	0.081	−0.023**	−0.047**	−0.031	−0.055**	−0.065**	−0.071
$W \times \ln G_{it}$	0.107***	0.102***	0.109***	0.101***	0.104***	0.109***	0.093***	0.102***	0.113***
R^2	0.672	0.638	0.644	0.568	0.611	0.621	0.532	0.661	0.562
Log likelihood	353.974	274.051	310.124	320.342	223.501	265.321	319.102	258.569	270.224

Numbers in the parentheses represent *t*-values. ***, ** and * indicate significance at the 1, 5, and 10% level.

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4.6. Spatial econometric regression results

The aim of the Hausman test is to determine whether a model with fixed or random effects is more appropriate. The Hausman test results of the impact of industrial agglomeration on industrial wastewater emissions, industrial SO_2 emissions, and industrial soot emissions are all significant at the 5% level, rejecting the original assumption of random effects (Table 6). It was found by the Hausmann test that the results significantly reject the original hypothesis, suggesting that the fixed effect should be chosen (56). Therefore, this study should choose a fixed model to analyze the impact of industrial agglomeration on industrial wastewater emissions, industrial SO_2 emissions, and industrial soot emissions. The fixed model includes a pace fixed effect, time fixed effect, and time–space double fixed effect, and the most suitable effect is selected according to R^2 and log likelihood (57). As is shown in Table 7, the estimation results of the spatial fixed effect, time fixed effect, and time–space double fixed effect, the significance, and significance test of each explanatory variable have not changed significantly, which indicates that the SDM is robust. The R^2 and log likelihood parameters of SDM with the spatial fixed effect of industrial agglomeration on industrial wastewater emissions are the largest. The R^2 and log likelihood parameters of SDM with the spatial fixed effect of industrial agglomeration on industrial SO_2 emissions are the largest, and the R^2 and Log likelihood parameters of SDM with the spatial fixed effect of industrial agglomeration on industrial soot emissions are the largest. Therefore, the SDM with the spatial fixed effect is used to estimate the impact of industrial agglomeration on industrial wastewater emissions, industrial SO_2 emissions, and industrial soot emissions (58). According to the estimation results of SDM with fixed spatial effect, the spatial lag coefficients of industrial wastewater emissions, industrial SO_2 emissions, and industrial soot emissions are 0.202, 0.244, and 0.230, respectively, and they are all significantly positive at the 1% level (Table 7). This indicates that there is a spatial endogenous interaction effect among the explained variables, indicating that industrial wastewater emissions, industrial SO_2 emissions, and industrial soot emissions in each county are affected by the relevant factors of the county. They are also affected by the discharge of industrial wastewater emissions, industrial SO_2 emissions, and industrial soot emissions from adjacent counties.

The regression coefficients of industrial agglomeration with industrial wastewater emissions, industrial SO_2 emissions, and industrial soot emissions are 0.254, 0.262, and 0.233, respectively, and they are all significantly positive at the level of 1%, indicating that the increase in the industrial agglomeration level in the Lanzhou–Xining urban agglomeration will promote industrial wastewater emissions, industrial SO_2 emissions, and industrial soot emissions. The spatial term coefficients of industrial agglomeration and industrial wastewater emissions, industrial SO_2 emissions, and industrial soot emissions are 0.120, 0.110, and 0.139 respectively, and they are all significantly positive at the level of 1%. This indicates that the improvement in the industrial agglomeration level of this county will lead to an increase in the industrial production scale, thus increasing the industrial pollutant emissions of this county, as well as the industrial pollutant emissions of neighboring counties through the scale effect. The trans-boundary nature of industrial pollution discharge is demonstrated here.

The regression coefficients of population density, industrial wastewater emissions, industrial SO_2 emissions, and industrial soot emissions are 0.178 and 0.227, respectively, which are significantly positive at the level of 1%. The regression coefficient between population density and industrial soot emissions is 0.165, which is significantly positive at the 5% level, indicating that the increase in population density can promote an increase in economic vitality and expansion of the industrial scale, thus increasing industrial wastewater emissions, industrial SO_2 emissions, and industrial soot emissions. The spatial term coefficients of population density on industrial wastewater emissions, industrial SO_2 emissions, and industrial soot emissions are 0.043, 0.051, and 0.069, respectively, and they are all significantly positive at the 5% level, indicating that the increase in population density in the county will lead to an increase in resource consumption and industrial pollutant emissions, which will lead to an increase in industrial pollutant emissions in the county. The increase in industrial pollution and environmental deterioration in this country will lead to a flow of residents to the neighboring counties through various policies, resulting in an increase in industrial pollution emissions from the neighboring counties.

The regression coefficients between economic level and industrial wastewater emissions, industrial SO_2 emissions, and industrial soot emissions are 0.132, 0.145, and 0.127, respectively, and are significantly positive at the 5% level, indicating that industrial pollutant emissions have not crossed the peak of Kuznets curve. At this stage, with an increase in the economic level, industrial wastewater emissions, industrial SO_2 emissions, and industrial soot emissions will increase. The spatial term coefficients of economic level, industrial wastewater emissions, industrial SO_2 emissions, and industrial soot emissions are 0.050, 0.083, and 0.037 respectively, which are significantly positive at the 5% level, indicating that the improvement in the economic level of this county will lead to an improvement in the industrial pollution discharge of this county, and the significant promotion of economic level of adjacent counties will lead to an improvement in the industrial pollution discharge of this county. The reason is that due to the economic development in this district, the residents will pay more attention to the quality of their living environment, causing the polluting industries to relocate to the adjacent areas.

The regression coefficients of technical level and industrial wastewater emissions, industrial SO_2 emissions, and industrial soot emissions are −0.117 and −0.102, respectively, which are significantly negative at the 5% level. Although the regression coefficients of technical level and industrial soot emissions are also negative, they fail to pass the significance test, indicating that technical level has "crowding-out effect" on industrial soot emissions and industrial wastewater emissions and can reduce industrial SO_2 and wastewater emissions. However, the "technology rebound effect" is more common in industrial production. Although the technology level reduces the industrial soot emissions per unit of production, it does not effectively reduce the total industrial soot emissions, which is not conducive to reducing the industrial soot emissions. The spatial term coefficients of the technical level with industrial SO_2 emissions and industrial wastewater emissions are −0.093 and −0.077, respectively, which are significantly negative at the 5% level, indicating that the improvement of the technical level of the county can reduce the industrial SO_2 emissions and industrial wastewater emissions of the county, leading to a reduction in industrial SO_2 emissions and industrial wastewater emissions of adjacent counties through the demonstration effect. The spatial term coefficient of the technical level on industrial soot emissions is negative, but it fails to pass the significance test. The reason for this result may be the special feature of pollutants and the specific regional distribution of industrial activities.

The regression coefficients of industrial structure with industrial wastewater emissions, industrial SO_2 emissions, and industrial soot emissions are 0.204, 0.221, and 0.218, respectively, and they are all significantly positive at the 1% level, indicating that with the increase in the proportion of the total output value of the secondary industry in the regional GDP, industrial wastewater emissions, industrial SO_2 emissions, and industrial soot emissions will increase. The spatial term coefficients of industrial structure and industrial wastewater emissions, industrial SO_2 emissions, and industrial soot emissions are 0.107, 0.102, and 0.109, respectively, which are significantly positive at the 1% level, indicating that the increase in the proportion of the total output value of the secondary industry in the GDP of the county will not only promote improvement of the industrial pollution discharge of the county, but also lead to improvement of the industrial pollution discharge of adjacent counties through structural effects. That is, when the county increases the proportion of the total output value of the secondary industry in the regional GDP, the neighboring county will race to the bottom to avoid becoming disadvantageous in regional competition and then increase the proportion of the total output value of the secondary industry in the regional GDP, resulting in an increase in industrial pollutant emissions. This shows that joint prevention and control are needed in the process of industrial pollution management.

5. Discussion

5.1. Research contributions

Scholars have different ideas on the relationship between industrial agglomeration and industrial pollutant emissions. However, there is no consensus on the research conclusion. These differences in variant studies come from the differences in time period, sample, and selection of industrial agglomeration indicators in different studies (59). In the initial stage of industrial agglomeration, it usually leads to an increase in industrial pollution emissions, but under the influence of scale effect and technology effect, it will reduce industrial pollution emissions (60). The industrial agglomeration of Lanzhou Xining urban agglomeration is in its initial stage, and this study is of reference significance to other regions or countries.

The possible innovation of this study mainly lies in the following two aspects. First, this study considers the Lanzhou–Xining urban agglomeration as the sample area to explain the impact of industrial agglomeration in western China on industrial pollutant emissions. The Lanzhou–Xining urban agglomeration is the main reason for the increase in industrial pollutant emissions, owing to the expansion of production scale in the process of industrial agglomeration. The Lanzhou–Xining urban agglomeration in western China needs to achieve high-quality economic development by increasing the proportion of technology intensive industries in the national economic structure, as well as upgrade and transform existing traditional industries. Second, the industrial pollutant emissions of the counties under the jurisdiction of the Lanzhou–Xining urban agglomeration in western China are spatially related, which indicates that the spatial effect of industrial pollutant emissions is closely related to the industrial pollutant emission characteristics of neighboring counties. Therefore, when formulating industrial pollution control policies, an environmental pollution control linkage mechanism at the level of urban agglomeration should be established to prevent the formation of a pollution paradise.

The possible significance of this study mainly lies in the following two aspects. First, in this paper, spatial analysis technology and spatial econometric analysis were not only used to analyze the impacts of industrial agglomeration on industrial pollutant emissions, but also used to analyze the impacts of population density, economic level, scientific and technological level and industrial structure on industrial pollutant emission. Second, the industrial pollutant emission

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characteristics of the counties in the Lanzhou–Xining urban agglomeration in western China are jointly affected by the industrial agglomeration, population density, economic level, technological level, industrial structure, and other factors of the county and neighboring counties. Therefore, when reducing industrial pollutant emissions, the counties of the Lanzhou–Xining urban agglomeration in western China need to consider the influencing factors of the surrounding counties to promote the overall green industrial transformation and quality improvement of the Lanzhou–Xining urban agglomeration in western China. It is concluded that the coordinated development of industry is the fundamental of joint prevention of pollution.

5.2. Deficiencies of the study

Owing to the limitations in research methods and data materials, this study may have some research deficiencies in the following three aspects. First, this study mainly focuses on analyzing the impact of industrial agglomeration on the characteristics of industrial pollutant emissions from the data of county scale industrial pollutant emissions of the Lanzhou–Xining urban agglomeration in western China. However, it fails to effectively dig deeper into the enterprise and industry level to analyze the difference in the impact of industrial agglomeration on industrial pollutant emissions from different industries. This will affect the comprehensiveness of the analysis of the impact of industrial agglomeration on industrial pollutant emissions. Second, owing to the change in the statistical caliber of industrial pollutant emission data, this study focuses on analyzing the impact of industrial agglomeration on industrial pollutant emission characteristics of the Lanzhou–Xining urban agglomeration in western China through the data from 2010 to 2018; thus, there is a lack of long-term and continuous tracking data. Third, the synergy and combination effects among industrial agglomeration, population density, economic level, technological level, and industrial structure have not been analyzed. Meanwhile, the interaction effects of the reverse effects of industrial pollutant emissions on industrial agglomeration have not been deeply analyzed. The above deficiencies will also be the areas and directions for further research.

6. Conclusion

The impact of industrial agglomeration on industrial pollutant emissions of the Lanzhou–Xining urban agglomeration in western China is analyzed by using spatial analysis and spatial econometric models. The main conclusions of this study are as follows.

Industrial agglomeration is an important factor leading to the increase in industrial pollutant emissions. Adhering to the environmental bottom line of economic development and promoting green industrial transformation are the primary ways for the Lanzhou–Xining urban agglomeration in western China to achieve high-quality development. Both industrial agglomeration and industrial pollutant emissions have spatial effects, and industrial agglomeration and industrial pollutant emissions of adjacent counties are closely related. Coordinated industrial development is the basis of comprehensive pollution control. Without the common industrial improvement and efficiency, there will be no long-term joint management and control of pollution. It is inevitable that the Lanzhou–Xining urban agglomeration in western China will form a spatial synergy of industrial co-construction and pollution control.

As industrial wastewater emissions, industrial SO_2 emissions, and industrial soot emissions are different types of pollutants, the spatial patterns are significantly different, leading to significant differences in the main influencing factors of the different pollutant emissions. Industrial pollution discharge is not only affected by the population density, economic level, technological level, industrial agglomeration, industrial structure, and other factors of the county but is also affected by the industrial pollution agglomeration and influencing factors of its neighboring counties. Social and economic factors play a role in industrial pollutant emissions of this county and neighboring counties through spatial effect, and different social and economic factors have different spatial effects.

Industrial pollutant emissions of the Lanzhou–Xining urban agglomeration in western China have spatial positive correlation and spatial spillover. Therefore, it is necessary to take full advantage of the coordination among the counties of the urban agglomeration, pay attention to joint prevention and control, co-construction and common governance, and form a joint force space-wise. Industrial pollutant emissions are a derivative problem in the process of industrial agglomeration development during urban agglomeration; thus, it is necessary to control industrial pollution agglomeration through the coordination of government power, enterprise power, market power, and social power. Industrial pollutant emissions are both an environmental problem and a developmental problem. Therefore, on the premise of maintaining economic development, we should promote industrial structure adjustment and industrial chain extension to improve the quality and efficiency of industry. Meanwhile, we need to optimize the energy structure and technology level as well as to promote and demonstrate emission reduction technologies, improving the overall technological contribution for the pollution reduction. It is concluded that the coordinated development of industry is the fundamental of joint prevention of pollution. It is an inevitable choice to construct a spatial synergy of industrial co-construction and pollution co-governance for the ecological protection and high-quality development of urban agglomeration.

Data availability statement

The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding author.

Author contributions

ZJ for conceptualization, methodology, software, validation, formal analysis, writing, and original draft preparation. QC and YY for investigation, resources, and data curation. HN and JZ for writing—review and editing, supervision, and project administration. All authors have read and agreed to the published version of the manuscript.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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Evolution and prediction of land use around metro stations

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Metro stations are considered high-quality resources for promoting urban development, which have great influences on the surrounding land use changes. The simulation and prediction of land use change can provide a scientific basis for urban land planning. In this work, the cellular automata (CA)-Markov model was adopted by taking into account point of interest (POI) kernel density and station accessibility as driving factors to predict the land use change of station surrounding areas. Then, the land type compositions of different years, temporal and spatial evolution of landscape patterns, and strategies of different metro stations were explored. The results show that the Kappa coefficients of the Zoo Station and the Lu Xiao Station are 87% and 79%, respectively, indicating that the improved CA-Markov model can predict land use changes more accurately by considering POI kernel density and station accessibility. Finally, different optimized strategies based on systematic predictions of land use landscape patterns according to the spatial and temporal distribution of metro stations were proposed. The work provides important references for predicting the impact of new metro stations on land use in the future and guides the adjustment and optimization of land use policy planning.

KEYWORDS

land use/cover change (LUCC), metro stations, landscape pattern, CA-Markov model, temporal and spatial evolution

1 Introduction

The rapid urbanization process has improved people's quality of life. However, it also brings about the contradiction between urban space, land development and transportation, accelerating the conversion between different land use types, resulting in the loss of farmland, woodland, ecosystem destruction, and other issues. In this case, land-use and land-cover change (LUCC) have become a research hotspot (Munsi et al., 2010; Wei et al., 2021). The transport network constitutes the spatial skeleton of urban development. The transformation and upgrading of urban transportation means and modes have a profound impact on the change of urban land use and the development of spatial structure (Yu, 2017).

As a high-quality resource to promote urban development, the efficient use of the land around metro stations becomes an important research topic (Suo and Zhang, 2015; Yang et al., 2022a; Yang et al., 2023a; Yang et al., 2023b), and the distribution characteristics of urban functional space can direct reflect land use (Wang et al., 2012). Land use change also leads to the change in regional landscape patterns. Landscape pattern is a core content in the field of landscape ecology, and its landscape patch types are usually expressed as land use types (Chu et al., 2018). By taking the research method of landscape ecology for reference, the landscape pattern index is used to analyze the urban landscape characteristics of the surrounding areas of the metro station to understand the impact characteristics of the metro station on its nearby areas (Cheng and Chen, 2019). Therefore, land use landscape patterns around metro stations have recently attracted much attention from academia alike.

Against this backdrop, this study takes two metro stations in Chengdu (China) as the study area and scrutinizes the relationship between the land use landscape patterns and the metro stations. This work aims to optimize the CA-Markov model by considering POI kernel density and station accessibility as driving factors, which are more applicable for small scales land use change predictions. Based on the GIS analysis platform, the CA-Markov model is used to empirically analyze the urban functional structure characteristics of Chengdu metro stations, which provides suggestions for the planning and layout of metro stations and the development of cities around them.

The contributions of this study can be summarized as follows. On the one hand, this study improved the accuracy of the CA-Markov model by including POI kernel and station accessibility as driving factors at first. Then, this study predicted the land use change around two selected metro stations in the west of China by the optimized CA-Markov model. Finally, this study proposed different optimized strategies of land use landscape pattern according to spatial and temporal distribution of metro stations. On the other hand, previous academic research on the relationship between metro and land use has focused more on the coordinated relationship between metro and land use at the urban scale, and there has been less in-depth discussion on the differences in land use around the station. This study analyzes the land use differences around specific stations, making up for the lack of such research.

The implications for future research are as follows. The research results of this paper focus on the accessibility direction. The main innovation is to couple the traffic network into the land use spatial and temporal evolution pattern of CA-Markov, and find out the influence of the traffic factor of the metro station on the prediction accuracy of the future scene of the CA-Markov model. The research results will realize the future multi-scenario planning of land use around the old urban metro station and the new urban metro station in the process of urban renewal, and provide reference for the decision-making of the city's functional management department. At the same time, it is also a meaningful innovation and exploration of the coupling model method and predicting the impact factors of future scenarios under LUCC theory and landscape pattern theory.

2 Literature review

The correlation between the metro station and land use/cover change has always been a hot research topic. With the rapid construction and development of metro stations, Cervero and Kockelman proposed a transit-oriented development (TOD) model with reasonable land development intensity, diversified functions, and a comfortable walking space scale (Robert and Kockelman, 1997). Binaco found that the price of land along Polish metro is dominated by traffic accessibility, and the development of metro promotes the value of surrounding land (Dueker and Bianco, 1998). Some scholars have focused on the station selection (Li and Lei, 2016), the type (Duan and Zhang, 2013), the impact of the station on the surrounding areas (Feng et al., 2011), and the coordinated development and planning of the surrounding areas (Xu et al., 2015).

According to the existing research, the continuous expansion of metro will have a profound impact on the land around the traffic stations, such as land development intensity, land use structure, land value, accessibility, etc (Fla, Zl, Hc, Zc, Mla; Higgins and Kanaroglou, 2016). Within the scope of the new metro, the increase of the surrounding land passenger flow and accessibility leads to the increase of the whole land development intensity. The proportion of business land, residential land, public services land and traffic land changed significantly. Land use change leads to the change of regional landscape patterns. The impacts of the land use on landscape patterns have also been extensively studied. Simulating the future changes in land use landscape patterns and studying the formation process and mechanism of the current land use landscape pattern has important scientific values and practical significance (Li et al., 2016). At present, many models are developed to simulate land use change. CLUE-S model, PLUS model, FLUS model, and CA-Markov model are commonly used, among which the CA-Markov model has outstanding advantages in time series and spatial prediction (Rahnama, 2021; Mathewos et al., 2022). It can simulate land use change in quantity and geographical space (MartzLawrence and Hyandye & Canute, 2017; Thaden et al., 2018), so it is widely used in the study of land use landscape pattern change. Previously, most of the research objects were selected on a large scale. For example, (Jana et al., 2022), (Sma et al., 2019), (Aksoy and Kaptan, 2021), Etemadi et al. (2018) used the CA-Markov model to simulate and predict the large-scale land use evolution of the Mahi River in India, mountainous cities in Oman, Ulus district in northern Turkey, mangroves along the coast of Iran. Meanwhile, (Fu et al., 2022) simulated and predicted the landscape pattern of county land use in Mianzhu City. However, academic research on the relationship between metro stations and land use has focused more on the coordination at the urban scale. Few studies focused on the simulation and prediction of small scale. Most of the previous studies considered that road factors will have an impact on land use change, but pay less attention to POI kernel density and station accessibility as driving factors of the CA-Markov model, which could improve the accuracy of the simulation.

3 Materials and methods

3.1 Overview of the research area

This work chooses two metro stations in need of economical, intensive, and high-quality development but have obvious time and space differences (Ryan and Throgmorton, 2003). The metro stations under study are located in the old and new districts of Chengdu. Zoo Station and Lu Xiao Station are the representative of the old district and the new district, respectively. The Zoo Station is located on Metro Line 3, an old urban area of Chengdu, and began operation on 31 July 2016. The construction of the metro station has brought an opportunity for land development around the Chengdu Zoo and Chengdu Research Base of Giant Panda Breeding. With the establishment of the station, the land value will be greatly improved. The transformation of this type of area mainly lies in optimizing and upgrading the stock space, promoting the organic renewal of the city, enhancing the value of the city space, and promoting the development of the connotation of the park city. The development of such old urban metro station is relatively early and mature, and the supporting public service facilities are relatively perfect. The Zoo Station is a model of the old city station. The analysis of the

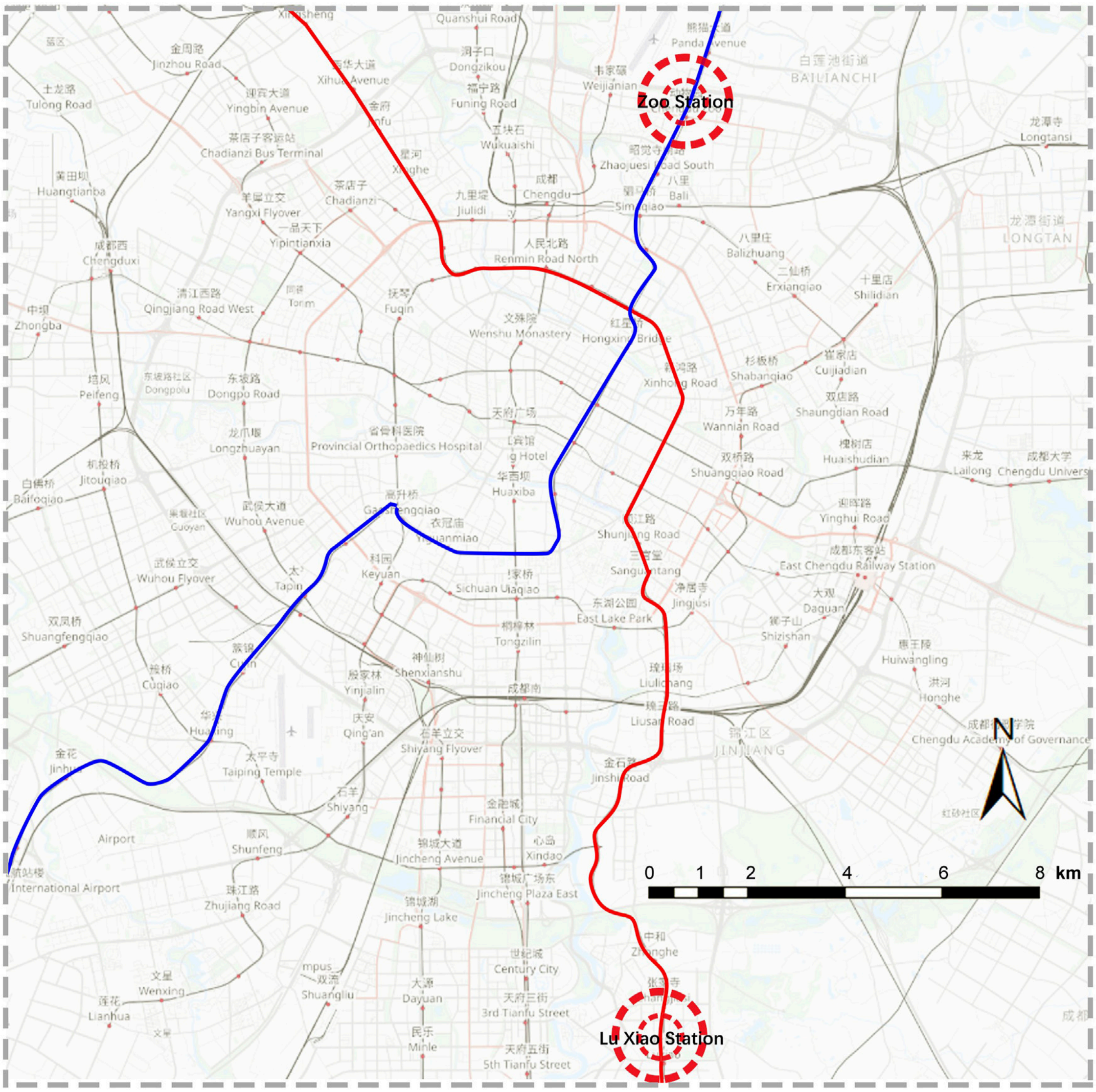

FIGURE 1
Distribution location of two metro stations (https://www.openstreetmap.org/relation/3287346).

surrounding land use changes is conducive to the improvement and optimization of this type of station land.

The Lu Xiao Station is located on Metro Line 6, in Chengdu High-tech Center, and it was operated to traffic on 18 December 2020. As the first TOD demonstration project in Chengdu, the Lu Xiao Station takes metro stations as the center of a circle. In its planning and design, it has a mixed-function development of land, equipped with medical, education, shopping centers, parks, office buildings, etc. Such new urbanstations implement efficient and intensive TOD comprehensive development. According to the concept of "station-city integration, industry priority, functional compounding, and comprehensive operation", with rail transit as the guide, the city's central vitality zone featuring park communities forms a new economic and new kinetic energy cultivation center. It is the representative of the overall construction of TOD urban design area. Therefore, the Lu Xiao Station has a certain demonstration effect.

At present, the research mostly adopts the spatial range of 400–800 m around the subway station as the research object (Qiang, 2009). Based on this result, combined with relevant theories and the characteristics of the research object, this study takes the two stations as the core and the 800 m radius as the research scope. Investigating two metro stations with different time and space distributions but the same area range helps to verify the simulation accuracy of the model and reveal the reasons for the regional differences of metro stations impact on land use change in old and new urban areas through comparative analysis, as shown in Figure 1. The qualitative and quantitative analysis of this article is helpful in understanding the influence of metro stations on the land use structure around the stations and can provide a reference for the local government to formulate urban development policies related to metro stations.

3.2 Data source and processing

1) The vector data of land use in the planning and construction year is obtained from the Sichuan Third Academy of Surveying and Mapping Engineering. The land use map of the operating year is based on the land use data of the planning year, combined with

TABLE 1 Classification of land use types in the study area.

Serial number	Land type	Include land types
1	Farmland	Irrigated land, paddy field and dry land etc.
2	Forest	Woodland, shrubs; gardens etc.
3	Business	Commercactial land, financial land, recreational land etc.
4	Industrial	Land for industry, logistics and storage, and land for storage etc.
5	Residential	Single urban residential land and mixed urban residential land etc.
6	Public services	Cultural land, educational land, sports land, medical and health land, and social welfare land etc.
7	Traffic	Metro station land, urban road land and highway land etc.
8	Water	Ponds, lakes, and ditches etc.
9	Unused	Bare land, wasteland etc.

the Google satellite map of the operating year. Compared with the land use status data interpreted by remote sensing images, direct use of the vector data of land use status can reduce errors in supervised classification and manual visual interpretation, and the accuracy of land use simulation and prediction research will also be greatly improved. Moreover, in the current geographic information system based on vector data structure, to solve the problem of combining with remote sensing, vector data is often converted into raster data. The ArcGIS10.5 software is adopted to rasterize the vector data of land use, and the data is then manually interpreted.

Compared with Chengdu Urban Master Plan (2016–2035), this article analyzes the interactive relationship between metro stations and surrounding land use. According to the latest national standard of "Land use status classification" (GBT21010-2017), combined with the status of the study area, the land use types are divided into nine categories, as shown in Table 1.

2) Road information data comes from Chengdu's comprehensive traffic planning map.
3) The geospatial data cloud of the Global Digital Elevation Model (GDEM) with a resolution of 30 m is downloaded from the website (http://www.gscloud.cn/). Then, the GIS software is employed to obtain the slope from DEM.
4) The POI data such as residence, commercial services, industrial and mining, public service, etc. are obtained from Baidu's national map POI (https://lbsyun.baidu.com/solutions/fanxing).
5) The accessibility data are obtained from the lightweight route planning data of the Baidu web Service API (https://lbsyun.baidu.com/index.php?title=webapi/directionlite-v1).

In addition, to meet the needs of research, Beijing_1954_3_degree_GK_zone_35 is used as the unified projection coordinate system of the above data, and the spatial res-olution is 5 m × 5 m.

3.3 Research method

3.3.1 CA-markov model

Cellular Automata (CA) is a dynamic system with discrete space and state (Chudech et al., 2016), and each cell is in a discrete state. Synchronize updates based on the same transformation rules that are local in time and space. The formula is as follows (Sang et al., 2011):

$$S_{t+1} = f(S_t, N) \quad (1)$$

S, the set of cellular states; N, the cellular domain; $t, t+1$, is different time; f, the cellular transformation rule of local space.

Markov model is a stochastic model in the time dimension (Behera et al., 2012). The transition matrix is the application of the Markov Model in Land Use Change. The transition matrix is a digital reflection of the possibility of the event changing from t state to t+1 state, and it is an important quantitative basis for the simulation and prediction results under the Markov plate. The formula is as follows:

$$S_{t+1} = P_{ij} \times S_t \quad (2)$$

S_t, S_{t+1} is the state of land use system of $t, t+1$; P_{ij}, the state transition matrix, and its formula is expressed as (Ongsomwang and PimjaiMontree, 2015):

$$P_{ij} = \begin{bmatrix} P_{11} & P_{12} & \dots & P_{1n} \\ P_{21} & P_{22} & \dots & P_{2n} \\ \dots & \dots & \dots & \dots \\ P_{n1} & P_{n2} & \dots & P_{nn} \end{bmatrix} \quad (3)$$

We choose the CA-Markov model, which combines the advantages of the two models to simulate. The kappa coefficient was calculated to reflect the consistency between the simulation results and the real results. When .8 < Kappa ≤1, it shows that the reference map is almost completely consistent with the simulation map. When .6 < Kappa ≤.8, the simulation result is highly consistent with the actual drawing.

3.3.2 POI kernel density

POI is the abbreviation of "Point of Interest", the core data of location-based service, and it is of great value for studying cities (Chen and Xu, 2019; Yang et al., 2021; Yang et al., 2022b). The POI data set carries the spatial information and attribute information data of geographical entities closely related to people's lives, and can quickly and intuitively reflect their distribution in cities, which is superior to the traditional survey data (Shu et al., 2019). Moreover, the function agglomeration of cities around metro stations has a great relationship with the location of urban space (Wu, 2021). The distribution density of different POI types around the station will

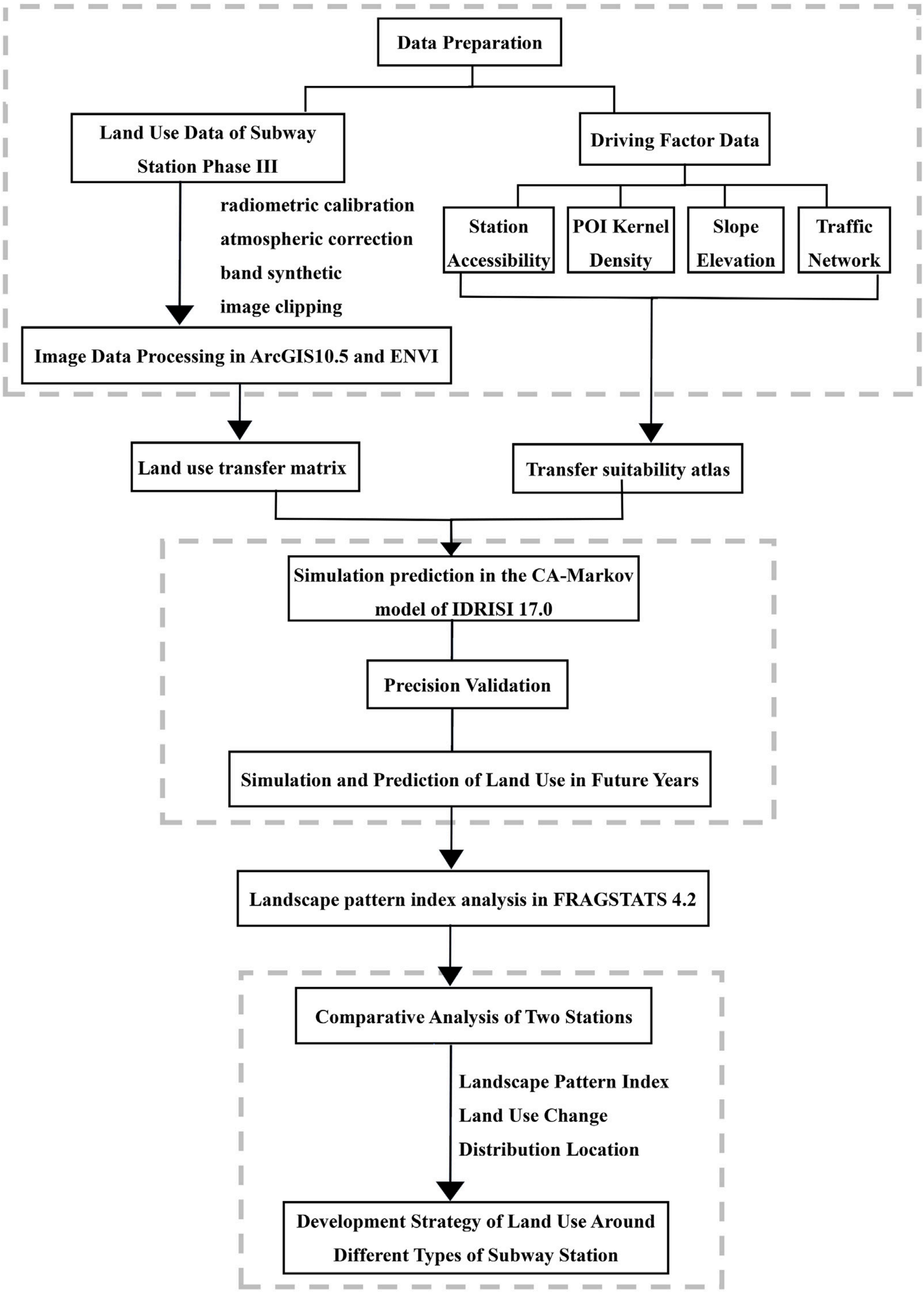

FIGURE 2
Technical Route. First, based on the land use data of the planning, construction and operation years of the two stations, the suitability atlas is constructed by combining the driving factors such as POI kernel density and station accessibility. The CA-Markov model was used to simulate the land use and cover situation in the operation year of the station, and the Kappa coefficient was calculated by comparing it with the current land use map. After the accuracy verification, the land use and cover change in the future year were simulated, and the landscape pattern index of the two stations was compared and analyzed. Finally, put forward the development strategy of different types of stations.

affect the transformation of the corresponding land use types. The kernel density estimation method transforms the data of interest points into continuous density surfaces so as to evaluate the distribution intensity of human activities in urban space (Yu et al., 2015). The higher the kernel density, the more concentrated the urban functions in the region and the higher the suitability of the corresponding land use types. Therefore, using ArcGIS's kernel density analysis tool, mask extraction, reclassification and other

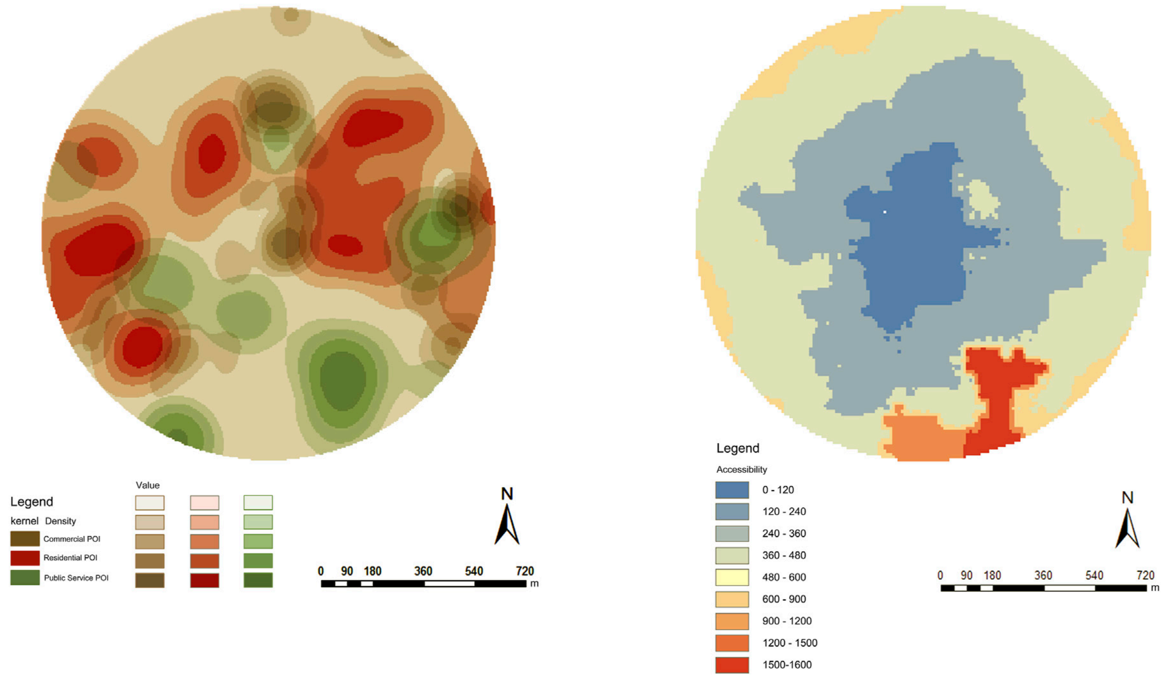

FIGURE 3
Analysis of POI kernel density (left) and accessibility (right) around Zoo Station.

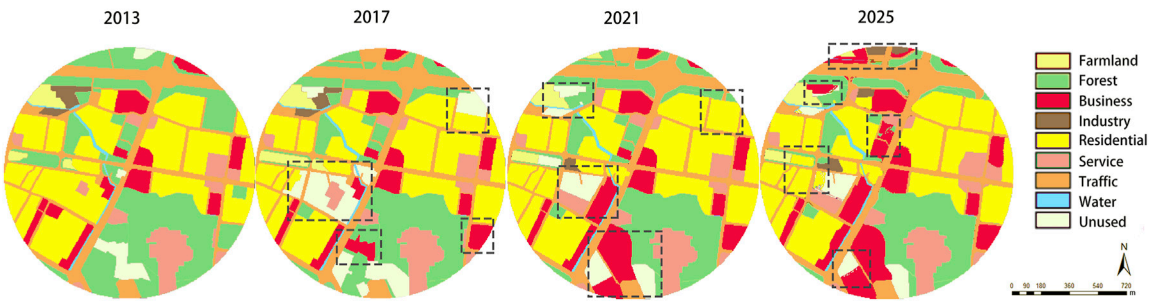

FIGURE 4
Land use maps of 2013, 2017, 2021 and predicted land use maps of 2025 at Zoo Station.

operations, the kernel density values are divided into five grades of 1–5 according to the natural discontinuity classification method, which is the most commonly used method in ArcGIS. And then imported into IDRISI to obtain the corresponding land suitability factor layer for simulation prediction.

3.3.3 Station accessibility research

American scholar Hanson formally expounded the concept of accessibility for the first time, defining accessibility as the interaction opportunity of each node in the transport network (Guo et al., 2014). Accessibility is the key link between land use and traffic construction, and it is directional to urban development (Yang et al., 2020). The accessibility of a certain area can effectively reflect the value of the area.

Based on the 'walking plan return parameter' provided by the Baidu map Web service API, the 'duration' field is the required parameter. Through web crawler technology, the 'duration' field data is automatically captured and exported to an Excel table to form the basic data source of the GIS database. ArcGIS software is used for interpolation, and the inverse distance weight method is selected for interpolation. The interpolation results are fine-tuned and classified based on the geometric interval classification method. The grid image is extracted with the current regional land use image as the mask, and the projection coordinate system is unified to realize the visual expression of the accessibility of metro stations, which is used as an important factor affecting the change of construction land (Xiao, 2021).

3.3.4 Construction of suitability atlas of CA-Markov Model

Multi-criteria evaluation (MCE) model is often used to generate the atlas of suitability evaluation in CA-Markov

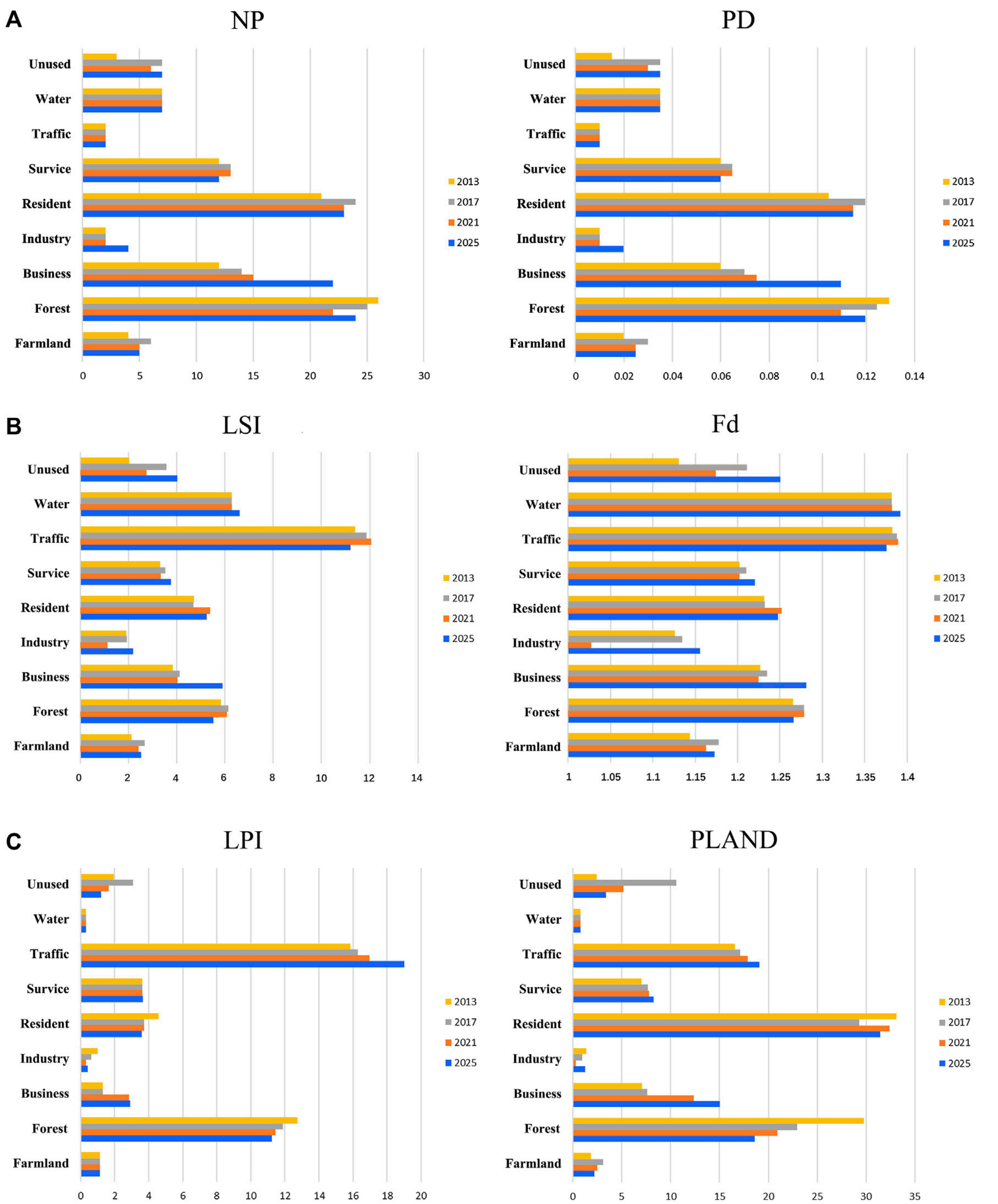

FIGURE 5
Landscape pattern indices of each landscape land type in the study area from 2013 to 2025 **(A)** Landscape fragmentation indices, **(B)** Landscape shape indices, **(C)** Landscape dominance indices.

model construction. According to the unique geographical conditions and the characteristics of land resource utilization in Chengdu, this article selects non-natural factors such as distance from road or metro stations, POI data, accessibility, and ecological factors such as elevation and slope as the driving factors affecting land use change. The driving factors are applied to the MCE model in IDRISI 17.0. Under the MCE module, different function forms are set for these two types of driving factors to determine the degree of influence of each factor on various types of land, which is used as a suitability atlas to participate in LUCC simulation prediction.

3.3.5 Landscape index selection

A landscape pattern index based on land use/land cover map is an important method of landscape spatial analysis (Yanhong, 2010). Fragstats is a commonly used landscape pattern analysis software

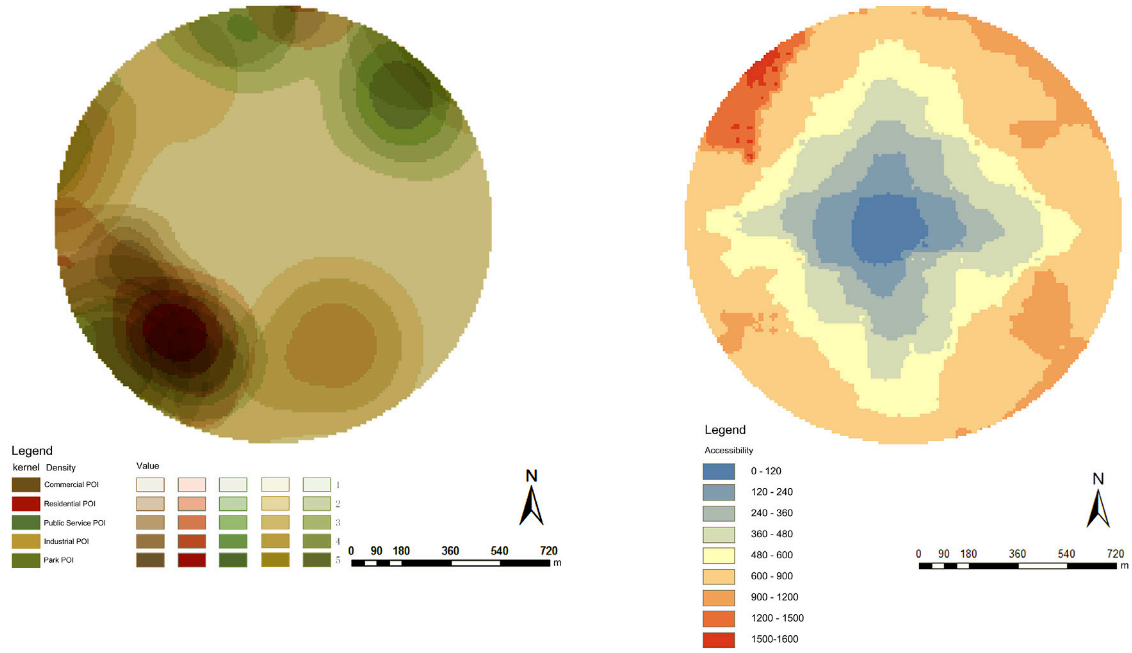

FIGURE 6
Analysis of POI kernel density (left) and accessibility (right) around Lu Xiao Station.

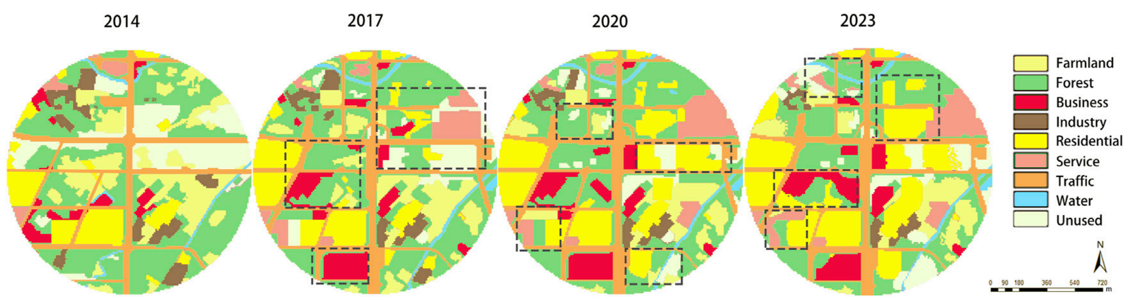

FIGURE 7
Land use maps of 2014, 2017, 2020 and predicted land use maps of 2023 at Lu Xiao Station.

with powerful calculation and analysis functions (Riitters et al., 1995; Jones et al., 2010). There are many landscape pattern indices. According to the characteristics of envi-ronmental impact assessment of metro stations, this article selects the landscape pattern index with strong predictability that changes with the land use classification system for analysis, including Number of Patches (NP), Patch Density (PD), which describe the relationship between landscape size and landscape fragmentation; Landscape Shape Index (LSI) and Fractal Dimension (Fd) measure the complexity of patch shape; Landscape dominance index, Largest Patch Index (LPI) and Percentage of Landscape (PLAND) can determine the dominant type of landscape. The above indexes respectively reflect the area, density, diversity, and aggregation of patches.

The research of this article combines the research methods described, and the technical route is shown in Figure 2.

4 Results

4.1 Zoo Station

4.1.1 Verification results of Zoo Station simulation

The analysis results of POI core density of Zoo residences, commerce, public services, and the analysis results of walking accessibility are shown in Figure 3. Other factors affecting land use change mainly include DEM terrain data, slope data, the distance of the transport network, etc. Taking 2013 and 2017 as the starting year and 4 years as the interval, the station accessibility analysis and POI kernel density analysis are coupled to make various land suitability atlas and calculate the Markov transition matrix. The CA-Markov model is used to simulate and predict the land use simulation map of the study area in 2021 as shown in Figure 4. Calculated by the Validate

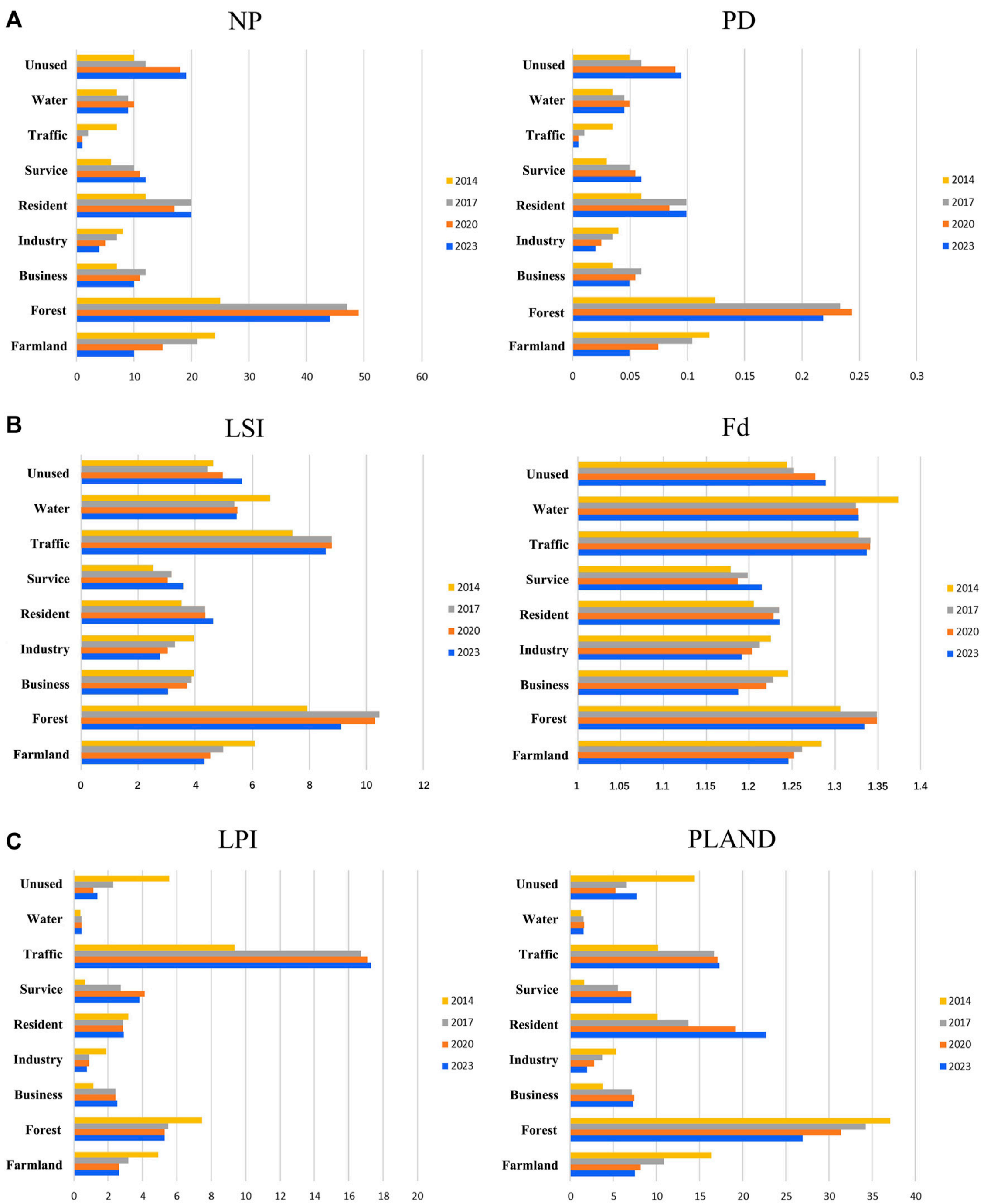

FIGURE 8
Landscape pattern indices of each landscape land type in the study area from 2014 to 2023 **(A)** Landscape fragmentation indices, **(B)** Landscape shape indices, **(C)** Landscape dominance indices.

module in the IDRISI which can verify the accuracy, the kappa coefficient of the 2021 forecast map and the 2021 current map is 87%. The results show that the simulation accuracy is high, showing that the model is feasible. So, the simulation results of land use in 2025 will be closer to reality.

After simulating and predicting the land use in 2025, the forecast map of 2025 is compared to the present map of 2021. Among them, the growth of business land, residential land, and the decrease of farmland are larger. More business land was added around the station and along the road, mostly forest land and unused land were converted into business land. Compared with the land use in 2021, the amount of industrial land increases, especially in the north of the station. Metro stations are more attractive to business and residential land, but it is more exclusive to industrial land (Guo and Li, 2015) and has little impact on public services land.

Under the guidance of policy, the construction of urban stationsleads to a change in population density, and then the land in the area will turn into living, functional land. Due to the sudden change in policy factors, such as new urban planning, there is a certain error between the simulation result and the reality. In subsequent simulation predictions, policy factors should be fully considered to increase simulation accuracy.

Figure 4 shows the evolution of land use in the Zoo Station and the simulation and prediction of land in 2021. On this basis, the kappa coefficient is calculated separately from the current situation in 2021 to ensure the accuracy of the simulation. After validation, land use in 2025 is simulated. The black dotted box is the location where land use changes greatly.

4.1.2 Analysis of landscape pattern of Zoo Station

Six indexes are selected from aspects of landscape fragmentation, shape, and dominance to analyze the landscape pattern of the Zoo Station. The landscape land type data from 2013 to 2025 are converted into TIF. file format and imported into the Fragstats software to calculate the above-selected landscape index, as shown in Figure 5. The evolution law of landscape types of land use from 2013 to 2021 and the prediction result in 2025 are studied, and the evolution characteristics of landscape patterns in the region are analyzed.

NP and PD are important indicators to measure the fragmentation of landscape patterns, as shown in Figure 5A. The higher the PD value, the higher the fragmentation degree of the landscape type; the smaller the value, the higher the aggregation degree of the landscape type. The results show that the fragmentation of forest land decreases, and the aggregation increases with time, but the fragmentation of patches is at a high level. Meanwhile, business land, residential land, and farmland show an opposite development trend, which indicates that farmland and unused land are constantly used in urban construction during this period.

The LSI can directly measure the complexity of the landscape patch shape. The higher the LSI value, the greater the complexity of the landscape patch shape. LSI can show the development intensity of the surrounding areas. The LSI values of forest land and transportation land around the station increase first and then decrease, while those of other lands generally indicate an upward trend. This indicates that the future shape of land use is complex, the development intensity of the city increases during the construction process, and the fragmented forest land patches gradually spread and connect.

Fd is similar to the landscape shape index, and its variation trend can reveal the degree of border folds of each landscape patch. Its value range is 1–2. The closer the value of Fd is to 2, the more complex the patch shape is, and the less the interference of human activities is. Except for the water area and traffic land, the Fd values of all types of patches in the Zoo Station are all lower than 1.35, indicating that human disturbance is large and the development intensity is large. The overall Fd value of unused land, industrial land and farmland is low, indicating that these three types of land patches are most disturbed by human beings, as shown in Figure 5B.

The largest patch index (LPI) and the proportion of patches in the landscape area (PLAND) can confirm each other, thus reflecting the dominant types of landscape patches. From 2013 to 2025, the LPI and PLAND values of residential land patches always rank first, and forest land and traffic land are also at the forefront. These are dominant landscape types in the study area; The LPI and PLAND values of traffic land and residential land are constantly rising, which indicates that these patches in the old city area are becoming perfect and abundant, as shown in Figure 5C.

4.2 Lu Xiao Station

4.2.1 Simulation results of Lu Xiao Station

Based on POI kernel density and station accessibility, as shown in Figure 6, the land use of Lu Xiao Station was simulated by the same method as that of Zoo Station. The results of the Validate module of the IDRISI software show that the standard Kappa coefficient, random Kappa coefficient, and position Kappa coefficient of the 2021 prediction map and 2021 current map are 75%, 76%, and 79%, respectively. From the perspective of spatial position and comprehensive analysis, the simulation results are more accurate.

Figure 7 presents the simulation results from 2014 to 2023. With the completion and operation of the Lu Xiao Station, the spatial structure of the surrounding land use has changed obviously, and the most significant one is that the farmland has decreased greatly. In the place close to the Lu Xiao Station, more public service lands have been added in the northeast in 2017 than those in 2014, and the surrounding farmland and ecological land show a decreasing trend, while residential land has increased. In the south of the Lu Xiao station, a new piece of commercial service land is added, and the industrial land shows a decreasing trend. Compared with 2017, the business land near the station will increase in 2020, and the farmland will also decrease, while the forest land will decrease. The TOD planning space is usually within a walk distance of 5–15 min, with a radius of about 400–800 m. In the comparison of the current situation of 2020 with the prediction of 2023, it can be seen that the short-distance farmland of the station is greatly reduced, and the commercial and service land increases in circles around the station, while the residential land shows an obvious growth trend. This is consistent with the planning concept of the Lu Xiao TOD, and it also shows that the simulation results have a policy-guiding significance.

Figure 7 shows the evolution of land use in the Lu Xiao Station and the simulation and prediction of land in 2020. On this basis, the kappa coefficient is calculated separately from the current situation in 2020 to ensure the accuracy of the simulation. After validation, land use in 2023 is simulated. The black dotted box is the location where land use changes greatly.

4.2.2 Landscape pattern analysis of Lu Xiao Station

The same method is used to study the evolution law of land use landscape types under each landscape index in the Lu Xiao Station from 2014 to 2020 and the predicted result in 2023 as shown in Figure 8.

The analysis results of PD in different periods around the Lu Xiao Station show that with the increase of time, the fragmentation degree of farmland, industrial, and mining storage land generally decreases, while the aggregation degree is constantly increasing; the business land, public land, and residential land show an opposite variation trend, while the fragmentation degree of ecological land first increases and then decreases, indicating that ecological land and unused land are constantly used from in urban construction during this period, and ecological land is mainly used in the initial stage of construction, as shown in Figure 8A.

The variation trend of LSI in different periods around the station shows that the LSI of ecological land first increases and then decreases; the LSI of industrial and mining land, commercial and service land, and farmland shows a downward trend.; the LSI of unused land, residential land, and public land shows an upward trend. These results indicate that the land development intensity in this area is strong. Also, the probability of unused land transfer is high, and it mainly occurs within 300 m of the station.

According to the Fd of Lu Xiao Station, the Fd values of industrial and mining storage land, commercial and service land, and farmland show a downward trend, the patch shape tends to be regular, and the intensity of human interference gradually increases. Meanwhile, the Fd values of public and residential land in the Lu Xiao Station show an upward trend, the patch shape tends to be complex. Although the intensity of human interference is strong, it gradually decreases. Moreover, the Fd values of traffic land and ecological land first increase in 2017 and then decrease in 2023, indicating that the patch shape of ecological land is initially complex and then becomes simple and regular, as shown in Figure 8B.

According to the calculation results of the LPI and the PLAND, the LPI and PLAND values of ecological land patches always rank first from 2013 to 2025, and residential land and traffic land are the main patches, which indicates that this land-scape type is dominant in the study area, as shown in Figure 8C.

5 Discussion and strategies

5.1 Discussion on the driving factors of the CA-Markov Model in metro station scale

When setting the parameters of the CA-Markov model, the choice of station driving factors and the size of parameters directly affect the spatial distribution of land use. The existing research fails to investigate the selection of driving factors of small-scale metro stations and the influence of parameter range on land use prediction results. Therefore, when using the CA-Markov model to predict the metro stations in Chengdu on a small scale, land POI data and accessibility factors are added to more accurately reflect the current government's land use intensive development policy for optimizing the stock of the Zoo Station and increasing the TOD development of the Lu Xiao Station. The investigation results can provide a scientific basis for urban planning, environmental pollution caused by traffic, energy saving, and green development.

5.2 Analysis of simulation results of the CA-Markov model and its quasi-optimization

In the process of applying the CA-Markov model simulation, because of the complexity of model transformation rules, the influences of natural, social, and economic factors on the change of land use landscape pattern should be comprehensively considered (Zhou et al., 2020). However, it is found that human factors such as passenger flow and economy cannot be well reflected in this model as driving factors. Meanwhile, the change in the landscape pattern of land use is greatly influenced by policy, and metro station also affects the land structure in terms of geographical location, surrounding facilities, and density. And it is difficult to introduce qualitative law or sudden political trends in the model. Therefore, in future research, we will constantly improve the cellular transformation rules of the CA-Markov model, comprehensively consider various models, and discuss the driving factors of the metro station more comprehensively. Also, we will conduct a more indepth and comprehensive study on the landscape pattern index and explore a landscape pattern index that reflects the changing characteristics of regional landscape patterns more pertinently. This article takes small-scale metro stations as the research object, and future research will be developed in the direction of important metro stations to comparatively analyze linear land use landscape patterns with different spatial and temporal distributions.

5.3 Optimization strategy of landscape structure

Under the guidance of planning, urban land use change is affected by the comprehensive effects of economic development, population growth, industrial structure adjustment, and other factors, which lead to the outer expansion of urban space and the renewal of urban land. Specifically, metro, as an urban subsystem, is increasingly characterized by openness and publicity under the concept of a compact city (Xiaoyuan and Bingjie, 2020). The relationship between metro stations and land use is complex, and traffic accessibility is a key factor in the relationship between them, which is important for determining the scale, intensity, and spatial distribution of urban land (Xu et al., 2017). Based on the result of the study, the following strategies are proposed.

1) Choose the mode of land use and development according to local conditions. Different sites are located in different cities, and their surrounding land use and development patterns are also different. The optimization of land use in metro station areas needs to be coordinated in various aspects, such as land use function, development intensity, radiation population, and supporting service facilities, to improve the station efficiency. In the future, the development mode of metro stations should be determined according to their advantages and local conditions, and the organic mixing of commerce, parks, offices, and other functions should be guided to promote the 800 m radiation space around the metro to form a suitable urban structure.
2) Optimize the landscape pattern around the station. The fragmentation degree of forest land around the Zoo Station is obvious, but the fragmentation degree of forest land decreases. The human disturbance has an obvious intensity, so it is necessary to increase stepping stone patches among the forest land in this area, thus increasing landscape connectivity and keeping its ecological benefits in a good state. In landscape pattern evolution, the landscape pattern state of the study area is generally good, but the influence of human disturbance on the landscape pattern needs to be effectively controlled. The land development intensity around the Lu Xiao Station is high, and the edge of forest land is regular, which is not conducive to protecting biodiversity. Therefore, for the boundary of green patches in the region, the straight single-layer boundary should be replaced by twists and turns, and the landscape pattern index around the metro station needs to be optimized by carefully designing each ecological land patch.
3) Improve the policy planning system. In the construction and development of metro, priority should be given to land use efficiency, protection of urban ecological land, control of construction land, full protection of land use during construction, and reasonable adjustment after completion. Meanwhile, the three-dimensional and comprehensive development of metro should be encouraged to reduce the

occupation of farmland and forest land. Moreover, it is necessary to strengthen the connectivity and aggregation between patches, improve the stability of landscape structure, optimize the landscape spatial pattern, reduce carbon emissions and increase carbon absorption, and enhance the socio-economic and ecological benefits of the landscape.

6 Conclusion

In this article, the Zoo Station and Lu Xiao Station of Chengdu Metro are taken as study areas. Based on the validation of land use simulation prediction, it is found that the simulation accuracy of the CA-Markov model is higher by adding POI kernel density and station accessibility. Therefore, this model is selected to predict and simulate the future landscape pattern of land use. This study aims to research the temporal and spatial change in land use landscape patterns of the study area under the influence of urbanization and to provide a reference for the economic, intensive, and high-quality development of Chengdu. The following observations are obtained: (Munsi et al., 2010) The landscape land types at the two metro stations changed greatly, the area of residential and business land continues to increase, and the area of farmland and forest land continues to decline. In the future, thefarmland and forest land around the Zoo Station in the study area will decrease by 13% and 11%, respectively, the business land will increase by 21%, and the other land will change slightly. The farmland and forest land around the Lu Xiao Station decreased by 9% and14%, respectively, residential land increased by 18%, and other land changes are small. In future urban construction, we should reasonably protect farmland and forest land, and control the growth of construction land, thus promoting the sustainable development of the city (Wei et al., 2021). Among all types of land in the study area, residential land, business land, and forest land have a large degree of landscape fragmentation, showing the characteristics of numerous patches and high patch density. From the perspective of the landscape level, the fragmentation of the study area is increasing, so it is necessary to strengthen the connectivity among patches to improve the stability of the landscape pattern (Yu, 2017). Aiming at the small-scale regional research of metro stations, the influence of POI and accessibility on land use types in the CA-Markov model is discussed. Different spatial scales have different sensitivity to driving factors, so we should pay attention to discussing the parameters of driving factors when making predictions for other scales. Based on the concept of a compact city and the requirement of low-carbon development, the research on landscape patterns of land use should focus on the optimization of regional landscape patterns of land use and provide a reference for sustainable urban construction in the future (Li et al., 2020).

Data availability statement

The original contributions presented in the study are included in the article/Supplementary Material, further inquiries can be directed to the corresponding author.

Author contributions

FF: Conceptualization, funding acquisition, supervision, and writing—original draft. XJ: Formal analysis, methodology, writing—review and editing. DW: Formal analysis, writing—review and editing. QZ: Formal analysis, writing—review and editing. HF: Validation, writing—review and editing. LL: Validation and writing—review and editing. LA: Validation and writing—review and editing. All authors contributed to the article and approved the submitted version.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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Associations between neighborhood environment and sense of community belonging in urban China: Examining mediation effects of neighborly interactions and community satisfaction

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Introduction: Improving sense of community belonging (SCB) would help people live longer, happier lives. Although the importance of neighborhood environment on SCB is stressed in the literature, few studies have paid attention to perceived environment, as well as consider mediation effects such as neighborhood social interactions and place satisfaction.

Methods: Relied on a sample of 1051 respondents in Shanghai in 2018, this study investigates the associations between both objective and perceived neighborhood environment attributes and SCB in urban China, mediated by neighborly interactions and community satisfaction using structural equation modeling.

Results: The results suggest that the influence of perceived neighborhood environment on SCB is more prominent than that of objective neighborhood environment. In detail, perceived pedestrian facilities and perceived leisure facilities are vital to SCB, while among objective neighborhood environmental elements, the influence of land use entropy, park density and street greenery are significant. Then, neighborhood environmental attributes can influence SCB by affecting neighborly interactions and community satisfaction. We also identify gender differences in the effects of neighborhood environment upon SCB.

Discussion: Given increasing awareness of the connection, neighborhood environment may prove to be valuable assets to improve individuals' psychosocial constructs such as SCB.

KEYWORDS

neighborhood design, walkability, community belonging, structural equation modeling (SEM), urban China

1. Introduction

Community plays a vital role in shaping our physical and mental health (1–4). It offers stability, solidity, and secureness that facilitate individuals' prosperity and growth. Francis et al. (3) state that people often own high levels of intellectual wellness and positive emotions when they live in communities that are inclusive, stable, and safe, and acceptance and respect across differences, including the vulnerable groups. Due to huge impacts, we recently see increasing research and urban planning interest in the relationship between the built environment and social and mental constructs like sense of community belonging (SCB) (5, 6).

According to McMillan and Chavis (7), SCB is conceptualized as a perception and feeling that community members perceive important to each other. It is a belief or conviction that their physical and social needs and demands would be satisfied through the promise to be together. French et al. (4) point out that SCB embodies the common, mutual and social values that are owned by community members, and represents the adherence, attachment, and coherence that can be embedded in and integrated into geographic establishments. In urban planning and health studies, SCB is closely related to many neighborhood-based results and consequences such as membership, neighborhood attachment, fulfillment of needs, engagement, etc. (8). It is argued that although increase in global mobility homogenizes sense of place, causing a loss of identity and traditional local community, people emotionally tend to search for local propinquity, belonging and identity (4, 5). Thus, many scholars urge that policy makers, researchers and urban planners alike create the opportunities and conditions that facilitate and enhance SCB in living neighborhoods (9–11).

In the field of urban planning, one of the centric goals of New Urbanism principles is to enhance SCB and improve people's sense of belonging (12). The underlying assumption is that the patterns the street grid is organized, and the structure a neighborhood is planned would influence neighborly interactions and activities and influence people's sense of that place (13). For instance, neighborhoods and blocks providing a mix of shops, offices, recreation, and residences would make walking more convenient, services more cost-effective and living places more comfortable and enjoyable (4). Then, communities designed to promote face-to-face interactions and develop social associations and support systems offer pedestrian-friendly streets and blocks, working and housing in close proximity, and approachable public spaces, and accommodate multimodal transportation such as transport use, walking, cycling and driving (1). Consequently, members of these neighborhoods experience greater residential satisfaction and belonging.

Although a range of studies examined the relationship between the built environment and SCB, evidence is mixed, and there is a lack of studies discussing the specific characteristics of the subjectively measured neighborhood environment that contribute to SCB and under what conditions (4, 11, 14). In fact, perceived neighborhood attributes and elements that increase opportunities for neighborly interactions and communication may be a stronger predictor of neighborhood satisfaction and SCB (11). For instance, people have a higher level of SCB when perceiving the circumstance to be secure, having the chance engaging community activities, and owning local enjoyable spots and sites within the community (15).

Then, there is an ignorance by researchers of the gender differences in the association between neighborhood environment and SCB. As Lo (16) suggests, psychosocial constructs like SCB vary between males and females since their use of neighborhood space and perceptions of residential environment differ. For instance, it is often pointed out that females would encounter more social and environmental restraints and the physical-social environment seem to have greater influences on their daily behavior than males (17). Despite the importance, the gender issue relevant to the relationship between neighborhood environment and SCB is hardly explored.

Furthermore, previous research examining the pathways from environmental elements to SCB often overlooks the mediation effects of neighborly interactions and place-based satisfaction like community satisfaction (6, 11, 18). According to Smith (19), the neighborhood environment may influence SCB *via* its impacts on neighborly social interactions and place satisfaction.

To fill the gaps, the aim of this paper is to investigate how objective and subjectively measured neighborhood environment attributes influence SCB, mediated by neighborly interactions and community satisfaction. Based on data from Shanghai in 2018, we use structural equations modeling to analyze structural relationships. This study has the following three key contributions. First, it enriches the literature on the relationship between SCB and both objective and subjectively measured environmental elements in neighborhoods. Second, this study assesses the relative importance of perceived environmental attributes in predicting SCB. Third, this study reveals new pathways from the environment to SCB, that is, neighborly interactions and community satisfaction play critical mediation roles in the structural relationship.

2. Literature review

According to McMillan and Chavis (7), a strong SCB is often closely related to place satisfaction, physical and mental health, and life wellbeing, whereas a low SCB can result in feelings of alienation, insignificance, loneliness, and social and cultural isolation. Thus, taking action to facilitating a greater connection of residents to their community would improve their feelings of belonging, trust, and security, and thereafter their physical and mental health (7, 14).

Among various public policies to improve SCB, built environment and neighborhood planning is one of many possibilities and ways (4, 15). In the literature, it is commonly recognized that the neighborhood environment is a contributor to SCB as it influences individuals' emotion, feeling and satisfaction with many of their daily life aspects (6). A range of studies have discussed the association between neighborhood environmental attributes and SCB (4, 5, 20). For instance, some authors found that communities with low and medium floor area ratios would give members of community more private space and offer more available and approachable community resources, which brings more positive feelings and sense of belonging to their communities (21, 22). On the contrary, Foster et al. (23) found that communities instability attributes such as large number of floating population and high crime rates would reduce people's chances of establishing relationships and building dialogues with one another, and consequently reducing people's perception of community. Note that the relationship between the built environment and SCB is underestimated (4, 15). Because of the widely differed prediction techniques, it shows that some studies reported a positive association between neighborhood environment elements and SCB, whereas others show negative effects. The results are hybrid and thus more empirical studies are needed to understand the associations.

Then, previous studies disproportionately center on the association of objective neighborhoods environment on SCB (24), whereas the effects of the subjectively measured neighborhood environment have been largely ignored, except for a few exceptions (4, 11). According to Guo et al. (11), subjectively measured neighborhood environments may contribute to SCB given that people would feel a greater connection to their community when they have a better perception and feeling of their living circumstances. The perceived environment consists of residential characteristics

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relevant to the social exchanges and interplay among community members, which are vital for enhancing community cohesion and integrity (3). A number of studies show that people's satisfaction and attitudes toward their communities is closely related to perceived convenience of local transport, perceptions about whether services are accessible easily, perceived greenery or attractiveness, perception of incivilities, and perceptions of violent and property crimes (6, 7, 25, 26).

In fact, perceptions of neighborhood attributes play as much of a role in influencing individuals' sense of their surroundings as objective features, and sometimes even more vital (15). In their study of walkable cities, Hoehner et al. (27) identified that perceived and objective environmental measures would influence people's levels of physical activity and their attitude toward their local communities. Rather than the objectively measured environment, the perceived environmental measures have larger effects and was necessary for improving individual's feeling, understanding, perception and attitude (12, 28). In another study, Ries et al. (29) found that perceived plentifulness of facilities were connected with increased community physical-social activity such as neighborly interactions and communication. Abdullah et al. (9) also identified that only perceived availability of parks and sports facilities had a significant influence on residential satisfaction rather than objective elements. It shows that perception could be an unignorable mediator between the objective built environment and SCB. Thus, examining such intervening factors is vital to develop and implement effective strategies and policies to promote sense of community and belonging.

Consistent with certain previous studies, the gender differences in SCB seemed to vary significantly (30, 31), indicating that while some neighborhood environments might influence the SCB of men and women, the influences differ considerably. It is said that females are more likely to use the neighborhood space for their recreation and leisure activities compared to males (32). Consequently, residential environment shows a considerable variation in predicting SCB between females and males. For instance, studies indicate that females seem to be more sensitive to environmental features (30, 32). The finding agrees with increasing proofs that there exist stronger environmental relationships in women regarding their use, perceptions and sense of their community. It implies that support of physical and psychosocial environment is critically needed to facilitate females to use neighborhood space and could be a strategy for reducing the gender inequality. However, most neighborhood-based studies merely offer the overall relationship between neighborhood environment and neighborhood satisfaction and SCB, ignoring the likelihood that this relationship differs between males and females (33). In other words, the overall effect potentially conceals vital information and message concerning how neighborhood environment has a differed influence on the SCB of females and males. Thereafter, more attention is needed to discern gender differences in the impacts of environmental attributes on SCB.

In addition, the pathways from the environment to SCB hardly consider the mediation effects of mediators like satisfaction domains and neighborly social interactions. First, recent studies indicate that place-based satisfaction would influence perception of community and their life satisfaction (18). When people perceive walkable street quality, high accessibility, quality architecture and design, and environmental quietness (26), they are more likely to be satisfied with their neighborhoods and have better sense of their community. Second, neighborly interactions could play a mediating role in the association of the neighborhood environment with SCB (4). In a pedestrian-friendly and walkable environment, an intensified use of public spaces improves the frequency of information sharing, exchange and interactions between members of community, thus facilitating the establishment of social ties and affiliation among neighbors (6). According to Jorgensen et al. (34), neighborly interactions promote neighboring relations and improve individuals' perception of empowerment from others. For instance, in a survey concerning neighborhood interactions, Smith (19) states that 86.3% of respondents revealed that they often stop and talk with community members and 98% would help others in an emergent situation. The results demonstrated that neighborly social interaction enable residents to experience instrumental and psychosocial support, consequently leading to high residential satisfaction, SCB, and sense of belonging (35).

Despite the argued potential of the mediation effects, studies have less focused on the potential pathways from neighborly interactions and community satisfaction to SCB. Individuals engaged in the community experience faithful psychological and social help, neighborhood stability and growth, few social isolation and community satisfaction, all of which contributes to the improvement of SCB (15). Therefore, it is necessary to distinguish compound associations among the environment, neighborly interactions/community satisfaction, and SCB.

3. Methodology

3.1. Data collection

In this study, we use two types of data to analyze the association of neighborhood environment with SCB. One is the Shanghai Built Environment and Resident Behavior Survey data, collected by the East China Normal University, China. The data set includes respondents' sociodemographic data, perception data incorporating individuals' perception of neighborhood environment, and feeling and attitude toward their residential community. Two is the objective neighborhood environment data, which was calculated based on the respondents' location address provided in the Built Environment and Resident Behavior Survey.

The survey was implemented in urban Shanghai, from August 2018 to February 2019. By adopting a stratified sampling method, respondents were randomly selected from 38 housing estates of 30 primary sampling units—jie dao or town in the 13 districts of Shanghai (Figure 1). In each housing estate, 35 households were invited to participate the questionnaire survey (the targets include either the household head or spouse between the ages of 18 and 60 years old). The survey collected a total of 1,127 respondents and 1,051 respondents finished all the questions, with a response rate of 93.3%. Respondents' living locations was geocoded for further analysis of the built environment characteristics.

3.2. Conceptual framework and variables

Based on the literature review, a conceptual framework is developed to examine how objective and perceived neighborhood

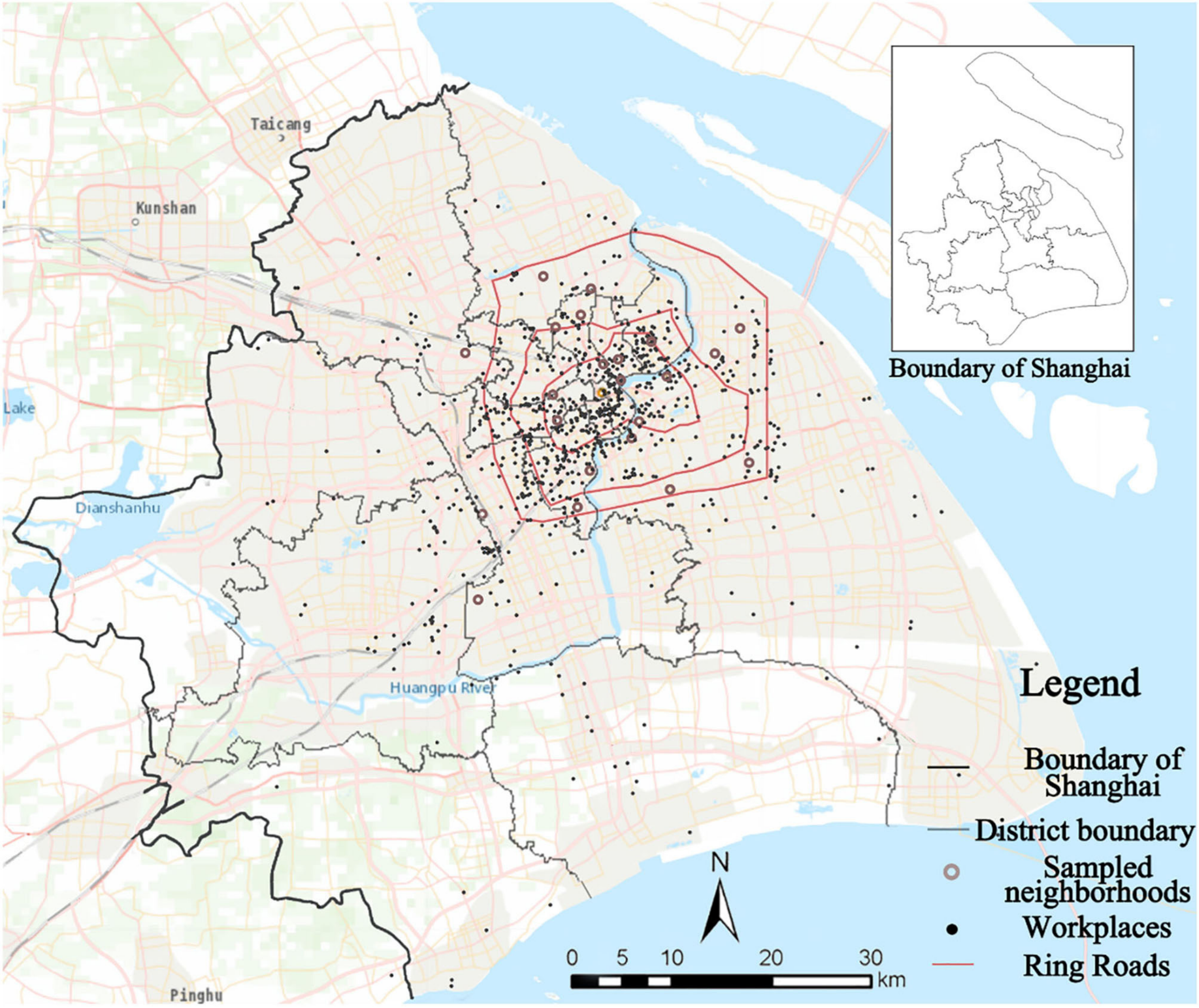

FIGURE 1
Distribution of the sampled neighborhoods (36).

environment influence SCB, mediated by neighborly interactions and community satisfaction (Figure 2). We hypothesize that individual perception of the environment as well as objective environment influence SCB through the mediation effects of neighborly interactions/neighborhood satisfaction. Demographic and socioeconomic attributes are also hypothesized to influence individuals' SCB directly.

SCB is the dependent variable. Normally, a single and overall question is deemed of being good reliability, thus the question "To what extent you have a feeling of community belonging?" was formulated to assess the domain satisfaction. Since we hypothesize that neighborly interaction mediates the association between the built environment and SCB, neighborly interaction is established as a latent variable, comprised of interaction frequency and interaction intensity. Interaction frequency includes 4 four-point Likert-type scale items (1 = extremely low, 5 = extremely high), and the mean score for the 4 items was measured and adopted for each participant. Interaction intensity was measured by three five-point Likert-type scale items; and questions interpreting the variable include "I am willing to help other members of community," "I have a good relationship with other members of community," and "I think other members of community are trustable". Then, the question "How satisfied are you with your residential neighborhood?" was used to measure the mediating variable neighborhood satisfaction, designed with a 5-point scale, ranging from "1" (very dissatisfied) to "5" (very satisfied).

Based on respondents' geolocation, we measured the objective built environment attributes in residential area through creating a 1,000 m circular buffer. Street view data based on Baidu Maps was employed to measure individuals' perception of the built environment on the ground. The street network of Open Street Map for 2018 was applied to generate regular sampling points every 30 m along the streets. We obtained the street view images with a dimension of 1,024 × 1,024 pixels for each sampling point. The deep machine learning model was applied to divide the amount of greenery per image. The aggregated greenery level of each sampling point within each residential neighborhood was calculated through using the average greenery of the four images.

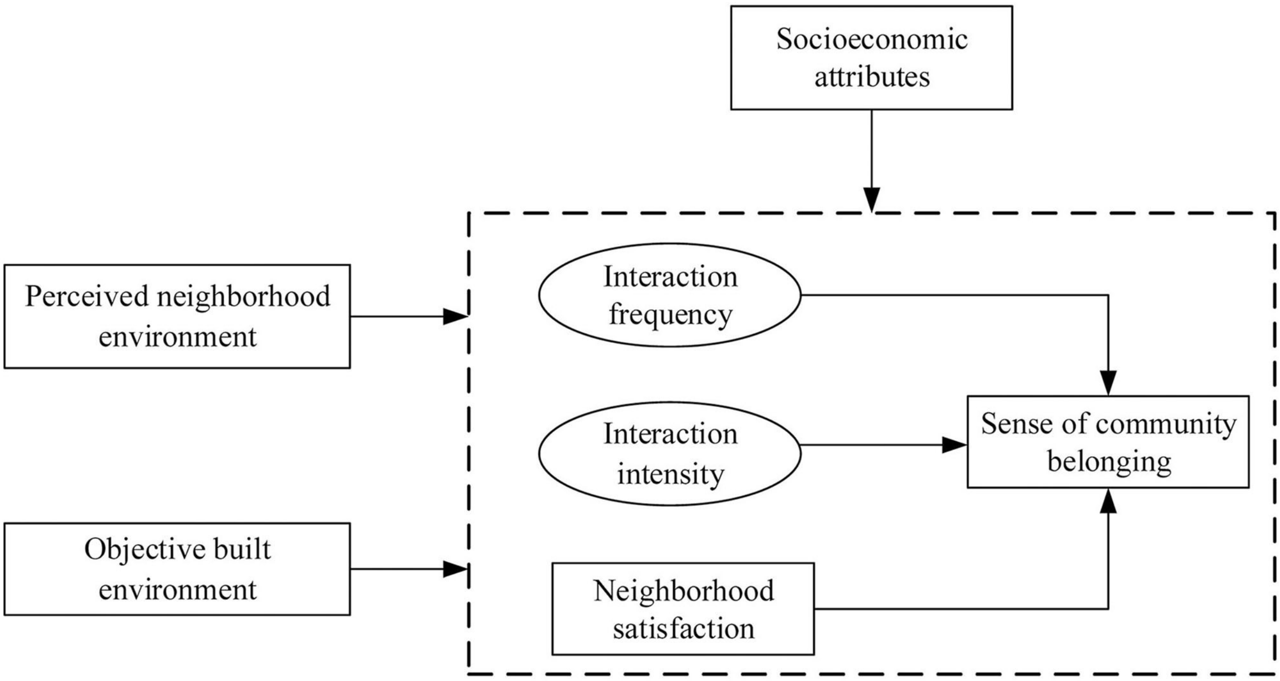

FIGURE 2
Conceptual framework.

Wood et al. (15) point out that leisurely walking environmental attributes influence SCB. Thus, some walkability-related measures were also applied. Floor area ratio was obtained by dividing a building's total floor area to the area of the circular buffer. The number of parks within residential neighborhoods were measured within the 1,000 m buffer. By employing the Shannon entropy index, we measured the land use diversity relied on 15 different Point of Interest (POI) categories (e.g., utilities, and retail and wholesale). We also used the Gaode Map platform to calculate the number of road intersections within the 1,000 m buffer to operationalize the street connectivity.

Perceived neighborhood environmental attributes were obtained from the questionnaire survey. Based on the work by Nguyen et al. (37) and Wood et al. (15), variables depicting subjectively measured environment attributes include public transport convenience, pedestrian and leisure facility, safety, road accessibility, and environmental quality. Note that these variables were also developed on a five-point Likert scale, ranging from "1" (extremely unimportant) to "5" (extremely important).

Sociodemographic variables were used as control variables, which include gender, age, hukou, marital status, education level, income, perceived overall health, car ownership, children under 18, household structure, and living duration (years).

3.3. Descriptive analysis

The descriptive analysis of the variables is provided in Table 1. Among the 1,051 respondents, 570 were males (54.2%) and 481 were females (45.8%), with a mean age value of 39.56. Concerning the education level, 65.2% of the respondents have received a college degree or above. Percentages of respondents with low-, middle- and high-level income account for 31.7, 34.4, and 33.9% respectively. Then, most of the respondents have local hukou (76.9%), and the average living duration is around 12.15 years. More than 75% (76.7 %) of the respondents are married and 45.7% of them have children under the age of 18. The percentage of car ownership is around 45%.

Regarding objective neighborhood environment attributes, the average population density reaches 27 thousand people per square kilometer, while the average floor area ratio is 1.56. The mean value of land use entropy and the number of road intersections are 2.29 and 33.51, respectively. Street greenery and park density have an average value of 2.64 and 0.20 separately. In terms of the perceived environment, the average score of the perceived neighborhood safety is the highest (mean = 4.74), followed by perceived environmental air quality (mean = 4.62), perceived environmental quietness (mean = 4.49), perceived convenience of public transport (mean = 4.49), and perceived road accessibility (mean = 4.40). Perceived pedestrian facilities and perceived leisure facilities received relatively lower scores of 4.19 and 4.15, respectively. All indicators describing the latent variable interaction frequency have scores of <3 whereas that describing interaction intensity score larger than 3.8. In addition, the average value of neighborhood satisfaction is 3.99. SCB have a mean value of 3.94, indicating the relatively high level of SCB of the locals.

3.4. Method

This study employs structural equation models (SEMs) to investigate the relationship between built environment and SCB. Composed of measurement equation and structural equation, SEM is able to estimate both the causal relationships among observed

TABLE 1 Explanations of variables and descriptive statistics (N = 1,051).

Variables	Description	Explained	Distribution	
Endogenous variables			Mean	SD
Sense of community belonging	To what extent you have a feeling of community belonging (1 = extremely low, 5 = extremely high)	Categorical variable: {1, 2,...,5}	3.94	0.729
Interaction frequency	Please evaluate the frequency you interact with your neighbors in the following aspects:		2.18	0.861
Frequency of dialogue	(1 = never, 4 = often)	Categorical variable: {1, 2,...,4}	2.88	0.897
Frequency of visit	(1 = never, 4 = often)	Categorical variable: {1, 2,...,4}	1.88	0.850
Frequency of going out together	(1 = never, 4 = often)	Categorical variable: {1, 2,...,4}	1.99	0.893
Frequency of helping each other	(1 = never, 4 = often)	Categorical variable: {1, 2,...,4}	1.99	0.806
Interaction intensity				
Mutual aid	I am willing to help other members of community (1 = very disagree, 5 = very agree)	Categorical variable: {1, 2,...,5}	3.92	0.688
Inter-relationship	I have a good relationship with other members of community (1 = very disagree, 5 = very agree)	Categorical variable: {1, 2,...,5}	4.01	0.645
Trust	I think other members of community are trustable (1 = very disagree, 5 = very agree)	Categorical variable: {1, 2,...,5}	3.88	0.69
Neighborhood satisfaction	How satisfied are you with your residential neighborhood (1 = very dissatisfied, 5 = very satisfied)	Categorical variable: {1, 2,...,5}	3.99	0.599
Exogenous variables				
Objective built environment				
Road intersection	Number of road intersections within 1,000 m	Continuous variable: R+	33.51	18.463
Park density	Number of parks within 1,000 m	Continuous variable: R+	2.64	2.284
Population density	Population density within 1,000 m	Continuous variable: R+	27,225.17	17,674.226
Land use entropy	Land use entropy within 1,000 m	Continuous variable: R+	2.29	0.148
Street greenery	Street greenery within 1,000 m	Continuous variable: R+	0.20	0.064
Floor density	Floor area ratio within 1,000 m	Continuous variable: R+	1.56	0.657
Perceived neighborhood environment				
Perceived public transport convenience	To what extent do you think public transport in your surrounding is convenient?	Categorical variable: {1, 2,...,5}	4.46	0.558
Perceived pedestrian facilities	To what extent do you think pedestrian facilities in your surrounding are sufficient?	Categorical variable: {1, 2,...,5}	4.19	0.639
Perceived leisure facilities	To what extent do you think leisure facilities in your surrounding are sufficient?	Categorical variable: {1, 2,...,5}	4.15	0.667
Perceived neighborhood safety	To what extent do you think your neighborhood is safe?	Categorical variable: {1, 2,...,5}	4.74	0.502
Perceived road accessibility	To what extent do you think the road systems in your surrounding is accessible?	Categorical variable: {1, 2,...,5}	4.40	0.623
Perceived environmental quietness	To what extent do you think your living environment is quiet?	Categorical variable: {1, 2,...,5}	4.49	0.605
Perceived air quality	To what extent do you think the air quality in your surrounding is satisfactory?	Categorical variable: {1, 2,...,5}	4.62	0.557
Socioeconomic attributes			Frequency	%
Gender	Gender (%) (Female = 1)	Categorical variable: {0, 1}		
	0		570	54.2%
	1		481	45.8%

(Continued)

TABLE 1 (Continued)

Variables	Description	Explained	Distribution	
Age	Age (years)	Continuous variable: R+	Mean	SD
			39.56	10.171
Education	Education level	Categorical variable: {1, 2,…,4}	Frequency	%
	Middle school or below		123	11.7%
	High school		243	23.1%
	College		665	63.3%
	Master or above		20	1.90%
Hukou	Hukou (%) (Yes = 1)	Categorical variable: {0, 1}		
	0		243	23.1%
	1		808	76.9%
Living duration	Living duration (years)	Continuous variable: R+	Mean	SD
			12.45	9.932
Income	Income	Continuous variable: R+	Frequency	%
	Low (<100,000 CNY)		333	31.7%
	Mid (100,000–200,000 CNY)		362	34.4%
	High (>200,000 CNY)		356	33.9%
Children under 18	Children under 18 (yes = 1)	Continuous variable: R+		
	0		571	54.3%
	1		480	45.7%
Marital	Marital (yes = 1)	Categorical variable: {0, 1}		
	0		245	23.3%
	1		806	76.7%
Car ownership	Car ownership (yes = 1)	Categorical variable: {0, 1}		
	0		578	55.0%
	1		473	45.0%

variables and the influences of latent variables on others (38, 39). Besides, it can also reveal the nature of the mediation effect on the association of an independent variable with a dependent variable. A structural equation model with latent variables is generally composed of two equations (39, 40). First is the measurement equation which specifies the relationship between factor indicators (F_{kin}) and the latent variable:

$$F_{kin} = \alpha_{ikn} z_{in} + \xi_{ikn}$$

where F_{kin} = factor indicator k of latent variable i for individual n, z_{in} = latent variable i for individual n, α_{ikn} = coefficient for latent variable i and factor indicator k, ξ_{ikn} = measurement error term.

Second is the structural equation which specifies the relation of a predictor (either endogenous or exogenous) with other latent or observed variables:

$$Y_n = \beta_i z_{in} + \gamma_j X_{jn} + \varepsilon_n$$

where Y_n = dependent variable, either endogenous or exogenous, X_{jn} = observed variable j for individual n, β_i *and* γ_j = coefficient values, ε_n = structural error term.

In this study, SCB was used as the final endogenous variable in the model, and interaction frequency, interaction intensity and neighborhood satisfaction as the mediating variables. Objective neighborhood environment, perceived neighborhood environment and socio-demographic variables are the exogenous variables. After confirmatory factor analysis (CFA) in the software AMOS26, the latent variables including interaction frequency and interaction intensity were constructed with an acceptable fit and internal consistency (Table 2). The VIF values of explanatory variables are below 5, indicating that no multicollinearity exists.

4. Results

4.1. Modeling fitness

We used the maximum likelihood (ML) method of estimation in this study. Note that the validity of ML theoretically depends on whether the SEM meets the assumption of multivariate normality of its variables. Therefore, we used a bootstrapping approach to draw repeated sample from the data (41, 42) and generate a sample of 5,000. Meanwhile, the bias-corrected bootstrap confidence intervals were used to detect significant effects.

All models fit the data adequately (Table 3). The $\chi^2/d.f$ is 2.543 (values of 3 or less indicate a good fit), and other goodness-of-fit

TABLE 2 Confirmatory factor analysis results.

	Estimate	S.E.	C.R.	P
Interaction intensity→Inter-relationship	1.000			
Interaction intensity→ Mutual aid	0.941	0.035	27.236	***
Interaction intensity→Trust	0.923	0.035	26.458	***
Interaction frequency→Frequency of visit	1.000			
Interaction frequency→Frequency of chat	0.852	0.048	17.796	***
Interaction frequency→Frequency of outdoor activities	0.925	0.051	18.269	***
Interaction frequency→ *Frequency* of mutual aid	0.735	0.045	16.267	***

(1) The estimated correlation between interaction intensity and interaction frequency is 0.604 (>0.5). (2)***$P < 0.001$.
Model fit c²/df. 2.719, CFI 0.995, AGFI 0.980, RMSEA 0.040, chi 24.472, df 9.

TABLE 3 Goodness-of-fit statistics of the model and reference value.

	χ^2/d.f.	RMSEA	GFI	CFI
Model 1. Overall model	2.543	0.038	0.955	0.949
Model 2. Multilevel SEMs	1.819	0.028	0.940	0.950
Reference value	<3	<0.05	>0.9	>0.9

indices, such as RMSEA = 0.037 (values <0.05 indicate a good fit) and CFI = 0.949 (values range from 0 to 1, and values >0.9 are acceptable), also indicate that the model fit is good. Regarding the multilevel structural equation models, the fit indices also show an acceptable fitness.

4.2. Modeling results

4.2.1. Relationship between the built environment and sense of community

Consistent with previous research, both objective and perceived neighborhood environment attributes have significant influences on SCB, but the influence of perceived attributes is more prominent (12, 28) (Table 4). In detail, perceived pedestrian facility has a positive and significant impact on the SCB. The result supports the finding by Lund (43) that in a pedestrian-friendly environment, people are more likely to use public spaces for information exchange and social activities, thus promoting a closer community relationship. Perceived safety has a positive impact on the SCB whereas perceived neighborhood quietness has a negative impact.

As for objective neighborhood environment, park density has a significantly positive effect on the SCB, indicating that the more parks there are around a community, the stronger the SCB belonging among the locals. Land use entropy has a positive impact on community sense, indicating that a mixed land use brings more positive feelings and sense of belonging to their residents. The influence of street greenery is negative, which contradicts with previous studies that street greenery positively influences SCB. One possible explanation is that when street greenery is relatively high, the benefits or utility of physical activities turns to be saturated, consequently resulting in low neighborhood satisfaction (44). Other variables like floor area ratio and population density have negative impacts on SCB belonging, which accords with previous studies (21).

When we consider about the influence path, the results show that neighborhood environment influences SCB by affecting neighborly interaction and neighborhood satisfaction (Figure 3). In other words, neighborly interaction and neighborhood satisfaction play a mediating role between subjective neighborhood environment and SCB.

First, interaction intensity and neighborhood satisfaction have partially mediating benefits between perceived pedestrian facility and SCB. The path coefficients of perceived pedestrian facility→interaction intensity/community satisfaction→SCB are all significant, indicating a significant mediating effect. Besides, perceived pedestrian facility also exerts a significant direct effect on SCB, consequently contributing a total positive effect on SCB. Then, perceived leisure facility is positively and significantly related with SCB *via* affecting neighborly interaction. Perceived leisure facility has a positively significant effect on both interaction frequency and interaction intensity, and the latter of which is positively and significantly related to SCB.

Perceived public transport convenience has positive effects on SCB, which means that the more convenient the perceived public transport, the lower the frequency of community interaction. A possible explanation of this odd result is that when public transport is perceived to be convenient, people tend to do more social activities outside their own community. Nevertheless, the overall influence of perceived convenience of public transport on SCB is still positive considering its positive impact on interaction intensity and community satisfaction, as well as its direct positive correlation with SCB.

Perceived neighborhood safety has a significantly positive effect on SCB by positively affecting interaction intensity. It is understandable that safer spaces would lead to a higher level of neighborly interactions, consequently better SCB. Perceived neighborhood quietness has a negative impact on SCB *via* negatively influencing interaction frequency. Note that this result differs from previous studies. One explanation is that the quieter a neighborhood is perceived, the less vibrant it is likely to be, thus leading to a lower level of SCB.

4.2.2. Heterogenous impacts of the built environment on SCB between males and females

The influence of neighborhood environment on SCB is different between males and females (Figures 4, 5). It shows that perceived neighborhood environment mainly has a significant influence on females' SCB, whereas both objective and perceived neighborhood environment attributes are significantly associated with males' SCB, and both of which are partially mediated by neighborly interaction and communication satisfaction. In the female group, those significant perceived neighborhood environment attributes include perceived leisure facility, perceived pedestrian facility, and

TABLE 4 Relationships between the neighborhood environment and SCB, mediated by neighborly interactions/community satisfaction.

Variables	Interaction frequency	Interaction intensity	Community satisfaction	SCB		
				Total effects	Direct	Indirect
Endogenous variables						
Interaction frequency	-	–	–	0.071	0.071	–
Interaction intensity	-	–	–	0.167***	0.167***	–
Neighborhood satisfaction	-	–	–	0.236***	0.236***	–
Exogenous variables						
Perceived neighborhood environment						
Perceived air quality	0.000	0.058	−0.019	0.023	0.018	0.005
Perceived public transport convenience	−0.120***	0.036	0.03	0.037	0.032	0.004
Perceived environmental quietness	−0.122***	−0.039	−0.011	−0.052	−0.034	−0.018
Perceived leisure facilities	0.158***	0.118***	0.068	0.032	−0.015	0.047***
Perceived pedestrian facilities	0.049	0.109**	0.125***	0.115***	0.064**	0.051***
Perceived road accessibility	0.031	−0.04	−0.003	−0.036	−0.031	−0.005
Perceived neighborhood safety	0.021	0.088**	−0.006	0.049	0.034	0.015
Objective built environment						
Floor area ratio	−0.071	−0.035	−0.02	−0.025	−0.009	−0.016
Land use entropy	0.005	0.046	0.031	0.086*	0.071*	0.015
Park density	−0.03	−0.041	0.042	0.076**	0.076**	0.001
Population density	−0.039	−0.003	−0.01	−0.012	−0.006	−0.006
Road intersections	0.009	0.051	−0.058	−0.028	−0.023	−0.005
Street greenery	−0.003	0.009	−0.03	−0.055*	−0.049	−0.006

*$P < 0.1$; **$P < 0.05$; ***$P < 0.01$; Model fit c^2/d.f. 2.448, CFI 0.959, GFI 0.965, RMSEA 0.037, chi 528.737, df 216.

perceived safety. In the male group, significant objective variables consist of park density and road intersections while those significant perceived variables comprise perceived pedestrian facility and perceived road accessibility.

Another finding is that although both females and males are sensitive to pedestrian or leisure facilities, females are more influenced by perceived neighborhood safety whereas males are more subject to the influence of road conditions like road intersections and road accessibility. In detail, the influence of perceived leisure facilities on SCB is significant in both the female and male group. However, road intersections and perceived road accessibility mainly significantly influence males' SCB, mediated by interaction intensity and community satisfaction respectively. In contrast, perceived neighborhood safety significantly influences SCB *via* influencing interaction intensity in the female group. This finding resonates with recent studies that there is evidence of substantial differences in perceptions of the importance of neighborhood environment between males and females (32).

5. Discussions

Researchers point out that the way neighborhood architectures and environments are designed shapes individuals' SCB, consequently individuals' mental health. The present study employs some indicators assessing SCB relevant to neighborly social interactions and satisfaction; and investigate its relationship with design characteristics of neighborhoods. However, research has seldom discerned the impacts of both objective and perceived neighborhood environment, as well as consider the mediation effects

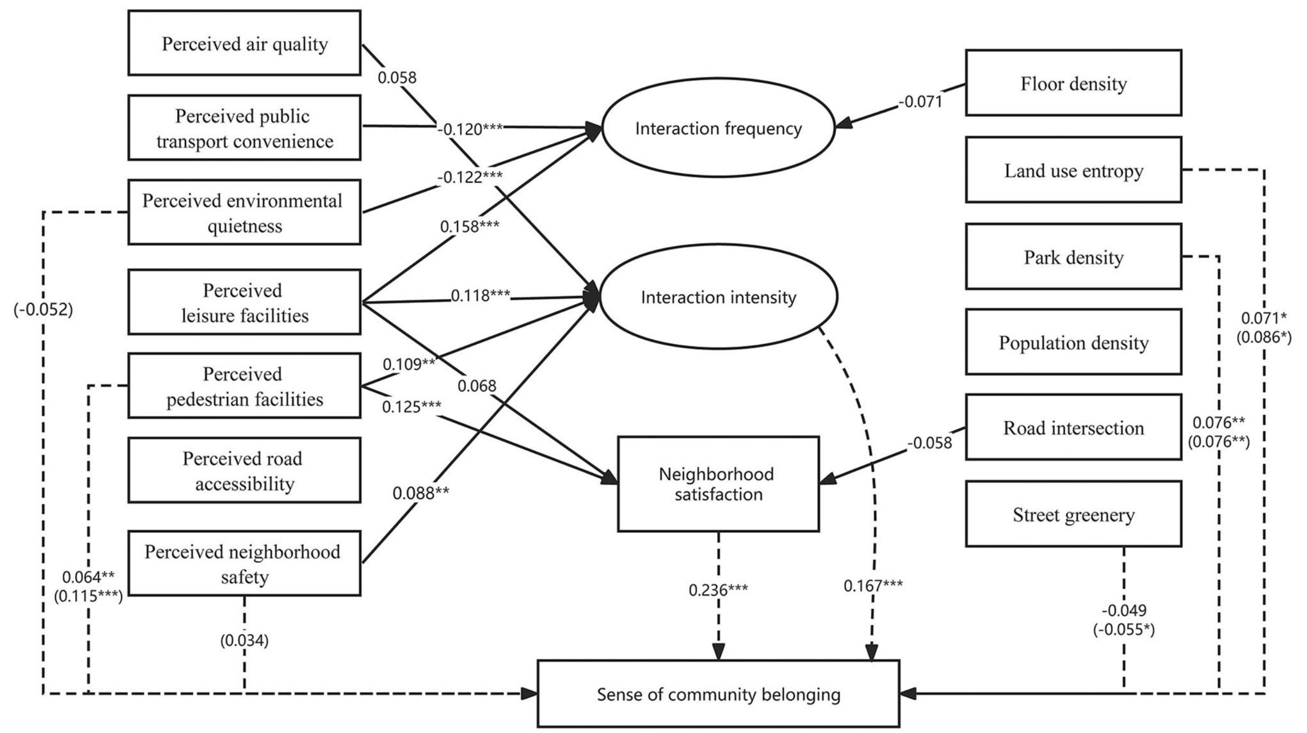

FIGURE 3
SEM analysis of the relationship between the built environment and SCB. (1) All the paths shown are significant at the 0.20 level ($P < 0.20$). (2) The dashed line shows the direct effect of variables to SCB, and values in parentheses represent total effects (the absence of a value before the parentheses means that the variable has no direct effect on SCB at the 0.20 level). Solid lines show the effect of exogenous variables on interaction behavior and community satisfaction. (3) $^{*}0.05 \leq P < 0.1$; $^{**}0.01 \leq P < 0.05$; $^{***}P < 0.01$.

of neighborly interactions and community satisfaction. Therefore, efforts are made in this study to investigate the mechanism through which the relationships take place.

First, the significant effects of neighborhood environment confirm the importance of taking into account both objective and perceived measures of neighborhood environment in predicting SCB. Specifically, we found that both objectively measured and perceived neighborhood environmental elements are significantly associated with SCB. Our findings regarding the role of objective neighborhood environment in SCB, corroborates the principles of New Urbanism that high quality architecture, walkable pedestrian streets and urban design enhance SCB through invoking neighborhood social interactions (12). In this study, we identified that the number of parks, land use entropy, and street greenery are significantly associated with SCB. The finding resonates with previous studies that SCB tends to be higher in these neighborhoods that encourage more active travel like walking and to be featured with mixed land use, connected street networks and plenty of leisure facilities (45, 46).

Note that the importance of perceptions of neighborhood environment on SCB are also verified and confirmed. In this paper, individual's perceptions of the neighborhood's features and appearance of dwelling significantly influence interactions within the neighborhood and ultimately SCB. According to Talen (47), although objective environmental elements could encourage neighborly interactions among members of community, improvement to SCB may never occur. This is because simply considering connection between objectively measured environments and SCB ignores the complexity of the process how individuals perceive, understand, and decide (19). As Smith (19) states, feelings of affect and normative beliefs are positively related to a preference. Therefore, identifying and interpreting the interaction between individuals and environment is as important as measuring the objective environment itself. In this study, of particular relevance to SCB was the strong significant impacts of factors such as perceived public transport convenience, perceived neighborhood quietness, perceived leisure facility, and perceived pedestrian facilities. The finding resonates with some recent studies that perceived environmental elements in residential neighborhoods have a vital role in shaping social interactions or psychosocial constructs such as SCB, neighborhood cohesion, social support, and community connectedness. From this perspective, considering the influences of perceived environmental attributes on neighborhood dynamics is indispensable.

Second, the mediation effects of neighborly interactions and community satisfaction are verified and confirmed in this study, indicating the chained pathways between neighborhood environmental elements and SCB. According to French et al. (4), SCB is a stable assessment since individuals and citizens interpret and perceive their lives from long-term experiences and involvement within their surroundings. It is a combination of feeling and psychological SCB with multiple psychosocial domains (e.g., neighborly interactions, place-based satisfaction, social support and social capital) (7). Bottini (10) states that neighborly social interactions lighten ones' mood, reduce the risk of dementia and facilitate a sense of belonging and safety. It enables individuals to build positive psychosocial constructs with others such as social exchanges, civic engagement, friendliness, and trust; and ultimately

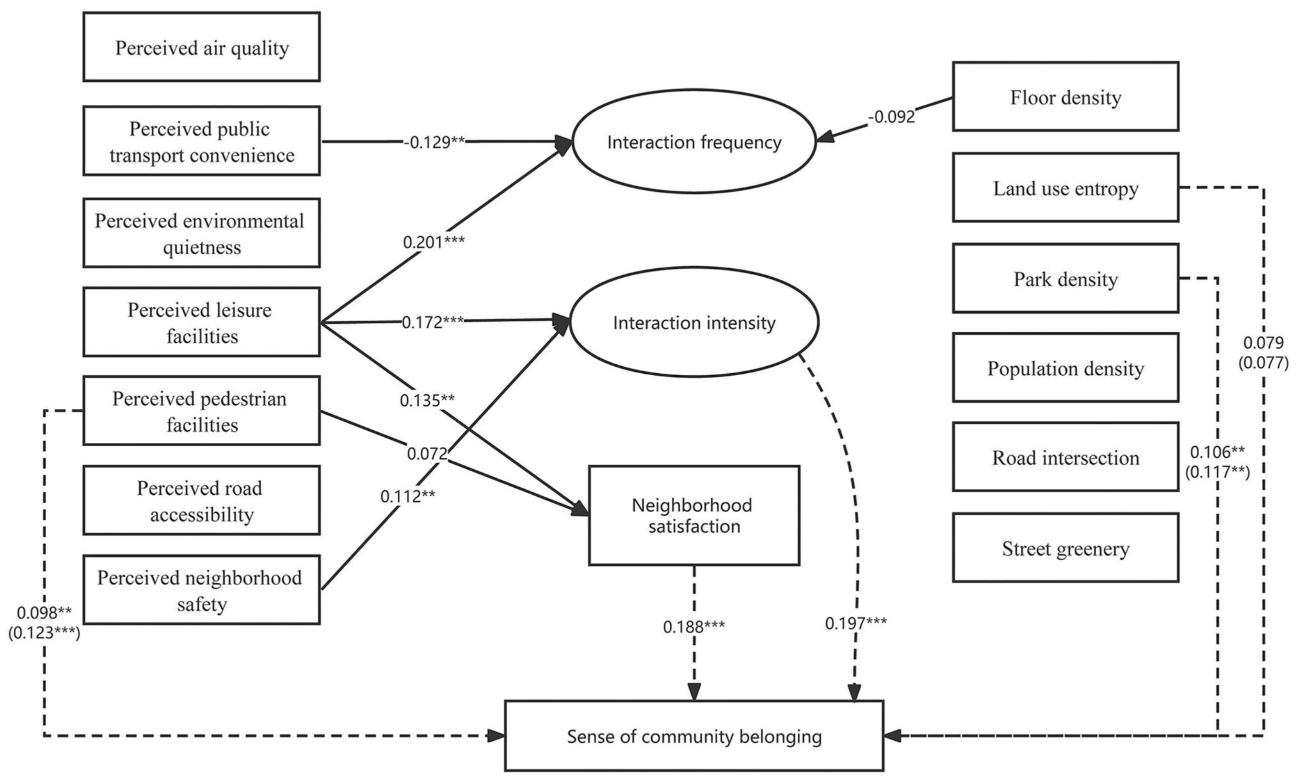

FIGURE 4
SEM analysis of the relationship between the built environment and SCB (female) (***p-value < 0.01, **p-value < 0.05, *p-value < 0.1).

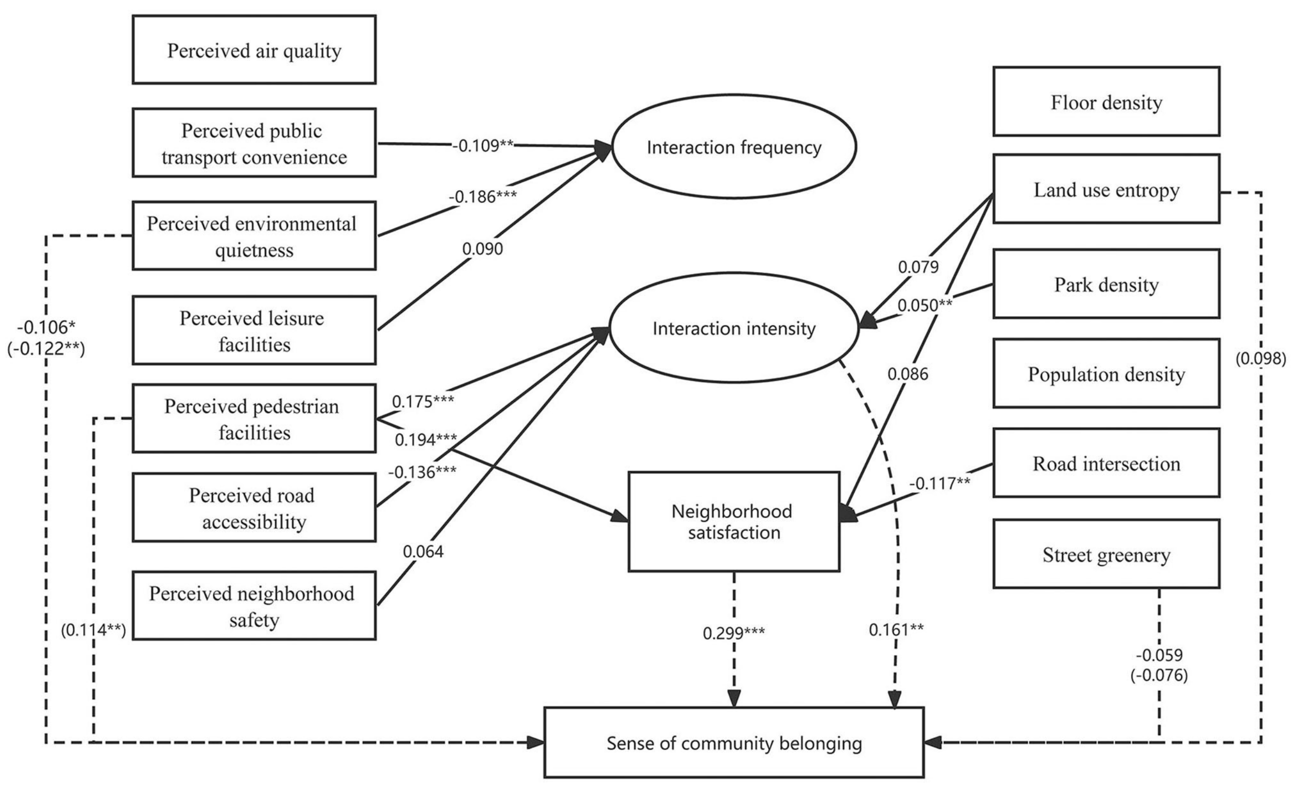

FIGURE 5
SEM analysis of the relationship between the built environment and SCB (male) (***p-value < 0.01, **p-value < 0.05, *p-value < 0.1).

helps improve people neighborhood sense and belonging (23). In this paper, frequency and intensity of neighborly interactions mediate the influence of perceived neighborhood environmental attributes such as perceived environment quietness and perceived leisure facility on SCB, especially on the female group. The findings confirm the argued importance of neighborly interactions in shaping individuals' feeling and psychological SCB. Thus, neighborly interactions become an important anchor of SCB.

Then, community satisfaction is also confirmed to be part of the chained pathways between neighborhood environmental elements and SCB. Hasanzadeh (48) state that residential neighborhoods have become the key spaces for people's daily activities. Members of community usually have high level of neighborhood satisfaction if they are satisfied with their living space that can fulfill their daily want, demand, requirement, and demands (49). In this paper, neighborhood satisfaction mediates the influence of perceived pedestrian facility on SCB. The identified new pathways from the environment to SCB enriches the literature on the relationship between SCB and perceived environmental elements.

Third, we also found heterogeneous influences of neighborhood environment on SCB between males and females; and the finding has implications for planning interventions based on gender difference. Firstly, it shows that females' SCB is mainly influenced by perceived neighborhood environment whereas males' SCB by both objective and perceived neighborhood environment attributes. This means males face more environmental restraints and experience greater opportunities for influence. The result differs a lot from previous studies that females faces more environmental restraints. According to Ma (50), although males deem that environmental features have a low influence on daily activities and emotional feelings, they still place considerable importance on them. In contrast, females often neglect the influence of neighborhood environmental features although they consider these features to be influential. Secondly, we identify that females' SCB is more influenced by perceived neighborhood safety whereas males' SCB more by road conditions like road intersections and perceived road accessibility. According to Jiang et al. (51), males spend more times on daily commuting, thus they put more weight on neighborhood environment like road conditions. As for females, a recent study by Hoffman et al. (52) shows that "women's perceptions of neighborhood sexual violence predicted perceived safety in their neighborhood", consequently, they are more sensitive to neighborhood safety. The heterogenous influence between males and females is vital from the perspective of neighborhood planning and social justice. It suggests males and females experience differed environmental restraints, and thus differentiated pro-environmental actions and behavior among urban designers and planners help develop higher level of SCB.

Two key limitations are acknowledged. First, this paper presumes a linear relationship between neighborhood environment and SCB. However, increasing research criticize the restrained assumption through proposing alternative non-linear associations (36, 53). For instance, when street greenery is not too high, people tend to walk in their residential area and have high neighborhood satisfaction; but after street greenery becomes too high, the benefits or utility of walking turns to be saturated, consequently resulting in low neighborhood satisfaction (44). Thus, there is considerable need for researchers to focus on non-linear relationship between neighborhood characteristics and SCB. Second, the generalizability of the findings may be limited since Shanghai is chiefly featured with high urban density development. For instance, self-reported measures of the neighborhood characteristics may differ considerably across residents (18), indicating differences in behavioral preferences, which could interpret the result discrepancy across cities and countries.

6. Conclusion

There is an increasing interest in the association between neighborhood environment and estimates of psychosocial wellbeing like SCB. However, limited research has been conducted to examine how this relationship occurs. This study investigates the mechanism through which objective and subjectively measured neighborhood environment attributes influence SCB, with a special focus on the mediation effect of neighborly interactions and community satisfaction. The results suggest that the influence of perceived neighborhood environment on SCB is more prominent than that of objective neighborhood environment. In detail, perceived pedestrian facility and perceived leisure facility are vital to SCB, while among objective neighborhood environmental elements, the influence of land use entropy, park density and street greenery are significant. Then, perceived environmental attributes influence SCB mainly through affecting neighborly interactions and community satisfaction. We also identify gender differences in the influence of neighborhood environment upon SCB and specifically males received more environmental restraints in terms of improving SCB. Given increasing awareness of the connection between neighborhood environment and SCB, neighborhood environment may prove to be valuable assets to improve individuals' psychosocial constructs such as SCB.

We acknowledge the limitations. First, due to the preference bias and socioeconomic favoritism, the evaluation of the perceived neighborhood environment variables could be overestimated or underestimated. Second, the 1,000-meter circular buffer was applied to calculate the objective built environment. However, results could differ if different buffer sizes are used. Third, this study focuses on cities with a higher population density which could confine the generalizability of the model and findings.

Data availability statement

The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding authors.

Author contributions

YD: conceptualization, methodology, and original draft and editing. HJ: conceptualization, supervision, and writing—review and editing. ZH: methodology, results analysis, and writing—review and editing. HY: supervision and writing—review and editing. All authors contributed to the article and approved the submitted version.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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Associations between neighborhood walkability and walking following residential relocation: Findings from Alberta's Tomorrow Project

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Introduction: Cross-sectional studies consistently find that the neighborhood built environment (e.g., walkability) is associated with walking. However, findings from the few existing longitudinal residential relocation studies that have estimated associations between changes in neighborhood built characteristics and walking are equivocal. The study objective was to estimate whether changes in neighborhood walkability resulting from residential relocation were associated with leisure, transportation, and total walking levels among adults.

Methods: This study included longitudinal data from the "Alberta's Tomorrow Project"—a province-wide cohort study (Alberta, Canada). The analysis included data collected at two time points (i.e., baseline and follow-up) from 5,977 urban adults. The International Physical Activity Questionnaire (IPAQ) captured self-reported walking. We estimated neighborhood walkability, an index capturing intersection, destination, and population counts for the 400 m Euclidean buffer around participants' homes. Using household postal codes reported at baseline and follow-up, we categorized participants into three groups reflecting residential relocation ("non-movers:" $n = 5{,}679$; "movers to less walkability:" $n = 164$, and; "movers to more walkability:" $n = 134$). We used Inverse-Probability-Weighted Regression Adjustment to estimate differences [i.e., average treatment effects in the treated (ATET)] in weekly minutes of leisure, transportation, and total walking at follow-up between residential relocation groups, adjusting for baseline walking, sociodemographic characteristics, and walkability. The median time between baseline and follow-up was 2-years.

Results: The three residential relocation groups mainly included women (61.6–67.2%) and had a mean age of between 52.2 and 55.7 years. Compared to "non-movers" (reference group), weekly minutes of transportation walking at follow-up was significantly lower among adults who moved to less walkable neighborhoods (ATET: −41.34, 95 CI: −68.30, −14.39; $p < 0.01$). We found no other statistically significant differences in walking between the groups.

Discussion: Our findings suggest that relocating to less walkable neighborhoods could have detrimental effects on transportation walking to the extent of adversely affecting health. Public health strategies that counteract the negative impacts of low walkable neighborhoods and leverage the supportiveness of high walkable neighborhoods might promote more walking.

KEYWORDS

urban design, longitudinal, physical activity, built environment, urban form

Introduction

Encouraging adults to participate in regular physical activity is important as it can protect against numerous modifiable chronic health conditions (e.g., cardiovascular disease, type II diabetes, hypertension, metabolic syndrome, overweight and obesity, cancer, and depression) (1, 2) and premature mortality (3, 4). There is a dose-response relationship between physical activity and health, meaning that even small amounts of moderate-intensity physical activity daily (e.g., walking) can provide health benefits (5). From a public health perspective, walking is a prime intervention target for encouraging the accumulation of physical activity because walking is a safe and innate behavior that most adults can efficiently perform as part of their everyday activities within various physical settings (6). Furthermore, walking is one of the most commonly undertaken physical activities (7, 8) and an essential contributor to the accumulation of total physical activity (9, 10). However, in Canada, less than one-third of adults walk regularly (≥4 times per week) (10), and on average, they accumulate <5,000 steps per day (11). There is an urgent need to identify effective population-level interventions that encourage more walking among Canadian adults.

Neighborhoods are popular settings where adults walk (12–15). The creation of walkable neighborhood built environments is an intervention strategy that can increase walking and increase physical activity (16–18), social connectedness (19), and improve health (20, 21). Walkable neighborhoods include several built attributes such as connected street layouts, pedestrian infrastructure, amenities, and safety, making walking an easy and convenient option (22). Cross-sectional evidence demonstrates that neighborhoods with higher walkability are associated with more walking (23, 24). However, cross-sectional studies provide no evidence with regard to temporality, limiting their ability to assess causality. It remains unclear whether associations between neighborhood walkability and walking result from neighborhood self-selection (seeking out walkable neighborhoods to fulfill walking preferences) or if exposure to a walkable neighborhood changes walking behavior. Recognizing this limitation, longitudinal studies (retrospective and prospective residential relocation studies and natural experiments) estimating the associations between changes in built environment exposure and physical activity have recently emerged (17, 18, 25, 26). Residential relocation studies, in particular, offer an opportunity to estimate the temporal relations between the built environment and physical activity and can account for residual confounding because participants serve as their controls (26). Moreover, residential relocation interrupts normal or habitual behavioral patterns, of which some of this behavior change might be due to exposure to a different built environment (26, 27).

Findings from residential relocation studies provide only modest and often mixed evidence for an association between the built environment and physical activity (26). Most residential relocation studies to date have been undertaken in the US, Australia, and in European countries, with few studies conducted in Canada (26). The geographical differences in physical activity and the built environment strengthens the need for more Canadian specific studies investigating associations between neighborhood walkability and walking (18). Moreover, prospective residential relocation studies undertaken to date have mostly focussed on associations and found consistent results in relation to the associations between land uses, destinations, and transportation and walking (26, 28) with fewer studies examining changes in exposure to overall neighborhood walkability and walking (26). In a residential relocation study in Canada (average follow-up period of 10 months), Adhikari et al. (29) found that an increase in walkability (residential density, commercial floor area ratio, land use mix, and intersection density combined) was associated with an increase in non-work transport-related walking trips adjusting for changes in neighborhood and travel preferences and life events. In another prospective residential relocation study (12 year follow-up) undertaken in Canada, Wasfi et al. (30) found that relocation to a more walkable neighborhood (measured using Walk Score®) was associated with an increase in the likelihood of participating in transportation walking. In a residential relocation study in the UK (2 year follow-up), Clary et al. (31) found that one standard deviation increase in walkability (i.e., connectivity, land use mix, and residential density combined) was associated with an increase of ∼300 steps and 1.7 min of MVPA per day. In contrast, in a prospective residential relocation study in the US (6 year follow-up), Braun et al. (32) found no significant associations between changes in walkability (population density, connectivity, and food and physical activity resources combined) and participation and frequency of overall walking among movers. A residential relocation study ("RESIDE") undertaken in Western Australia, which spanned 10-years found adults exposed to neighborhoods that incorporated liveable urban design features (i.e., safe, convenient pedestrian-friendly, access to shops, transit, and parkland) in general undertook more local walking (in particular transportation walking), and had a stronger sense of community and improved mental health (28).

Residential relocation studies to date have generated mixed findings regarding associations between the built environment and physical activity, few have investigated associations specifically between neighborhood walkability and walking, and the extent to which walkability and walking for different purposes are temporally related remains unclear (26). Further, there is a need for context specific evidence (i.e., Canadian data) to better inform local urban planning and public policy and practice decision-making. Therefore, the aim of our study was to investigate whether changes in neighborhood walkability resulting from residential relocation were associated with leisure, transportation, and total walking among adults in the Canadian context.

Methods

Study and sample design

Previous articles have described the methodological details of the Alberta's Tomorrow Project (ATP) (33, 34). Briefly, ATP is a longitudinal, province-wide study that began in Alberta (Canada) in 2000. From 2000 to 2008, a random sample of adults aged 35–69 years ($n = 63{,}486$) were invited to complete a health and lifestyle questionnaire (HLQ), of which $n = 31{,}072$ responded. In 2008, $n = 20{,}707$ participants completed a first follow-up survey and between 2009 and 2015, $n = 15{,}963$ completed a second follow-up survey (34). We undertook secondary (longitudinal) analysis of ATP data that were collected in 2008 and from 2009 to 2015 (herein referred to as "baseline" and "follow-up," respectively) because the walking outcome measures of interest were consistent between these two surveys. Participant's residential addresses were collected at each survey however, to comply with ethics and to maintain participant anonymity only postal codes could be used for analyses (e.g., linking with built environment data). In our analysis, we included participants from urban areas only, identified from the Forward Sortation Area (FSA) information contained in the first 3-digits of their 6-digit residential postal codes. Rural postal codes include a zero in the second position of the FSA and denotes an area where there are no letter carriers (mail delivered to a post office or postal box). We included only participants from urban areas only because there are urban-rural differences in land use and transportation planning processes, built characteristics may exert different effects on walking in urban vs. rural neighborhoods (35), and in Canadian there are urban-rural differences in the prevalence physical inactivity (36).

Further, we included data from participants that provided complete data on the variables of interest for both the baseline and follow-up surveys, with which built environment data were available and linkable to their survey data ($n = 5{,}977$). The median follow-up time between the baseline and follow-up surveys was 2 years. The University of Calgary Conjoint Health Research Ethics Board approved the acquisition and analysis of ATP data for this study (REB17-1466).

Variables

Self-reported physical activity

The International Physical Activity Questionnaire (IPAQ) (37), captured leisure and transportation walking at baseline and follow-up. Leisure walking included walking undertaken for recreation, sport or leisure and transportation walking included walking undertaken to go from place to place. Participants reported the number of days in the past week they undertook at least 10-min of leisure or transportation walking. Participants also reported time spent undertaking walking during a typical day. We multiplied reported days by reported daily minutes to estimate weekly minutes of leisure, transportation, and total walking (i.e., leisure plus transportation walking). As recommended (38), we truncated each walking outcome to 180-min per day to remove outliers and adjust for over-reporting.

Neighborhood walkability

The walkability index used in our analysis has been described elsewhere (39). We geocoded all Alberta 6-digit urban postal codes for 2008–2015 ($n = 77{,}602$–$84{,}115$) to create points. Canadian urban postal codes provide a reasonable approximation of household location, when complete street address information is not available (e.g., 50% of postal codes are located within a 69 m, and 88% of postal codes are located within 200 m, of the true household address location) (40). Using Geographical Information Systems, we created 400 m Euclidean buffers (polygons) around each geocoded postal code point. Neighborhoods were defined by a 400 m buffer boundary that captured neighborhood built characteristics located within about a 5–10 min walking distance from home (41). Overlaid with a street network file (CanMap Streetfiles and Route Logistics, DMTI Spatial Inc.), we calculated the count of 3-way and 4-way intersections within each buffer. Using the Enhanced Points of Interest (DMTI Spatial Inc.) and available Standard Industry Codes, we calculated the count of business destinations (e.g., hardware stores, department stores, grocery stores, restaurants, banks, libraries, laundry stores, stationery stores, liquor stores, jewelry stores, barbershops, museums, schools, colleges, and universities) within each buffer. To calculate population counts, we overlaid dissemination area census data from Statistics Canada (years 2006, 2011, and 2016) onto the buffers. Dissemination areas (DA) are the smallest standard geographical unit available for research purposes from Statistics Canada (each DA includes ~400–700 persons) (42). DAs have irregular-shaped boundaries that often follow roads or other features (e.g., railways and water features); therefore, they did not match the geographical shape of the circular neighborhood buffers. Thus, the total population count assigned to each buffer was based on a weighted sum that reflected the proportion of geometric overlap between each DA boundary and the buffer (i.e., multiple DAs could overlap a single buffer). For non-census years, we imputed population counts using the averages for years in which census data were available.

For each year (2008–2015) across all buffers, we converted raw counts for intersections (3-way and 4-way), destinations, and population to z-scores. The z-scores were summed to derive a walkability score (WS) for each buffer [WS = $[0.5 \times z$ (3-way intersections)] + z (4-way intersections) + z (destinations) + z (population)]. Higher positive scores reflected more walkability, while higher negative scores reflected less walkability. Relative to 4-way intersections, 3-way intersections contribute less to street connectivity and may offer less support for walking (43–45). Therefore, we down-weighted the contribution of 3-way intersections to the WS. The walkability score (estimated for 77,597 postal codes using 2,008 values) was positively correlated with each of the individual built environment variables (i.e., 3-way intersections $r = 0.400$; 4-way intersections $r = 0.753$; destinations $r = 0.794$, and; population count $r = 0.605$). We also found the WS to have concurrent validity compared against Walk Score®, a valid, widely-used, measure of walkability (46, 47) ($r = 0.648$; estimate for 81,114 postal codes using 2012 values). The intra-class correlation (ICC) for WSs estimated for postal codes available for all years from 2008 to 2015 (ICC = 0.974) showed that the estimated WS were relatively stable during this period.

We temporally matched participant survey data (baseline and follow-up) with buffer WSs using 6-digit postal codes and created three residential relocation groups. Among movers, the direction of the absolute difference between baseline (origin neighborhood) and follow-up (destination neighborhood) walkability scores, regardless of magnitude, was used to categorize participants as having relocated to either a: (1) less walkable neighborhood or; (2) more walkable neighborhood. Non-movers constituted the third category, regardless of the direction of change in walkability estimated between the baseline and follow-up surveys. Including a non-mover control group is vital for accounting for changes in walking that might have occurred had those moving not relocated neighborhood (i.e., the counterfactual) and for isolating the effect of a change in walkability (e.g., increase or decrease in walkability) on walking.

Sociodemographic characteristics

Sociodemographic variables from the baseline survey included sex, age, children under 18 years of age at home, highest educational attainment, annual gross household income, marital status, employment status, and dwelling type in origin neighborhood (i.e., single dwelling, duplex or row housing, apartment, and other). The season of survey completion was captured.

Statistical analysis

We used descriptive statistics (mean, standard deviation, and frequencies) and inferential statistics (One-way Analysis of Variance—ANOVA, and Pearson's chi-square) to estimate the differences in baseline sociodemographic and walking variables between the three residential relocation groups (i.e., non-movers, moved to less walkability, and moved to more walkability). ANOVA (with Tukey-Kramer *post hoc* tests) estimated between-group differences in the walkability of the origin and destination neighborhoods (or change over time in the origin neighborhood walkability only for non-movers) for the three residential relocation groups. Dependent (paired) *t*-tests estimated within-group differences between the walkability of origin and destination neighborhoods for each residential relocation group. Using pooled data (ignoring residential relocation groupings), we performed generalized linear regression (Gaussian distribution with identity link) to estimate the slope coefficients (b) for the baseline cross-sectional associations between walking outcomes and WS, adjusting for covariates (i.e., sex, age, number of children under 18 years of age at home, highest educational attainment, annual gross household income, marital status, employment status, and dwelling type).

We undertook analysis to estimate the average treatment effect on the treated (ATET)—i.e., the estimated difference in leisure, transportation, and total walking between those who moved to less walkability and those who moved to more walkability compared with non-movers. For analytical purposes, we regarded non-movers as a "control" group and those relocating to less or more walkability as the "treatment" groups. Estimating these differences relative to non-movers (control group) accounted for the change in walking behavior among the treatment groups that resulted from factors other than residential relocation and change in walkability exposure.

We used treatment effects models to estimate the ATET. We used the *teffects and ipwra* Stata commands (48) to derive inverse-probability-weighted regression adjusted estimates to optimize the balance in baseline covariates between the three residential relocation groups and to compute the average treatment-level predicted outcomes (leisure, transportation, and total walking). This approach was taken to make the three residential relocation groups conditionally exchangeable (49), allowing for the average causal effect of relocating to either a less or more walkable neighborhood to be estimated from the contrasts in the average predicted outcomes between these two (treatment) groups relative to non-movers (control group). To compute the inverse-probability-weights, a treatment model (multinomial logit) was first estimated in which the residential relocation group was regressed onto the baseline covariates (i.e., sex, age, number of children under 18 years of age at home, highest educational attainment, annual gross household income, marital status, employment status, dwelling type, WS in origin neighborhood, and total walking minutes). We applied the inverse-probability weights to regression (outcome) models and estimated treatment-specific predicted follow-up walking outcomes for each participant. To control for the influence of seasonality on physical activity (50) and, in particular, walking within the Canadian context (51), we included the season during which the participant returned the follow-up survey as a covariate in the regression models. The mean walking outcomes were calculated for each residential relocation group (treatment-specific predicted outcomes), and contrasts were performed to calculate the differences in the means between the two treatment groups relative to non-movers (control group) to provide the treatment-specific ATET estimates.

STATA's *tebalance summarize* and *teffects overlap* commands facilitated covariate balance checking between the three residential relocation groups. We assessed the balance of each baseline covariate using the average standardized absolute mean difference (SMD) and variance ratio (VR) and assessed the visual overlap in the group covariate distributions using box plots and cumulative distribution functions (52). Covariates of perfectly balanced groups have an SMD = 0 and VR = 1; however, we considered groups to be sufficiently balanced if the SMD was $|<0.1|$ and the VR was 0.5–2 for all covariates (53, 54). We estimated bootstrapped standard errors (1,000 repetitions with replacement) and 95% confidence intervals (95 CI) for the generalized linear and treatment effect models. We considered *p*-values < 0.05 as statistically significant. We undertook the analysis using Stata/SE 15.1 (StataCorp LLC, College Station, Texas, USA).

Results

Sample characteristics

The sample ($n = 5{,}977$) consisted mostly of participants that were female, married, employed and residing in single-dwelling homes and had completed post-secondary education (Table 1). Approximately 5% ($n = 298$) of our sample relocated neighborhood between the baseline and follow-up surveys. Non-movers, movers to less walkability, and movers to more walkability significantly differed ($p < 0.05$) concerning their baseline age, marital status, employment status, and dwelling type. Mean weekly minutes of leisure, transportation, and total walking at baseline and follow-up did not significantly differ by residential relocation group, except for follow-up transportation walking (i.e., movers = 119.5, movers

TABLE 1 Sample characteristics by residential relocation group.

Baseline sociodemographic characteristics	Residential relocation group		
	Non-mover	Moved to a less walkable neighborhood	Moved to a more walkable neighborhood
	($n = 5,679$)	($n = 164$)	($n = 134$)
	Estimate	Estimate	Estimate
Sex (female %)	61.6	64.6	67.2
Age [mean, (SD)]*	55.7 (9.1)	51.6 (8.2)	52.2 (9.6)
Number of children [mean (SD)]	0.5 (0.9)	0.5 (1.0)	0.5 (0.9)
Education attained (%)			
High school or less	17.9	17.7	19.4
Some post-secondary	23.6	20.7	26.1
Completed post-secondary	55.5	61.6	54.5
Annual household income (%)			
≤$49,999	17.2	25.6	21.6
$50,000–99,999	30.6	28.7	29.1
$100,000–149,999	23.8	19.5	22.4
$150,000–199,999	10.6	7.9	10.4
≥$200,000	10.2	14.0	11.2
Don't know/refused	7.6	4.3	5.2
Marital status (married/defacto %)*	73.2	62.2	64.9
Dwelling type in origin neighborhood (%)*			
Single dwelling home	79.3	62.8	65.7
Duplex or row housing	10.9	15.8	10.4
Apartment	7.6	16.5	19.7
Other	2.2	4.9	5.2
Employment status (employed %)*	67.5	78.0	77.6
Walking minutes per week [mean (SD)]			
Baseline transportation walking	118.0 (180.0)	100.7 (169.5)	134.0 (197.5)
Follow-up transportation walking*	119.5 (188.4)	83.5 (133.5)	128.6 (219.4)
Baseline leisure walking	123.8 (179.0)	109.1 (173.9)	97.3 (135.7)
Follow-up leisure walking	113.8 (167.7)	103.6 (167.5)	112.3 (175.1)
Baseline total walking	243.5 (285.6)	214.9 (285.5)	231.3 (268.0)
Follow-up total walking	234.8 (286.4)	187.0 (235.0)	240.8 (317.4)

SD, standard deviation.
Between group (relocation status) differences in continuous variables compared using ANOVA and in categorical variables compared using Pearson's chi-square.
*Statistically significant ($p < 0.05$).

to less walkability = 83.5, and movers to more walkability = 128.6; $p < 0.05$; Table 1). Among all participants from baseline to follow-up (pooled), we found, on average, significant decreases in weekly minutes of leisure walking ($\Delta = -9.28$, 95 CI: −4.26, −14.29, $p < 0.001$) and total walking ($\Delta = -8.77$, 95 CI: −0.94, −16.59, $p = 0.028$) but not transportation walking ($\Delta = 0.83$, 95 CI: −4.56, 6.22, $p = 0.764$).

Among the entire sample, mean (SD; median; minimum; maximum) walkability was −0.09 (2.15; −0.31; −4.32; 11.84) at baseline and −0.07 (2.19; −0.29; −4.37; 12.04) at follow-up. Mean walkability at baseline was significantly different between the residential relocation groups (Table 2). Notably, participants who moved to neighborhoods with less walkability came from origin neighborhoods that were significantly ($p < 0.01$) more walkable (WS = 0.86) compared with those who moved to more walkability (WS = −0.95) or non-movers (WS = −0.10). Among non-movers, change in walkability between the baseline and follow-up significantly improved ($\Delta = 0.03$; 95 CI: 0.02, 0.05, $p < 0.001$), albeit by a smaller magnitude relative to the absolute changes in walkability observed among those who moved to less ($\Delta = -2.14$; 95 CI: −2.43, −1.85)

TABLE 2 Walkability scores for origin and destination neighborhoods by residential relocation group.

	Residential relocation group		
	Non-mover (*n* = 5,678)	Moved to a less walkable neighborhood (*n* = 164)	Moved to a more walkable neighborhood (*n* = 134)
Origin neighborhood walkability (baseline)			
Mean (95 CI)	−0.10 (-0.16, −0.05)[a,b]	0.86 (0.53, 1.19)[a,c]	−0.95 (−1.32, −0.59)[b,c]
Standard deviation	2.14	2.31	2.13
Minimum and maximum	−4.32, 11.84	−3.11, 8.08	−4.22, 8.26
Median (25 and 75th percentiles)	−0.32 (−1.44, 1.07)	0.61 (−0.98, 2.20)	−1.13 (−2.31, 0.06)
Destination neighborhood walkability (follow−up)			
Mean (95 CI)	−0.07 (−0.13, −0.01)[a,b]	−1.28 (−1.61, −0.95)[a,c]	1.44 (1.08, 1.81)[b,c]
Standard deviation	2.16	1.72	2.95
Minimum and maximum	−4.37, 12.04	−4.33, 4.15	−3.57, 11.64
Median (25 and 75th percentiles)	−0.28 (−1.39, 1.11)	−1.36 (−2.52, −0.36)	1.07 (−0.27, 2.14)
Absolute change in walkability (follow−up minus baseline)			
Mean (95 CI)	0.03 (0.02, 0.05)*	−2.14 (−2.43, −1.85)*	2.40 (2.01, 2.78)*
Standard deviation	0.61	1.89	2.24
Minimum and maximum	−3.71, 4.29	−9.59, −0.01	0.01, 10.98
Median (25 and 75th percentiles)	−0.04 (−0.23, 0.22)	−1.57 (−2.99, −0.77)	1.77 (0.80, 3.16)

Same superscript ([a,b,c]) represents statistically significant ($p < 0.01$) pairwise between group differences in walkability (ANOVA and Tukey-Kramer *post-hoc* tests).
*Statistically significant ($p < 0.001$) within group differences in walkability (paired t-tests).

and more walkable neighborhoods (Δ = 2.40; 95 CI: 2.01, 2.78; Table 2).

Baseline cross-sectional associations between walkability and walking outcomes

Adjusting for all covariates, WS was positively associated with baseline weekly minutes of transportation walking ($b = 3.17$; 95 CI: 0.82, 5.53; $p = 0.008$), but not with baseline minutes of leisure walking ($b = -1.33$; 95 CI: −3.59, 0.94; $p = 0.251$) or total walking ($b = 1.89$; 95 CI: −1.60, 5.38; $p = 0.288$).

Covariate balance between the residential relocation groups

The inverse-probability-weights generated from the treatment model improved covariate balance between the three residential relocation groups concerning the SMDs (unweighted: range = −0.473 to 0.433 vs. weighted: range = −0.117 to 0.247) and VRs (unweighted: range = 0.598 to 2.737 vs. weighted: range = 0.738–1.298; Table 3; Figure 1). Although improved after weighting, the SMD for baseline walkability (SMD from 0.433 to 0.247) did not meet the criteria for establishing covariate balance (i.e., SMD = |<0.1| and the VR = 0.5–2; Table 3). As a result, we doubly-adjusted for baseline walkability by including it as covariate in the treatment effect model.

Differences in walking behavior by residential relocation group (ATET)

Compared to non-movers, weekly minutes of transportation walking was significantly lower at follow-up among those who moved to a less walkable neighborhood (−43.48 min/week; 95 CI: −68.17, 17.78, $p < 0.01$; Table 4). Furthermore, the difference in weekly minutes of total walking at follow-up between non-movers and those who moved to a less walkable neighborhood approached statistical significance (−50.86; 95 CI: −102.67, 0.99, $p = 0.054$). We found no other statistically significant between-group differences in walking.

Discussion

Residential relocation studies provide a unique opportunity for generating rigorous causal evidence that can inform urban design and public health policy (55, 56). Our study investigated whether a change in neighborhood walkability resulting from residential relocation was associated with leisure, transportation, and total walking levels among adults in the Canadian context. Our findings suggest that relocating to a less walkable neighborhood may have detrimental effects on transport-specific and total walking. Specifically, we found that compared with non-movers, adults moving to less walkable neighborhoods undertook ∼41 min less of transportation walking per week. A difference in walking of this magnitude is of clinical relevance, and could have negative physical and mental health consequences (57–60). Our findings are congruent with other studies demonstrating that a change in walkability following

TABLE 3 Covariate balance of baseline covariates before and after weighting between residential relocation groups.

	Standardized differences		Variance ratio	
	Unweighted	Weighted	Unweighted	Weighted
Moved to more walkable neighborhood				
Total walking	−0.044	−0.006	0.880	0.945
Sex	−0.116	0.001	0.939	1.000
Age	−0.369	−0.001	1.105	1.292
Income (cat2)	−0.033	0.007	0.978	1.006
Income (cat3)	−0.034	0.005	0.964	1.007
Income (cat4)	−0.005	0.002	0.995	1.005
Income (cat5)	0.032	−0.001	1.094	0.997
Income (cat6)	−0.095	0.005	0.714	1.019
Education (cat2)	0.059	−0.003	1.079	0.996
Education3 (cat3)	−0.081	0.018	1.029	0.997
No. children	0.037	0.005	1.072	1.054
Marital status	−0.179	0.010	1.169	0.994
Employment	0.228	0.010	0.798	0.986
Walkability	−0.399	0.014	0.995	1.152
Dwelling (cat2)	−0.014	0.009	0.972	1.023
Dwelling (cat3)	0.329	−0.008	2.161	0.988
Dwelling (cat4)	0.163	−0.009	2.373	0.966
Moved to less walkable neighborhood				
Total walking	−0.100	−0.078	1.000	1.251
Sex	−0.063	−0.029	0.972	0.978
Age	−0.473	−0.010	0.820	0.950
Income (cat2)	−0.043	0.112	0.968	1.094
Income (cat3)	−0.105	−0.117	0.870	0.837
Income (cat4)	−0.092	0.037	0.775	1.097
Income (cat5)	0.117	0.035	1.325	1.086
Income (cat6)	−0.140	−0.011	0.589	0.956
Education (cat2)	−0.068	0.038	0.918	1.040
Education3 (cat3)	0.063	0.005	0.980	0.999
No. children	0.089	−0.039	1.239	1.255
Marital status	−0.236	0.012	1.205	0.993
Employment	0.238	0.024	0.786	0.968
Walkability	0.433	0.247	1.173	0.738
Dwelling (cat2)	0.146	0.111	1.384	1.298
Dwelling (cat3)	0.272	0.084	1.956	1.130
Dwelling (cat4)	0.148	−0.044	2.220	0.834

Number of unweighted observations: Non-movers (n = 5,679); Moved to more walkable neighborhood (*n* = 134); Moved to less walkable neighborhood (*n* = 164).
Number of observations after applying inverse probability weighting: Non-movers (*n* = 2,054.4); Moved to more walkable neighborhood (n = 2,042.4); Moved to less walkable neighborhood (*n* = 1,879.8).

residential relocation was associated with transportation walking (29, 30) however; our findings are novel in that we only found a significant difference in transportation walking for those relocating to neighborhoods of less, but not to more walkability. Our cross-sectional and longitudinal findings support the consistent evidence demonstrating that the neighborhood built environment may be

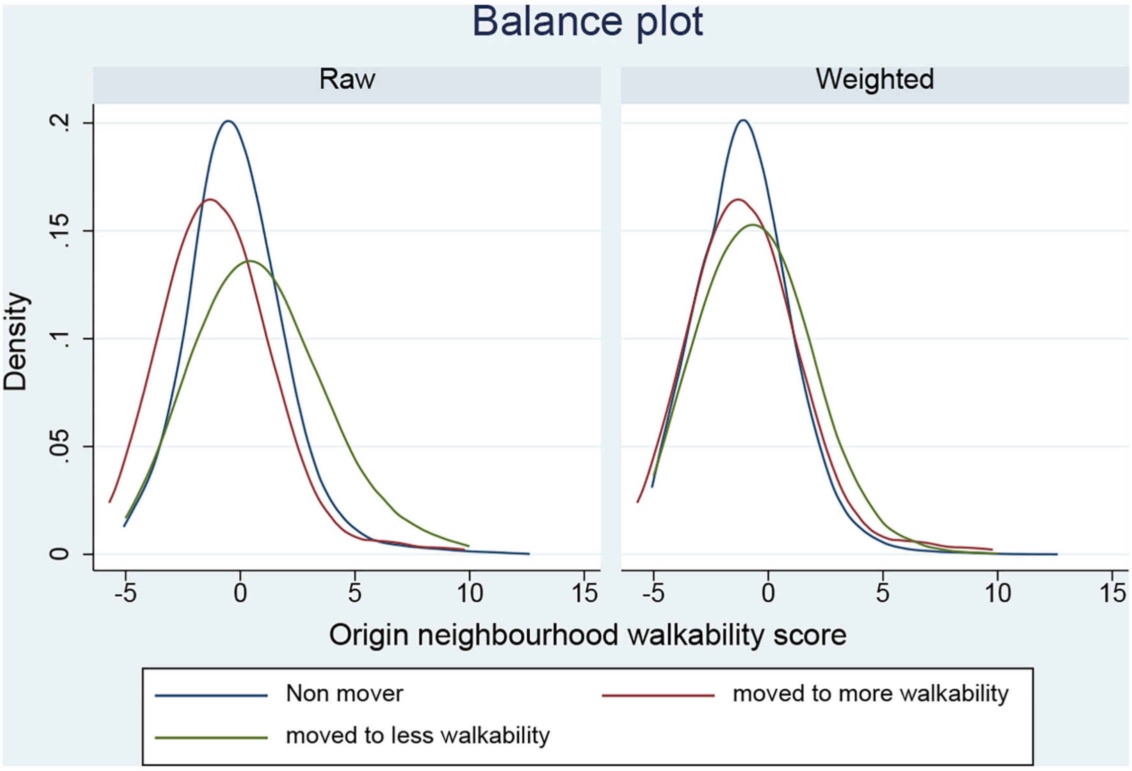

FIGURE 1
Balance in origin neighborhood walkability scores between residential relocation status groups before and after weighting.

more strongly associated with transportation versus leisure walking (18, 23, 24).

A notable finding from this study was that relocating to a less walkable neighborhood may have a greater impact on transportation walking than relocating to a higher walkable neighborhood. The reduction in transportation walking (41 min per week, on average), was in response to an average reduction in walkability (between origin and destination neighborhood) by ∼2 standard deviations, independent of the walkability of the origin neighborhood. However, given that walkability was measured as a score which combined three built environment variables (z-scores representing transformed counts of intersections, destinations, and population) translating this score into a description of the change in built environment is difficult. Nevertheless, this finding aligns with the general scientific consensus that higher neighborhood walkability is better for walking, and in particular transportation walking. Our novel finding may reflect the mismatch between walking preferences and built environment characteristics that provide opportunities to walk (61, 62). Specifically, adults preferring to walk for transportation but who relocate to a neighborhood that has an unsupportive built environment (i.e., low walkability) may have no option but to walk less (i.e., a discouraging effect). Alternatively, an adult who relocates to a neighborhood with a built environment that is more supportive (i.e., high walkability) have the option to choose to walk for transportation or not walk according to their preferences. Our finding might also suggest that the transportation walking patterns or habits formed while residing in less walkable neighborhoods remain even after relocating to a more walkable neighborhood. That is, those who did not walk for transport in their origin neighborhoods may be less likely to initiate transportation walking after relocating to a more walkable neighborhood.

Unlike transportation walking, we found that walkability was not associated with leisure walking in either the cross-sectional or longitudinal analysis. Notably, weekly minutes of leisure walking was not impacted by relocating neighborhood (whether it be less or more walkable), which might suggest that preferences for and opportunities to undertake this type of walking is less constrained by the neighborhood built environment. Other studies however, have found changes in leisure walking following neighborhood relocation. For instance, improvements in participation of transportation and leisure walking have been reported among adults who relocated to a mixed-use (e.g., more walkable) neighborhood (63). Nevertheless, leisure walking may be more strongly determined by proximal intrapersonal factors (e.g., self-efficacy, intentions, enjoyment, and perceived barriers) with a smaller influence from the built environment (64, 65). Our lack of significant findings regarding leisure walking may also reflect the built environment characteristics included in our walkability measure. The walkability measure did not include built attributes such as parks and pathways that may be important for supporting leisure walking (66). More research on how changes in exposure to individual built characteristics influences walking undertaken for different purposes is needed (26).

Our findings have important implications. For adults considering relocating neighborhood and wanting to continue to walk for transportation, our findings suggest that these adults should seek

TABLE 4 Differences (ATET) in weekly minutes per week of walking duration post relocation by relocation group.

	Group	Transportation walking		Leisure walking		Total walking	
		b (95 CI)	p	b (95 CI)	p	b (95 CI)	p
Naïve estimate[a]							
Non-mover	Control	0		0		0	
Moved to more walkable neighborhood	Treatment 1	9.07 (−29.06, 47.21)	0.641	−1.61 (−30.92, 27.70)	0.914	6.01 (−47.84, 59.87)	0.827
Moved to less walkable neighborhood	Treatment 2	−36.03 (−56.54, −15.53)	0.001	−10.28 (−36.35, 15.78)	0.439	−47.77 (−83.19, −12.34)	0.008
Adjusted estimates[b]							
Non-mover	Control	0		0		0	
Moved to more walkable neighborhood	Treatment 1	13.75 (−22.40, 49.89)	0.456	1.43 (−29.84, 32.71)	0.928	14.15 (−39.55, 67.85)	0.604
Moved to less walkable neighborhood	Treatment 2	−43.48 (−69.17, −17.78)	0.001	−6.36 (−49.70, 36.98)	0.774	−50.86 (−102.67, 0.99)	0.054

ATET, Average Treatment Effects in the Treated.
[a]No adjustment for covariates in the treatment or outcome models.
[b]Based on inverse probability weighting to balance covariates between residential relocation groups (treatment model) and inclusion of season and baseline walkability as covariates in the outcome model.
95 CI estimated from bootstrapped standard errors (1,000 replications with replacement).

out new neighborhoods with at least similar or higher levels of walkability relative to their origin neighborhoods. Publically available tools, such as Walk Score®, Bike Score®, and Transit Score® (available on real estate sites such as Redfin: https://www.redfin.com/) may be useful for identifying new neighborhoods that can support preferences for transport-related physical activity. Moreover, real estate professionals may play an important role in matching home-seekers with neighborhoods that include built characteristics that support their walking preferences (67–69). More importantly, our findings highlight the need for urban development and planning authorities, municipalities, and land developers to increase the supply of newly developed walkable neighborhoods and invest in the redevelopment of existing neighborhoods to increase their supportiveness for transportation walking. Broadening the availability of walkable neighborhoods may reduce the number of people who decrease their transportation walking following relocation as poor design might overshadow people's intentions to walk. Improving the built environment and implementing strategies for improving awareness and education on the importance of walkability among home-seekers is important. Further, our findings lend support for public health strategies (e.g., mass media campaigns and individualized trip planning) that counteract the negative impact of poor urban design in low walkable neighborhoods and capitalize on the supportive pedestrian infrastructure available in walkable neighborhoods.

Our study has several strengths. Our objective-measure of walkability, estimated change in walkability exposure resulting from neighborhood relocation, inclusion of measures of walking for different purposes, statistical adjustment for baseline walking and walkability, inclusion of a control group ("non-movers"), and our two-staged modeling strategy that balanced the observed covariates between the groups prior to treatment effect estimation strengthened internal validity. Non-movers were observed to have a relatively small change in walkability between the baseline and follow-up suggesting that the neighborhood built environment remained relatively stable during the short term (70, 71). Moreover, this temporal stability was also supported by our estimated intra-class correlation for the neighborhood walkability score for years 2008–2015 (ICC = 0.974). Participants included in our study were from urban areas that spanned an entire Canadian province, thus contributing to the representativeness of the sample and our findings.

Our study also has several limitations. The median follow-up time of 2 years, limits our ability to infer whether long-term changes in walking might occur as individuals become more aware, accustomed, and exposed to their new neighborhood surroundings. The walkability variable represented the combination of three built environment variables (intersections, destinations, and population), and while these are important characteristics for supporting walking (16–18), they do not represent all neighborhood built characteristics that might facilitate walking. Examining changes in walking resulting from changes in exposure to neighborhood built characteristics such as transit availability and accessibility, green space, pathways, traffic and personal safety, and aesthetics may be important to consider in future research. Moreover, the small sample of movers did not allow us to examine and test different cut-off scores for change in walkability exposure (i.e., sensitivity analysis), thus we are not able to determine the extent to which magnitude of walkability change affected walking or whether a minimum exposure threshold to elicit a change in walking existed. Walking outcomes were self-reported and may not accurately reflect actual walking (72). Moreover, despite most walking being undertaken close to home (12–15), our walking outcomes were not context-specific (73), thus some of the walking reported likely occurred outside the neighborhood (i.e., at locations further than 400 meters from home). We defined neighborhoods using a 400 m Euclidean buffer representing a 5–10 min walking distance from home (41). Relative to network buffers, Euclidean defined boundaries can result in underestimates of associations between the built environment and walking irrespective of boundary size (74, 75). Speculatively, our walking measure and neighborhood boundary definition likely resulted in conservative estimates of the relationships between neighborhood walkability and walking. The sample included middle-aged to older adults and thus the patterns found in relation to walkability and walking may not generalize to younger adults, limiting the study's generalizability.

Our findings demonstrate that adults who relocate to new neighborhoods that are less walkable than their origin neighborhoods undertake less transportation walking. More longitudinal studies need to investigate the short and long-term changes in walking associated with changes in neighborhood walkability exposure following residential relocation.

Data availability statement

Data that support the findings of this study are available from the Alberta's Tomorrow Project (https://myatp.ca/) following data requisition approval. Requests to access these datasets should be directed to Alberta's Tomorrow Project (https://myatp.ca/).

Ethics statement

The studies involving human participants were reviewed and approved by the University of Calgary Conjoint Health Research Ethics Board (REB17-1466). The patients/participants provided their written informed consent to participate in this study.

Author contributions

GRM, JV, GM, JC, and RM were involved in the conception of the study. JV was involved in the study design and data collection for ATP. GRM, MK, KO, and TN advised on the analysis and interpreted the results. GRM drafted the original manuscript. All authors reviewed and approved the final manuscript.

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Conflict of interest

RM was employed by Toole Design Group.

The remaining authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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Sleep – the guarantee of health! Does the environmental perception characteristics of urban residential areas affect residents' sleep quality?

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A complex urban living environment and residents' sleep quality are intrinsically linked. Nonetheless, there is little evidence that the residential environment affects sleep quality. Based on the results of subjective questionnaires, this study uses the multiple regression combined with mediation analysis to construct a mechanical model of the impact of urban residential environmental perception characteristics on residents' sleep quality. Moreover, the differences among the influence intensities of the significant factors are compared and the results show that (1) in low-density environments (FAR < 2) and lower floors (4–6), residents sleep longer and have better sleep quality; (2) the environmental quality and service facilities of the physical environment and the sense of safety in the social environment have a significant impact on residents' sleep quality; and (3) the mental health of residents play a significant intermediary role in the relationship between social environment and sleep quality, with the highest effect accounting for 33.88%. The influence mechanisms of various environmental factors in a residential area on sleep quality were revealed and a more refined design basis for a healthy urban living environment, community renewal, and renovation was provided.

KEYWORDS

environmental perception, sleep quality, positive mental health, physical environment, wellbeing, social environment

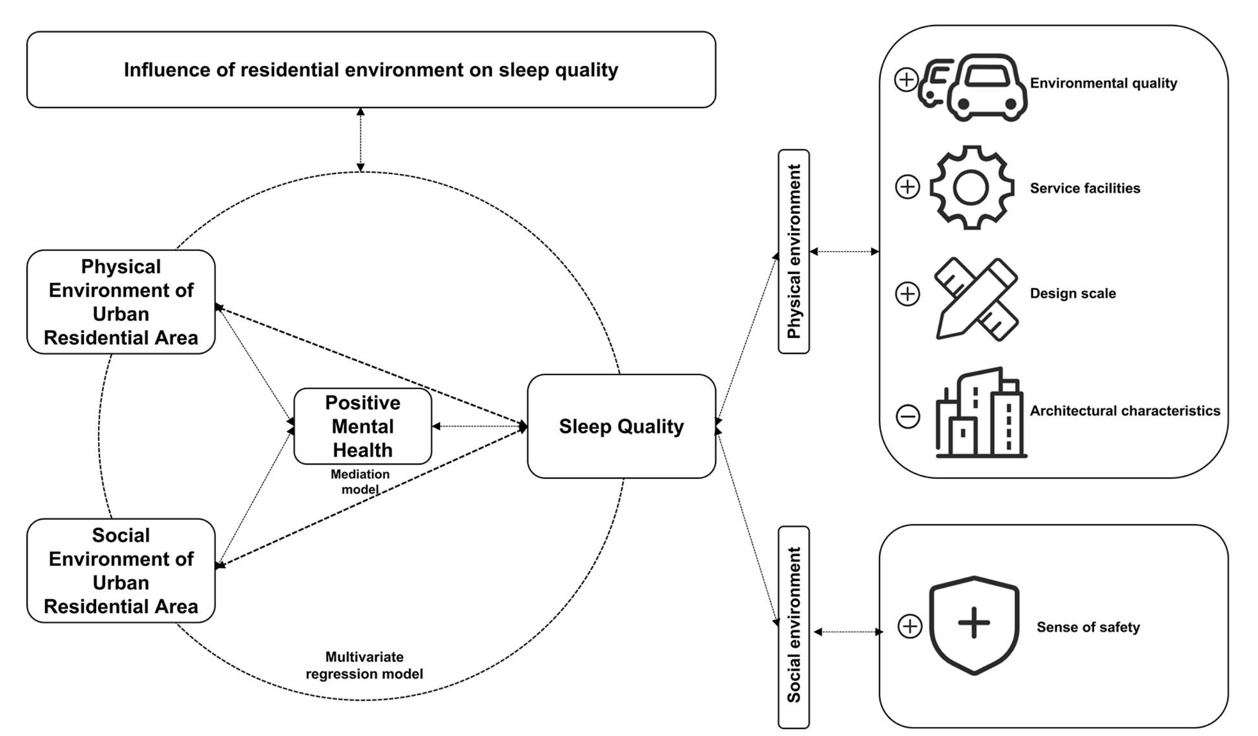
1. Introduction

Good sleep quality can improve human health and wellbeing (1, 2). However, urban residents are vulnerable to the impact of the urban residential environments, which will inevitably affect their sleep level. For urban dwellers, sleep is essential not only for their physical and mental health but also for their work, study, and life. Sleep quality significantly impacts workplace accidents, productivity, job satisfaction, and wellbeing (3–5). Sleep is essential for the effective cognitive and emotional processing of the people (6). However, in modern cities with rapid technological growth, it is difficult for urban residents to sleep well (7). In addition, insufficient sleep has been associated with many health benefits, including cardiovascular abnormalities (8), hypertension (9), diabetes (10), and a higher risk of death (11). The incidence of sleep disorders among college students in China is close to 20% (12), and the overall prevalence of sleep deficiency among the elderly has reached 35.9% (13). Moreover, the age-adjusted rate of insomnia in the United States is 18.8% (14). Concerning the high incidence rate of sleep and its harmful effects, sleep has gradually become a noticeable public health problem (15).

To improve the sleep quality of urban residents, it is vital to identify the residential environmental factors that lead to sleep disorders. The factors affecting sleep quality were confirmed by exposure to the urban physical environment. The most common impact factors are ambient noise (16) or the built environment [e.g., urbanization and residential density (17), roads (18), and recreational use (19)]. Other physical environmental exposures include air pollution (20, 21), thermal comfort (22), outdoor lighting at night (23, 24), residential green space (25, 26), and mobile phone radiofrequency electromagnetic field (RF-EMF) (27). The urban residential environment is complex and unique, and the characteristics of residents' sleep quality in different residential environments may differ. However, the internal mechanism of the impact of a residential environment on residents' sleep quality still needs to be determined.

Among the psychosocial and environmental factors in the ecosystem (28), neighborhoods are potential factors for good sleep and insomnia prevention. Adverse neighborhood and social environment (low security and social cohesion) are related to high incidences of short sleep and insomnia (29). Residents in daily life can perceive the environmental characteristics of these urban settlements, such as the road width of the residential area, the abundance of vegetation, and the quality-of-service facilities. They also include the social environmental characteristics formed by the residential area, such as neighborhood trust, social capital, and cohesion as perceived by the residents (30). In addition, a global analysis result of six countries shows that perceived neighborhood safety is negatively related to insomnia symptoms and poor sleep quality (31). Therefore, perception of the environment is also essential (32). The perceived physical environment has a direct impact on sleep quality. However, residents' perceived social environment may also affect sleep quality. Therefore, it is necessary to explore a multilevel environment, which will help fully understand the impact of environment on the sleep quality of urban residents.

In addition, the psychosocial determinants of insomnia have been further confirmed (33, 34). They are believed to play a role in developing sleep disorders (35). Some existing studies have found that better mental health (for example, reducing anxiety and depression) can improve the quality of life and sleep of the public (36, 37). Mental health is the experience of residents' satisfaction and subjective wellbeing, reflecting



GRAPHICAL ABSTRACT

the positive emotions, interpersonal satisfaction, and positive psychological functions of the individual's mental health about the environment (38). Therefore, mental health is one of the risk factors for sleep quality (1). Whether mental health has an indirect role in the impact of environment on sleep quality still needs to be explored. It is necessary to investigate how mental health are related to sleep (39).

This study aims to clarify the relationship between the urban residential environment and residents' sleep quality to find out the potential spatial environmental factors that affect sleep quality, examine the mediating effect of public mental health on the residential environment and sleep quality, as shown in Figure 1, and determine the impact of the environmental perception characteristics of urban residential areas on residents' sleep quality and provide theoretical guidance and optimization plans for the renewal and renovation of healthy cities and communities. In this work, we ask the following research questions:

- **Research question 1** (RQ1): Are there significant differences between residential density and sleep quality?
- **Research question 2** (RQ2): If the answer to research question 1 is positive, are there any residential environment characteristics associated with residents' sleep quality? Which environmental factors improve sleep quality and which reduce sleep quality?
- **Research question 3** (RQ3): If the answer to research question 2 is positive, does the mental health status of the residents affect the way the environment affects sleep quality?

2. Methods

2.1. Study sample

Combined with the characteristics of urban areas, the research scope is on the main urban area of Jilin City, China. Its characteristics are mainly characterized by a relatively stable population and economic structure. The types of residential areas are diverse and adjacent to the same area. It is guaranteed that the surrounding area of the residential area has similar landuse conditions and that the residential area has a similar construction period and housing price range to ensure a more reasonable community economy. Seven typical residential areas were randomly selected as research samples, including the basic information about residential areas, plot ratio, and greening rate. The floor area ratio (FAR) that is often used in residential areas is the indicator to define the high- and low-densities of the residential areas (FAR $>$ 2 is high density and FAR $<$ 2 is low density). When arranging and entering data, excluding the missing questions, conflicting information, and incomplete information in the research questionnaire, a total of 500 samples were distributed and 438 valid samples were obtained. The procedure of the experiment is shown in Figure 2.

2.2. Ethics statement

In China, universities are not required to undertake a formal ethics review. However, an ethical approach is expected, and for this research, providing information and seeking permission from all participants to provide written informed consent forms as part of the study. The consent of each participant was obtained and the information filled in was only used for academic research.

2.3. Measures

2.3.1. Residential environment

The residential environment is measured by physical and social dimensions as shown in Table 1. The physical environment mainly focuses on six aspects: environmental quality, architectural characteristics, service facilities, design scale, vegetation greening, and artistic features. The answer is set on a five scale from "very unsatisfactory to very agreeable." It assigns a value from 1 to 5 and the respondents rate each item according to their perceptions. In terms of social environment, based on the social cohesion and trust scale proposed by Sampson (50), the perceived social welfare scale proposed by Volker (54), and the indicators related to social capital proposed by Buckner, the subitems were extracted and integrated. The district's social environment characteristics are divided into three categories: a sense of participation (55, 56), a sense of attachment (51), and a sense of safety. Answers are based on a 5-point Likert scale, ranging from 1 (very satisfied) to 5 (very dissatisfied).

2.3.2. Sleep quality

Sleep quality was measured using the Pittsburgh Sleep Quality Index (PSQI) (57, 58). It contains 19 items in seven dimensions. Each item was rated on a 5-point Likert scale to facilitate statistics and analysis, ranging from 1 (strongly disagree) to 5 (strongly agree), with higher scores indicating a higher PSQI. Furthermore, the amount table has been used in various populations and countries, and its reliability and validity have been well verified (59). In the subsequent analysis, to be able to elaborate on the impact of the environment on various aspects of sleep, we calculated each dimension of the PSQI separately.

2.3.3. Mental health

The Warwick-Edinburgh Mental Well-Being Scale (WEMWBS) (60) was used to evaluate residents' mental

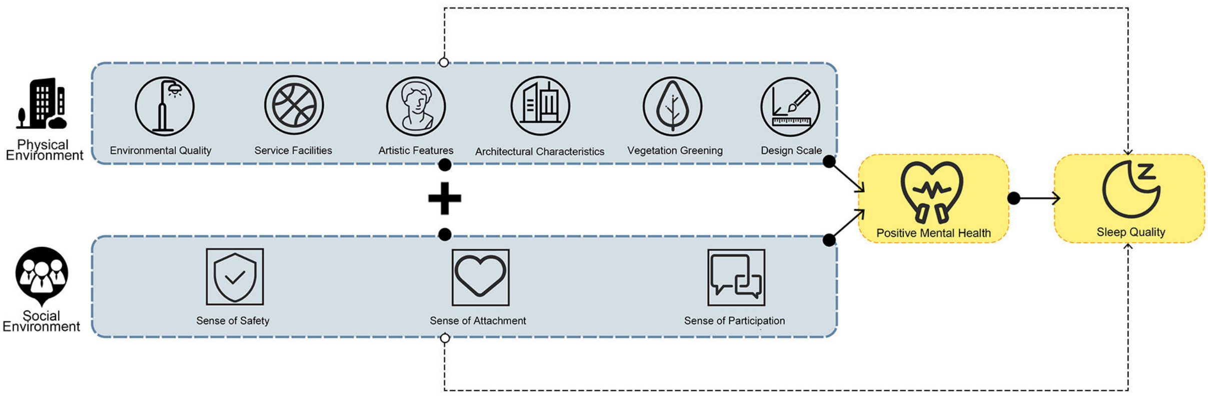


FIGURE 1
Research content framework.

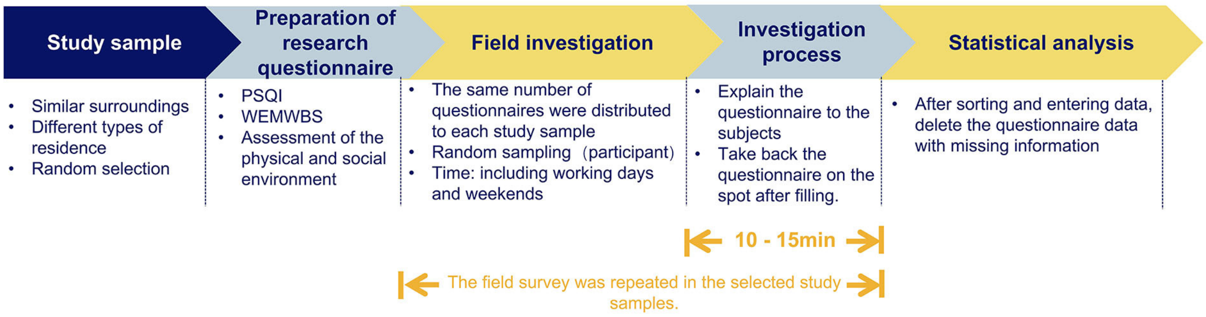


FIGURE 2
The procedure of the experiment.

TABLE 1 Residential physical environment and social environment assessment.

Category	Features	Evaluation dimension
Physical environment	Environmental quality	The degree of road cleanliness (40), the degree of vehicle aggregation, and the lighting conditions at night (41)
	Architectural characteristics	The degree of building enclosure, the degree of building transparency, and the degree of building continuity (42)
	Service facilities	Number of leisure facilities and the area of activity space (43)
	Design scale	Pedestrian road width (44, 45), building volume, and building (sunshine) spacing
	Vegetation greening	Green area (46), vegetation growth status, and vegetation collocation abundance (47)
	Artistic features	The richness of colors (48), the number of public art sculptures, and the degree of personalization of styles (49)
Social environment	Sense of participation	Neighborhood communication and trust (50)
	Sense of attachment	Place dependence and identity (51)
	Sense of safety	Environmental safety (52), communication safety, and traffic safety (53)

health. WEMWBS measures mental health and interpersonal satisfaction from two levels of pleasure and happiness (60). This scale is widely used by researchers at home and abroad to directly measure mental health and has good reliability and validity (61). According to the research purpose, each item is set with five grades of "exactly like me, not quite like me, unclear, somewhat like me, completely me," and assigns 1–5 points in turn.

2.4. Statistical analysis

On the basis of collecting sleep data questionnaires, Statistical Product and Service Solutions (SPSS) was used to conduct statistical analysis on the acquired data (62). The analysis of variance (ANOVA) was used to test the significant differences in self-rated sleep quality among related factors. The t-test was used to test the differences in residential density. It was used to test for significant differences at $p < 0.01$ and $p < 0.05$. The relationship between residents' sleep quality and the factors affecting the physical environment of the residential area, the relationship between sleep quality data and the influencing factors of the social environment of the residential area, and the relationship between mental health and sleep status were calculated by a Pearson correlation test. In addition, linear regression analysis was performed to examine the relationship between environment and sleep quality. Through the simple mediation model compiled by Hayes, using the process 3.3 plug-in in SPSS, the mediation effect test is carried out to explore the internal mechanism of the impact of the urban residential environment on sleep quality and decompose the complex influence path.

3. Results

3.1. Reliability and validity

In the research questionnaire, Cronbach's α coefficients of the urban residential environment assessment, positive mental health, and sleep quality scales were 0.80, 0.96, and 0.85, respectively, reflecting the high reliability of the scales in this study and the structure of the study. The Kaiser–Meyer–Olkin values of the Residential Environment Scale and the Positive Mental Health Dimension Scale are all >0.85. The Sleep Quality Scale is more significant than 0.75, and the Bartlett sphericity test is significant, indicating that the validity of the research questionnaire is effective.

3.2. Descriptive statistics

The physical and social environments of urban residential areas were analyzed using SPSS 25.0 statistical analysis software. The results of the statistical analysis are shown in Table 2. In the perceived physical environment, the public assessment scores for service facilities and design scale are relatively high, 4.4 and 4.2, respectively, and the lowest for artistic features is 3.11. As for the perception score of the social environment in residential areas, the highest security score is 4.1, followed by attachment and participation. In general, the residential area's perceived physical environment is slightly higher than the social environment score.

TABLE 2 Assessment scores of the physical and social environments of the urban residential area.

Category	Features	Mean value	Standard deviation
Physical environment	Environmental quality	3.844	0.878
	Vegetation greening	3.217	0.840
	Artistic features	3.110	0.871
	Architectural characteristics	3.511	0.822
	Design scale	4.264	0.870
	Service facilities	4.400	0.863
Social environment	Sense of participation	3.310	0.710
	Sense of attachment	3.419	0.756
	Sense of safety	4.172	0.707

3.3. Different results of different residential densities on sleep quality

Research question 1 (RQ1) focuses on the residents' sleep quality under the mapping of high- and low-density environments in urban residential areas. PSQI integrates all the dimensions of sleep and represents the overall sleep quality. Therefore, RQ1 can be answered by a t-test. It can be seen from Table 3 that the samples with different high and low densities showed significant significance ($p < 0.05$) for seven items: sleep quality, time to fall asleep, sleep efficiency, sleep disorder, drug hypnosis, disfunction, and sleeping time. Therefore, there are significant differences in sleep status under different-density environments in urban residential areas. According to the variance results, the sleep status in a high-density environment is generally lower than in a low-density residential environment. Compared with low-density residential areas, the sleep status of high-density residential areas (FAR > 2) is characterized by poor sleep quality, short sleeping time, long time to fall asleep, and poor sleep efficiency.

In addition, to further investigate the effect of the environment in which residents live on their sleep status, an ANOVA (known as a one-way ANOVA) was used to investigate the variability of the number of housing floors on seven indicators: sleep quality, sleeping time, sleep efficiency, sleep disorders, drug hypnosis, disfunction, and time to fall asleep. It can be seen from Table 4 that samples of different housing floors have significant effects on all dimensions of sleep quality ($p < 0.05$). Different floors also show significant differences in

TABLE 3 Sleep status *t*-test analysis results under different residential densities.

Definition	High and low density (mean ± standard deviation)		*t*	*p*
	Low density (n = 155)	High density (n = 282)		
Sleep quality	3.42 ± 0.61	3.20 ± 0.57	3.634	0.000**
Time to fall asleep	3.21 ± 0.99	2.87 ± 0.93	3.550	0.000**
Sleeping time	3.39 ± 0.96	3.08 ± 0.89	3.302	0.001**
Sleep efficiency	3.56 ± 0.95	3.24 ± 0.88	3.582	0.000**
Sleep disorder	2.60 ± 0.96	3.53 ± 0.79	−10.306	0.000**
Drug hypnosis	2.60 ± 0.86	3.39 ± 0.75	−10.028	0.000**
Disfunction	2.45 ± 0.88	3.24 ± 0.79	−9.605	0.000**

*p < 0.05, **p < 0.01. **When the confidence value (double test) is 0.01, the correlation is significant.

TABLE 4 Analysis of the variance results of different residential floors on residents' sleep status.

	Number of residential floors (mean ± standard deviation)					*F*	*p*
	1–3 (n = 75)	4–6 (n = 146)	7–15 (n = 80)	16–30 (n = 71)	Over 30 (n = 65)		
Sleep quality	3.08 ± 0.56	3.47 ± 0.57	3.40 ± 0.59	3.20 ± 0.55	3.03 ± 0.59	10.562	0.000**
Time to fall asleep	2.15 ± 0.77	3.40 ± 0.79	3.69 ± 0.72	2.92 ± 0.69	2.26 ± 0.83	64.466	0.000**
Sleeping time	2.91 ± 0.95	3.39 ± 0.88	3.55 ± 0.94	2.97 ± 0.84	2.85 ± 0.80	10.604	0.000**
Sleep efficiency	3.05 ± 0.82	3.55 ± 0.95	3.55 ± 0.90	3.28 ± 0.86	3.08 ± 0.87	6.612	0.000**
Sleep disorder	3.89 ± 0.75	2.84 ± 0.86	2.50 ± 0.80	3.23 ± 0.61	4.05 ± 0.74	58.559	0.000**
Drug hypnosis	3.85 ± 0.73	2.75 ± 0.73	2.46 ± 0.62	3.10 ± 0.56	3.88 ± 0.74	69.862	0.000**
Disfunction	3.73 ± 0.68	2.55 ± 0.79	2.41 ± 0.74	3.01 ± 0.64	3.62 ± 0.76	56.051	0.000**

*p < 0.05, **p < 0.01. **When the confidence value (double test) is 0.01, the correlation is significant.

residents' sleep status. The results showed that the sleep status of residents on the 4th and 6th floors was relatively good. With the increase in the number of floors, the residents' sleep status shows a trend of rising first and then declining, especially for the public sleep status of high buildings (30 floors and above) and low floors (1–3 floors); in short, through the macro perspective of the density of residential areas and the different floors of living. Low-density residential areas, as well as those living on low floors (<15 floors), perform better in sleep.

3.4. The influence of residential environment on sleep quality

3.4.1. The relationship between physical environment characteristics and sleep quality

To answer research question 2 (RQ2), Pearson correlation analysis was used to study the relationship between urban living perceived physical environment and residents' sleep status. Table 5 shows no significant correlation between vegetation greening, artistic features, and architectural characteristics in sleep quality, sleeping time, and sleep efficiency. The rest of sleep status are significantly related to the environmental quality, design scale and service facilities in the physical environment of urban residential areas, which confirms that the physical environment of residential areas has a regulatory role in sleep status. In general, according to the correlation analysis results of the physical environment characteristics and sleep quality, the environmental characteristics, vegetation greening, artistic features, architectural characteristics, design scale, and service facilities are all related to sleep, among which the environmental quality and service facilities are more closely associated with public sleep. This is an initial answer to RQ2.

3.4.2. The relationship between social environment characteristics and sleep quality

To further answer RQ2, as shown in Table 6, a Pearson correlation analysis was carried out between the residents' perceived social environment and sleep quality. Perceived social environment and sleep status showed a significant correlation, which further confirmed that the social environment in

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TABLE 5 Pearson correlation results of the physical environment and sleep.

	Environmental quality	Vegetation greening	Artistic features	Architectural characteristics	Design scale	Service facilities
Sleep quality	0.446**	0.036	−0.018	−0.063	0.231**	0.416**
Time to fall asleep	0.289**	0.168**	0.176**	0.133**	0.358**	0.312**
Sleeping time	0.340**	0.035	0.017	−0.021	0.175**	0.400**
Sleep efficiency	0.427**	−0.010	0.026	−0.015	0.180**	0.419**
Sleep disorder	−0.304**	−0.139**	−0.119*	−0.149**	−0.208**	−0.279**
Drug hypnosis	−0.280**	−0.154**	−0.177**	−0.191**	−0.206**	−0.296**
Disfunction	−0.236**	−0.224**	−0.158**	−0.170**	−0.191**	−0.239**

*p < 0.05, **p < 0.01.

TABLE 6 Pearson correlation results of social environment and sleep.

	Sense of participation	Sense of attachment	Sense of safety
Sleep quality	0.223**	0.275**	0.295**
Time to fall asleep	0.331**	0.333**	0.302**
Sleeping time	0.183**	0.219**	0.238**
Sleep efficiency	0.250**	0.305**	0.246**
Sleep disorder	−0.311**	−0.322**	−0.270**
Drug hypnosis	−0.355**	−0.343**	−0.286**
Disfunction	−0.342**	−0.340**	−0.276**

*p < 0.05, **p < 0.01. **When the confidence value (double test) is 0.01, the correlation is significant.

residential areas has a particular regulatory effect on residents' sleep status. The residents' sense of attachment and safety in the social environment is more strongly related to the public's sleep. Specifically, sleep quality, time to fall asleep, sleeping time, and sleep efficiency showed a significant positive relationship with the three aspects of the perceived social environment ($p < 0.01$).

3.4.3. Influence model of residents' sleep quality

With the help of the SPSS software, a multilayer multiple linear regression model was constructed for the dependent variable sleep quality. From the two previous sections, it can be confirmed that the residential area's physical and social environments significantly correlate with sleep quality. Step 1: According to the Pearson correlation analysis results of independent and dependent variables in the previous section, the relevant perceived physical environment characteristics are included to build model I. In Step 2, social environment features were added to build model II containing physical and social environment features. Beta in the model is the standard coefficient, the influence effect value. A positive value indicates that the variable and the residents' sleep quality level are positive influences. At the same time, multicollinearity was tested by a multiple regression linear analysis, and the variance expansion factor VIF values were all <2, indicating that these independent variables did not cause this problem.

The results of model I are shown in Table 7, in which environmental quality ($B = 0.333$, $P < 0.01$) > service facilities ($B = 0.281$, $P < 0.01$) > design scale ($B = 0.094$, $P < 0.05$) have a significant impact degree and positive relationship and architectural characteristics ($B = -0.083$, $P < 0.05$) have a negative relationship. With the addition of social environment variables in model II, as shown in Table 8, the R^2 increased to 0.296 after the model II adjustment (adjusted R^2 was statistically significant, and $P < 0.05$). Among them, the influence degree of sense of safety was the most significant ($B = 0.105$, $P < 0.05$), and there was a positive relationship with sleep quality. The purpose is to explore the common influence of multiple dependent variables on the dependent variables through the multiple regression model and screen out the more significant influencing factors, namely, the environmental quality in the physical environment, the service facilities, and the sense of safety in the social environment—all answers to research question 2 (RQ2) of this pair.

3.5. The relationship between mental health and sleep quality

3.5.1. The direct influence of mental health on sleep quality

The purpose of research question 3 is to explore whether public mental health plays a mediating role in an urban environment and residents' sleep quality. Correlation analysis was used to study the relationships between positive mental health and sleep quality, time to fall asleep, sleeping time, sleep efficiency, sleep disorder, drug hypnosis, and disfunction. Table 9 shows that the level of mental health has a significant correlation with sleep status, and the maximum correlation coefficient between mental health and sleeping time is 0.847,

TABLE 7 Results of multilevel regression equation model of sleep quality.

Variable types	Variable	Model I				Model II			
		Standardized coefficients Beta	t	p	VIF	Standardized coefficients Beta	t	p	VIF
Physical environment	Constant	–	11.080	0.000**	–	–	7.940	0.000**	–
	Vegetation greening	0.037	0.902	0.368	1.015	0.042	1.043	0.298	1.021
	Artistic features	−0.035	−0.855	0.393	1.006	−0.030	−0.734	0.463	1.010
	Environmental quality	0.333	7.615	0.000**	1.165	0.299	6.654	0.000**	1.248
	Design scale	0.094	2.211	0.028*	1.113	0.076	1.754	0.080	1.150
	Architectural characteristics	−0.083	−2.028	0.043*	1.013	−0.073	−1.802	0.072	1.019
	Service facilities	0.281	6.391	0.000**	1.175	0.251	5.616	0.000**	1.240
Social environment	Sense of participation					0.014	0.315	0.753	1.255
	Sense of attachment					0.053	1.135	0.257	1.341
	Sense of safety					0.105	2.271	0.024*	1.315

Dependent variable: sleep quality.
*$p < 0.05$, **$p < 0.01$.

TABLE 8 Fitting degree of multiple regression model for children's sense of safety.

Model	R^2	Adjusted R^2	F change	Significant F change
I	0.294	0.284	29.885	0.000
II	0.311	0.296	21.367	0.000

showing a significance level of 0.01. In short, it preliminarily proves a significant correlation between mental health and the quality of public sleep.

3.5.2. The mediating effect of mental health on sleep quality

A Pearson correlation analysis found that mental health impacts residents' sleep quality. Therefore, after the regression model was used to obtain the effect of sleep quality, an intermediary effect test was conducted on mental health to further explore the impact of residential perception environment on sleep quality. As shown in Table 10, the mediating benefit test of mental health on the physical environment and sleep quality of the residential area is carried out. Mental health can significantly mediate environmental quality, service facilities, and architectural characteristics, the effect ratios of which are 10.82, 11.93, and 24.17%, respectively. Regarding the public mental health level, sleep quality plays a relatively significant intermediary role in the physical environment of residential areas.

In addition, the intermediary benefits of positive mental health in the social environment and sleep quality of residential

TABLE 9 Pearson correlation results of positive mental health and sleep status.

	Positive mental health
Sleep quality	0.348**
Time to fall asleep	0.847**
Sleeping time	0.300**
Sleep efficiency	0.307**
Sleep disorder	−0.405**
Drug hypnosis	−0.445**
Disfunction	−0.415**

*$p < 0.05$, **$p < 0.01$. **When the confidence value (double test) is 0.01, the correlation is significant.

areas were tested again as shown in Table 11. In the influence path of positive mental health on residents' sleep quality in the social environment, mental health can have a significant intermediary effect on sense of attachment and safety. The effect accounts for 33.88 and 23.76%, respectively. Compared with the above mediating effects of positive mental health on the impact of the physical environment on residents' sleep quality, the mediating effect of positive mental health level on the impact of social environment on residents' sleep quality is more significant. These are the complete answers to Research Question 3 (RQ3).

4. Discussion

The results show significant differences in sleep quality among residents living in different densities and floors. After

TABLE 10 Summary of test results of physical environment through mental health mediation.

Item	C total effect	a	b	a*b mediating effect size	a*b (p-value)	a*b (95% BootCI)	c′ direct effect	Effect ratio	Test results
Environmental quality => positive mental health => sleep quality	0.225**	0.188**	0.130**	0.024	0.070	0.012–0.065	0.201**	10.820%	Partial intermediary
Vegetation greening => positive mental health => sleep quality	0.022	0.111**	0.130**	0.014	0.155	0.007–0.046	0.007	100%	Fully mediated
Artistic features => positive mentalh => sleep quality	−0.021	0.140**	0.130**	0.018	0.093	0.011–0.053	−0.039	100%	Fully mediated
Architectural characteristics => positive mental health => sleep quality	−0.048*	0.118**	0.130**	0.015	0.125	0.009–0.047	−0.063**	24.172%	Masking effect
Design scale => positive mental health => sleep quality	0.050*	0.218**	0.130**	0.028	0.139	0.019–0.092	0.022	100%	Fully mediated
Service facilities => positive mental health => sleep quality	0.193**	0.178**	0.130**	0.023	0.051	0.012–0.058	0.170**	11.938%	Partial intermediary

*p < 0.05, **p < 0.01.

TABLE 11 Summary of the test results of social environment through the mediating effect of mental health.

Item	C total effect	A	b	a*b mediating effect size	a*b (p-value)	a*b (95% BootCI)	c′ direct effect	Effect ratio	Test results
Sense of participation => positive mental health => sleep quality	0.087*	0.269**	0.175**	0.047	0.002	0.028–0.089	0.040	100%	Fully mediated
Sense of attachment => positive mental health => sleep quality	0.125**	0.227**	0.175**	0.040	0.013	0.021–0.085	0.085*	31.881%	Partial intermediary
Sense of safety => positive mental health => sleep quality	0.165**	0.224**	0.175**	0.039	0.013	0.020–0.081	0.126**	23.763%	Partial intermediary

*p < 0.05, **p < 0.01.

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exploring the physical and social perceptions of the factors of their residential environment, we built a multiple linear regression model. The environmental quality and service facilities significantly impact sleep quality, and the sense of safety in social environment and sleep quality also have a significant positive correlation. The quality of sleep in the urban high-density residential environment is not high. A higher green space rate of a residential area is not highly beneficial for the current high-density urban living environment. For community renovation, the residential design must reduce the negative impact of a high-density environment, improve residents' quality of living, and enhance social wellbeing. Therefore, the urban settlement model advocated by theories such as new urbanism and compact city still needs to be studied.

4.1. Optimize the quality of physical environment and improve sleep quality

The most important way to improve environmental quality is to design road traffic in the residential area in a clean and tidy manner, park the vehicles orderly, and improve the bright lighting at night. Among the multiple regression models, environmental quality has the most significant impact on sleep quality. Road cleanliness and disordered vehicle parking directly increase the "discomfort" at the psychological level. Night lighting has a strong relationship with residents' sense of safety when passing at night. The environmental quality may make the residents easily adapt to the environmental "diffraction" in their psychological state and emotions when sleeping, thus affecting their sleep quality (63).

On the other hand, the residential environment's service facilities carry the residents' activities to a greater extent and provide them with space for leisure, which is an environmental element with a "healing" function. The activities can relieve the pressure and negative emotions of the residents and make them have a relaxed physical and mental state when sleeping. The lack of activity space and service facilities may increase the possibility of sleep disorders (64). Therefore, service facilities are the "catalyst" to improve sleep quality. When building and transforming urban residential areas, we should emphasize the "restorative" leisure environment designs and facilities and the number of service facilities that cannot be ignored.

4.2. Create a social environment to reduce sleep disorders

The sense of safety significantly impacts residents' sleep in the social environment, which is the same conclusion of the previous study (65). Fear and restlessness may make a person vulnerable to negative thoughts and emotions, thereby increasing the interference with sleep quality (66). Residents who lack a sense of safety may be in a negative state of sleep quality in residential areas where they are unfamiliar with each other, distrustful, and have a poor living environment (e.g., messy roads and no street lights at night) (67). Therefore, we should strengthen the defensive image of the residential area, enhance the residents' sense of safety, and reduce the probability of residents' sleep disorders.

4.3. Improved mental health and enhanced pathways to influence

Previous studies have explored the effects of environment on mental health (68), and the relationship between environment and sleep quality (69, 70). This study further confirms the relationship among residential environment, residents' mental health, and sleep quality through the effect test of the intermediary model. The environment can affect the sleep quality through the residents' mental health. By optimizing the space environment design and improving the social atmosphere of the residential area, not only the sleep quality of the residents can be improved but also the mental health can be effectively promoted (71). This finding deserves the attention of urban planning managers and policymakers, considering the potential impact of urban housing planning and design on residents' sleep quality and their health.

4.4. Limitations and prospects

One of the limitations of this study is that there is no further quantification of the development intensity of urban settlements. The residential density is expressed through a plot ratio of settlements, which may affect the generality of the study. On the other hand, the cross-sectional design does not allow us to draw causal relationships and hence future analyses of longitudinal data are required to validate the findings. The findings add to the research on the regulatory effect of human settlements on residents' sleep health. Furthermore, it further emphasizes the importance of considering the residents' psychological state and the social atmosphere of the residential area as the entry point of residents' sleep intervention.

5. Conclusion

Based on the subjective questionnaire survey of sleep quality and perceived residential environment, this study explored the different impacts of urban residential environments on sleep quality. According to our findings, several conclusions can be drawn.

First, this quantitative cross-sectional study found that at the macro level, the residents' sleep quality reflected by the residential density and the number of residential floors was significantly different. The urban residential environment is closely related to the sleep quality of residents. Specifically, there are significant differences between the density of urban residential areas and the sleep level of residents. The sleeping level of high-density residential areas (FAR > 2) will be lower. Second, the residential area's physical and social environments significantly correlate with sleep quality to varying degrees, with a considerable level of $P < 0.01$. The most important feature of the environmental quality is 0.333 units of residents' sleep quality, which will be improved with each increase in the perceived level of environmental quality. The most significant factor of a social environment is the sense of safety; every increase in the level of sense of safety will improve the residents' sleep quality by 0.105 units. Finally, we confirmed that residents' mental health significantly mediates the residential environment and the residents' sleep quality.

The study used environmental perceptions and self-report to examine the relationship between the residential environment and sleep. The results provide evidence of human settlements' regulatory role in residents' sleep health. When designing sleep promotion interventions, it is essential to help the public find a balance between improving sleep levels and urban residential space. It further emphasizes the importance of considering the residents' psychological state and the social atmosphere of the residential area.

Data availability statement

The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding author.

Ethics statement

Ethical review and approval was not required for the study on human participants in accordance with the local legislation and institutional requirements. The patients/participants provided their written informed consent to participate in this study.

Author contributions

Conceptualization and writing—review and editing: XZ and MG. Methodology, software, writing—original draft preparation, and investigation: MG. Validation: XZ, MG, and XC. Formal analysis and data curation: XC. Resources and supervision: XZ. Project administration and funding acquisition: XZ and WZ. Visualization: MG and XC. All authors have read and agreed to the published version of the manuscript.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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Exurban and suburban forests have superior healthcare benefits beyond downtown forests

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Forests in urban areas provide great healthcare benefits to citizens, but it is less well known whether this benefit is related to different geographical spaces. We selected exurban forest, suburban forest, downtown forest, and urban control in Guangzhou, China to analyze the change characteristics of negative air ion concentration (NAIC), air oxygen content (AOC), and human comfort index (HCI). Based on Criteria Importance Through Intercriteria Correlation (CRITIC) method, the urban forest comprehensive healthcare index (UFCHI) was established. Finally, the evaluation criteria for UFCHI were identified by cluster analysis. The results demonstrated that (1) The NAIC in exurban forest (2,713±1,573 ions/cm^3) and suburban forest (2,147±923 ions/cm^3) was evidently better than downtown forest (1,130±255 ions/cm^3) and urban control (531±162 ions/cm^3). (2) The AOC was in the order of exurban forest (21.17±0.38%)>suburban forest (21.13±0.30%) > downtown forest (21.10±0.16%)>urban control (20.98±0.12%). (3) The HCI in urban control (5.56±2.32) and downtown forest (5.15±1.80) is higher than suburban forest (4.02±1.53) and exurban forest (3.71±1.48). (4) The UFCHI in exurban forest (1.000), suburban forest (0.790), and downtown forest (0.378) were beneficial to human health to some extent, while urban control (0.000) was at Level IV, having no healthcare benefit. Except in winter, the UFCHI in exurban forest and suburban forest were all at Level II and above; while downtown forest and urban control were all at Level III and below at all seasons. Overall, urban forests in the exurbs and suburbs have better healthcare benefits than those in the downtowns. Furthermore, it is recommended that urban residents visit exurban and suburban forests for forest therapy in spring, summer, and autumn.

KEYWORDS

urban forest, forest healthcare benefits, negative air ion concentration, air oxygen content, human comfort index, different geographical spaces

1. Background

The coronavirus disease 2019 (COVID-19) outbreak and spread has taken a toll on human physical and mental health. Adequate studies have manifested that the public may experience mild to severe symptoms of depression, anxiety, fear, confusion, emotional exhaustion, and even post-traumatic stress in the context of the COVID-19 pandemic (Jovarauskaite et al., 2021; Xia et al., 2022). When more risk information of the COVID-19 is released, it makes the citizens more concerned about health, triggering national reflection and awareness on lifestyle and health management, and thus enhancing the willingness of forest therapy tourism (Chae et al., 2021; Cheng and Yin, 2022). Humans have a natural sense of closeness to the forest, and it is thought to be the best place to release stress and relieve fatigue by the medical community (Zhang and Ye, 2022). Forests play a crucial role in sustaining human health and well-being, providing a pleasant climate, fresh air, clean water, and a tranquil environment, among others. Forest therapy has been defined as maintaining and promoting the health of participants by exposing them to the natural environment and utilizing the various healthcare factors therein (Zhang and Ye, 2022). Furthermore, abundant studies have scientifically proven that forest therapy has a positive effect on human physiology and psychology, such as reducing pulse rate and blood pressure, improving the immune system activity, even ameliorating negative emotion, depression and so on (Chae et al., 2021; Kim and Shin, 2021; Zhang and Ye, 2022). There is no doubt that while the COVID-19 pandemic continues, people with low immunity, especially sub-healthy people and the elderly, will be in high demand to upgrade their resistance and immunity, as well as to desire a good ecological environment. As a result, short-term, rational and regular forest therapy activities, or even just exposure to forests will be first choice of the public, and forest therapy will become an inevitable trend of future consumption. In line with this trend, research on forest healthcare factors and the comprehensive evaluation of forest healthcare benefits should be given more attention. So as to find out the suitable site conditions (forest area, stands, surroundings, distance from city center, etc.) and the best time for forest therapy.

Negative air ion concentration is one of the most essential indicators of air quality. Negative air ions plays a paramount role in dust absorption, air quality amelioration, and environmental and human health improvement (Yan et al., 2015; Jiang et al., 2018). As for human health, sufficient studies have reported that favorable effects of negative air ions on the respiratory (Alexander et al., 2013), improving sleep quality (Liu R. et al., 2017) and mood states (Pino and La Ragione, 2013), as well as treating chronic depression (Dauphinais et al., 2012; Bowers et al., 2018). Air oxygen content is also an imperative indicator of the healthcare benefits of forest environment. Oxygen inhalation can boost the body's metabolism to alleviate symptoms, treat diseases and promote healing (Hong, 2015). The pleasant forest microclimates contribute to human health, which is an invaluable resource for forest therapy tourism. Forest microclimates refer to the human body's perception of the forest environment's temperature, relative humidity, wind speed, and other factors, which is frequently measured by human comfort index (Zhu et al., 2021a,b).

The vast majority of investigation on urban forest healthcare benefits has focused on the evaluation and analysis of individual healthcare factors such as negative air ions (Li et al., 2021; Shi et al., 2021), phytoncide (Antonelli et al., 2020; Woo and Lee, 2020), human comfort (Jeong et al., 2016; Rahman et al., 2020) and so on. Only a few scholars, such as Han et al. (2012), Zhao et al. (2019), Wen (2020), Yang et al. (2022), and the team of Cheng Wang (Gu, 2013; Wang et al., 2018), have comprehensively considered the forest healthcare benefits of several indicators such as negative air ion concentration, air oxygen content, human comfort index, airborne particulate matter concentration, airborne bacteria content, noise level, and phytoncide relative content, providing a vital theoretical basis for the study of comprehensive healthcare benefits of forest communities. However, their research chiefly focused on different stands in the same location, and there was a lack of in-depth exploration on comprehensive healthcare benefits of urban forest in different geographical spaces. Moreover, most scholars used subjective experience, Delphi method in combination with the Analytic Hierarchy Process, synthetical index method, or fuzzy comprehensive evaluation method to construct the evaluation models, having strong subjectivity and arbitrariness in determining index weights. Zhang (2014) selected three types of urban forest: country forest, forest park, and community green space, along with an urban center as control group in Hangzhou, and analyzed the change characteristics of four indicators: outdoor comfort index, carbon dioxide concentration, negative air ion concentration and noise, including the correlation of each indicator. His findings provided a crucial theoretical foundation for the study of individual healthcare factors in different geographical locations, but without a comprehensive assessment of their healthcare factors. Additionally, his study only took the proximity to the urban center into consideration and ignored the impact of forest area and surrounding environment on the forest healthcare benefits.

Since the above methods were subjective and random, we innovatively introduced the CRITIC method to objectively determine the weight of indicators and to comprehensively evaluate the forest healthcare benefits from the exurban-suburban-downtown gradients. The existing literature indicated that the entropy method and the CRITIC method were widely applied in the objective weighting of criteria (Krishnan et al., 2021; Sharkasi and Rezakhah, 2022). However, the CRITIC method was found to have additional merit as it takes into account both the contrast intensity and the conflicting relationships held by each decision criterion, which was more objective than the entropy method. Therefore, in this study, three urban forest types and an urban control were selected in different geographical spaces in terms of the distance from city center, forest area, and surrounding environment. Through long-term simultaneous monitoring of negative air ion concentration, air oxygen content, and human comfort index, the CRITIC method was used to determine the objective weights of each index and form the UFCHI in different geographical spaces. Finally, a comprehensive evaluation of healthcare benefits of urban forest from the exurban-suburban-downtown gradients was presented. It is of great theoretical and practical significance for this study, which brings more innovative ideas for building a comprehensive evaluation method for forest healthcare benefits, coupled with imparting theoretical support for site selection and construction of forest therapy bases in Guangdong Province and even the whole country. Meanwhile, it provides a basis for citizens to choose the best season and destination for forest therapy tourism. The scientific problems of this study are: (1) Does the distance from city center, forest area, and surrounding environment have an impact on the comprehensive healthcare benefits of urban forests?, (2) Are the forest healthcare benefits consistent across seasons?, and (3) What seasons are suitable for forest therapy?

2. Materials and methods

2.1. Study area

The study area selection for urban forests in different geographical spaces is principally based on three considerations: the distance from city center, forest area, and surrounding environment. Consequently, urban forest types in different geographical spaces are mainly classified as exurban forest, suburban forest, and downtown forest, while an urban control is set.

2.1.1. Exurban forest

Shimen National Forest Park (23°36′50″N–23°39′20″N, 113°46′16″E–113°49′17″E) is located in the northeast of Conghua

Abbreviations: NAIC, Negative air ion concentration; AOC, Air oxygen content; HCI, Human comfort index; T, Temperature; RH, Relative humidity; V, Wind speed; LAI, Leaf area index; UFCHI, Urban forest comprehensive healthcare index; EF, Exurban forest; SF, Suburban forest; DF, Downtown forest; UC, Urban control; CRITIC, Criteria Importance Through Intercriteria Correlation.

District, 95 km away from Guangzhou central city (Wushan Street), which is selected as the study area of exurban forest. It is close to Guangdong Longmen Nankunshan Provincial Nature Reserve and Guangzhou Baishuizai Scenic Spots, and the adjacent forest area is concentrated and contiguous, as shown in Figure 1. Shimen National Forest Park has a total area of 2,636 hm^2 with 98.91% forest coverage, and a forest area of 2,607 hm^2 with an altitude ranging from 270 m to 1,210 m. It pertains to the south subtropical monsoon climate, with average temperature between 19.5°C and 21.4°C, and an annual average rainfall of about 1,800 mm (Zhu et al., 2021a,b).

2.1.2. Suburban forest

Guangdong Longyandong Forest Farm (23°16′41″N–23°18′31″N, 113°25′44″E–113°28′30″E), situated in the northeast suburb of Baiyun District, Guangzhou City, is 34 km away from Guangzhou central city, as the study area of suburban forest. It is adjacent to Maofengshan Forest Park and Causeway Bay Forest Scenic Area, surrounded by forest environments, as shown in Figure 1. Guangdong Longyandong Forest Farm covers an area of 524 hm^2, with a forest coverage of 94.56%, a forest area of 495 hm^2, and an altitude of 101–536 m. It has a subtropical maritime monsoon climate with an average rainfall of 1,694 mm and an average temperature of 21°C (Hong et al., 2020).

2.1.3. Downtown forest

Changgangshan Nature Reserve (23°09′29″N–23°09′44″N, 113°21′53″E–113°22′12″E), as the study area of downtown forest, is seated in the campus of South China Agricultural University in Tianhe District, Guangzhou City, Guangdong Province, seeing Figure 1. The total area is about 15 hm^2,with 89.47% forest coverage, and the forest area is about 13 hm^2, with an altitude of 40–50 m. The shape of Changgangshan Nature Reserve is quadrangular, with one side adjacent to the South China Expressway, and the other three sides surrounded by the campus buildings of South China Agricultural University, forming a small-scale isolated urban forest. It belongs to the subtropical monsoon maritime climate, with an average annual temperature of about 22.6°C and the annual precipitation of about 2,050 mm (Tong and Xiao, 2014).

2.1.4. Urban control

Wushan Street (23°09′22″N–23°09′26″N, 113°21′29″E–113°21′53″E), as the study area of urban control, is located near Wushan Station of Metro Line 3 in Tianhe District, Guangzhou City, Guangdong Province. The street area is long and narrow, with a study area of about 5–6 hm^2 and an altitude of about 40 m, as shown in Figure 1. It is surrounded by a commercial area with dense buildings, heavy pedestrian and vehicular traffic, and no vegetation other than trees along the roadside.

2.2. Plot settings

To eliminate the influence of stand factor differences on the experimental results, the stands in this study were all mature plantations with stand ages of 30 years and above, and canopy density between 0.7 and 0.8. Of these, the exurban forest picked *Phyllostachys edulis* forest and *Cunninghamia lanceolata* forest, for a total of seven sampling points in Shimen National Forest Park; *Castanopsis hystrix* forest and *Schima superba* forest were selected in suburban forest, amounting to six sampling points in Guangdong Longyandong Forest Farm; the downtown forest optioned mixed broadleaf-conifer forest, sum to three sampling points in Changgangshan Nature Reserve. Meanwhile, three sampling points were taken in Wushan Street as urban control for urban circumstances comparative experiment.

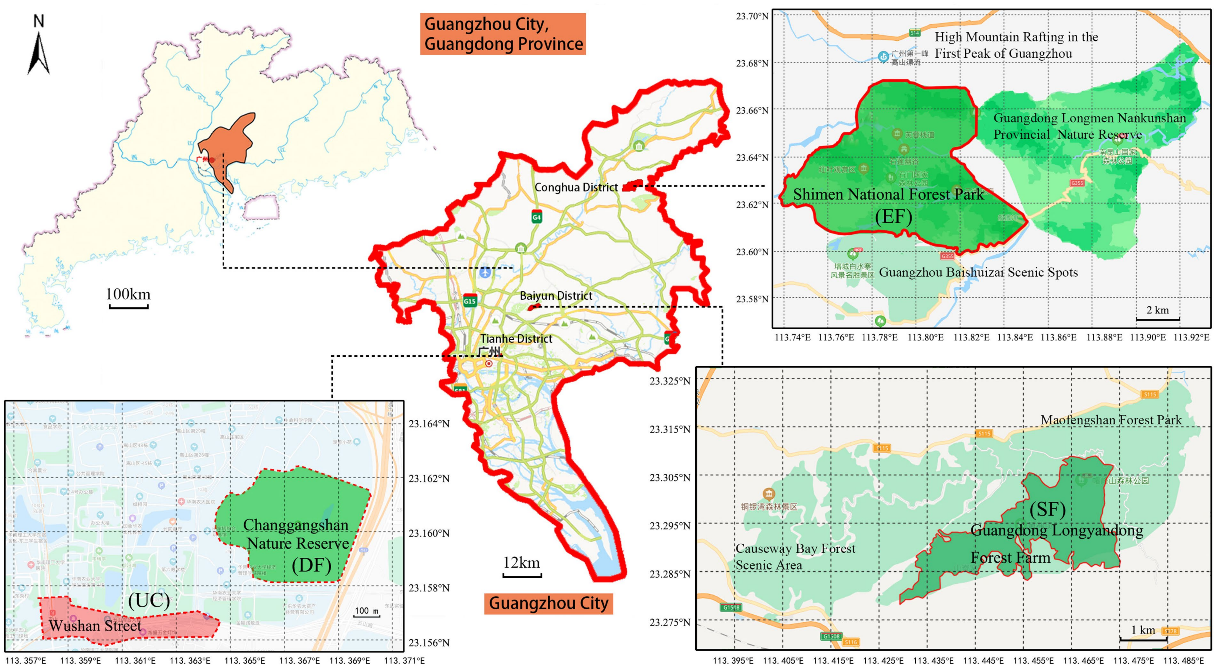

FIGURE 1
Location of study area selection of urban forests in different geographical spaces.

2.3. Methods

2.3.1. Observation methods

From September 2019 to January 2020 and from May to August 2020, the field data was measured from the 20th to 30th of each month, where the downtown forest and urban control were experimented commonly on the 20th, 21st, and 22nd; suburban forest was tested primarily on the 23rd, 24th, and 25th; and exurban forest was investigated ordinarily on the 27th, 28th, and 29th. The weather conditions during the sampling period were similar, either sunny or cloudy. Test times were appropriately adjusted for unexpected weather conditions. Three indicators of negative air ion concentration, air oxygen content, and forest microclimates were measured in three urban forest environments and an urban control. The negative air ion concentration was measured at a sampling height of 1.5 m above the ground using a COM-3200PRO II negative air ions monitor produced in Japan. This was repeated 3 times for a total of 12 data. The air oxygen content was measured by a TD6000-SH-O_2 oxygen content tester manufactured in China, which was repeated 3 times. Kestrel 5500 hand-held meteorological instrument fabricated in the United States was used to measure forest microclimates, including temperature (T), relative humidity (RH), and wind speed (V), which were each repeated 3 times at a sampling height of 2 m (Zhu et al., 2021a,b).

2.3.2. Specific evaluation methods

2.3.2.1. Negative air ion concentration

Zhang et al. (2006) collected the data of negative air ions in North China, Northwest China, East China, and South China, and evaluated the healthcare degree of NAIC in forest parks by fuzzy mathematics, which was divided into four grades, as can be seen from Table 1. In accordance with the suitable range of membership degree, the minimum NAIC in forest environment was set at 600 ions/cm^3, which was equivalent to that in urban parks and higher than that in residential regions (200–400 ions/cm^3).

2.3.2.2. Air oxygen content

The oxygen enrichment index proposed by Han et al. (2012) was used to appraise the degree of AOC. The higher the AOC, the higher the oxygen enrichment. The evaluation criteria for AOC was as listed in Table 2. Intending to eliminate the influence of altitude on AOC, the measured value was corrected based on the fact that the AOC decreased by 0.16% every 100 m above sea level (Zhao et al., 2012). The correction formula is as shown:

$$C = M + \frac{A}{100} \times 0.16\% \quad (1)$$

Where C denotes corrected value (%), M indicates measured value (%), A represents altitude (m).

2.3.2.3. Human comfort index

Lu et al. (1984) exploited the relevant data of environmental hygiene methods to comprehensively take account of the impact of temperature, relative humidity and wind speed on HCI, and the evaluation criteria for HCI was given. The lower the HCI value, the higher the comfort level, seeing Table 3. The formula for calculating HCI is as displayed:

TABLE 1 Evaluation criteria for negative air ion concentration.

Grades	Negative air ion concentration/ NAIC (ions/cm^3)	Healthcare benefits
Level I	NAIC > 3,000	Extraordinarily wholesome
Level II	2,200 < NAIC ≤ 3,000	Rather wholesome
Level III	1,100 < NAIC ≤ 2,200	Averagely wholesome
Level IV	600 < NAIC ≤ 1,100	Have no healthcare benefits

TABLE 2 Evaluation criteria for air oxygen content.

Grades	Air oxygen content/AOC (%)	Corresponding degree
Level I	AOC ≥ 22.0	High
Level II	22.0 > AOC ≥ 20.8	Relatively high
Level III	20.8 > AOC ≥ 20.0	Medium
Level IV	20.0 > AOC ≥ 19.5	Relatively low
Level V	AOC < 19.5	Low

TABLE 3 Evaluation criteria for human comfort index.

Grades	Human comfort index/HCI	Human feelings
Level I	HCI ≤ 4.55	Very comfortable
Level II	4.55 < HCI ≤ 6.95	Comfortable
Level III	6.95 < HCI ≤ 9.00	Uncomfortable
Level IV	HCI > 9.00	Extremely uncomfortable

$$HCI = 0.6 \times |T - 24| + 0.07 \times |RH - 70| + 0.5 \times |V - 2| \quad (2)$$

In which, HCI stands for human comfort index, T means temperature (°C), RH denotes relative humidity (%), and V implies wind speed (m/s).

2.3.3. Determination of objective weight of each indicator by CRITIC method

The CRITIC method proposed by Diakoulaki et al. (1995) and it is primarily adapted to ascertain the objective weights of criteria, based on the contrast intensity and conflicting relationships of the decision criteria. The CRITIC method uses standard deviation and Pearson correlation to measure the contrast intensity and conflicting relationships of each criterion, respectively (Krishnan et al., 2021). The main steps of this trick can be described as demonstrated:

1. Normalization of each indicator

The above three indicators are classified as positive or negative, depending on the impact of each indicator on environmental quality. Positive indicators signify that the greater the value, the better the healthcare benefits, such as NAIC. In keeping with medical measurements, when the AOC is 20.9%, it is normal; when it is more than 23.5%, it appertains to an oxygen-enriched environment, which is conducive to relieve brain fatigue and ameliorate body function (Hong, 2015). In this study, the AOC in different geographical spaces is below 23.5%, so the AOC can be considered as a positive indicator. The negative indicators reveal that the greater the value, the worse the healthcare benefits. The negative indicator in this study is HCI. In order to bring it into a unified evaluation system for comparison, the range normalization method is adopted for standardization, which is calculated as follows:

$$\text{Positive indicators}: \overline{x_{ij}} = \frac{x_{ij} - x_j^{\min}}{x_j^{\max} - x_j^{\min}} \quad (3)$$

$$\text{Negative indicators}: \overline{x_{ij}} = \frac{x_j^{\max} - x_{ij}}{x_j^{\max} - x_j^{\min}} \quad (4)$$

where $\overline{x_{ij}}$ is the normalized score of alternative i with respect to indicator j, x_{ij} is the actual score of alternative i with respect to indicator j, $x_j^{\max}$ is the maximum score of indicator j, and $x_j^{\min}$ is the minimum score of indicator j.

2. Calculate the standard deviation of each indicator

$$\begin{cases} \overline{x_j} = \dfrac{1}{n}\sum_{i=1}^{n} x_{ij} \\ S_j = \sqrt{\dfrac{\sum_{i=1}^{n}\left(x_{ij} - \overline{x_j}\right)^2}{n-1}} \end{cases} \quad (5)$$

where $\overline{x_j}$ is the mean score of indicator j and n is the total number of alternatives, S_j is the standard deviation of indicator j.

3. Calculate the correlation coefficient of every pair of indicators

$$R_j = \sum_{i=1}^{n}\left(1 - r_{ij}\right) \quad (6)$$

where R_j is the correlation coefficient between indicator j and other indicator, r_{ij} is the correlation coefficient between indicator i and j.

4. Compute the information content of each indicator

$$C_j = S_j\sum_{i=1}^{n}\left(1 - r_{ij}\right) = S_j \times R_j \quad (7)$$

where C_j denotes the information content of indicator j.

5. Determine the objective weight of each indicator

$$W_j = \frac{C_j}{\sum_{j=1}^{m} C_j} \quad (8)$$

where W_j reveals the objective weight of indicator j.

2.3.4. Establishing urban forest comprehensive healthcare index in different geographical spaces

The objective weight of each healthcare index was determined by CRITIC method mentioned above (Table 4), thus, the formula of urban forest comprehensive healthcare index (UFCHI for short) in different geographical spaces is shown:

TABLE 4 The weight calculation result by CRITIC method.

Indicators	S_j	R_j	C_j	W_j
Negative air ion concentration (NAI)	0.286	0.869	0.248	0.254
Air oxygen content (AOC)	0.267	1.300	0.347	0.354
Human comfort index (HCI)	0.268	1.435	0.384	0.392

$$UFCHI = 0.254 \times \text{NAIC}_i + 0.354 \times \text{AOC}_i + 0.392 \times HCI_i \quad (9)$$

In which, NAIC_i is the normalized value of i-th negative air ion concentration, AOC_i is the normalized value of i-th air oxygen content. HCI_i is the normalized value of i-th human comfort index.

2.3.5. Evaluation criteria for UFCHI

In SPSS22.0, the UFCHI values were systematically clustered using Ward's method and the squared Euclidean distance, and the UFCHI was divided into four classes based on the results of the cluster analysis, see Figure 2. The integrated healthcare benefits expressed in terms of different numerical intervals were explained in Table 5.

2.3.6. Data processing and analysis

SPSS22.0 was implemented for variance analysis, multiple comparison, CRITIC calculation, and cluster analysis; Origin 2022 was executed to draw the diagram.

3. Results

3.1. Characteristics of NAIC of urban forests in different geographical spaces

It can be seen from Figure 3 that the annual average (±SD) of NAIC of urban forests in different geographical spaces showed extremely significant differences ($p = 0.000 < 0.01$). The NAIC was as follows: exurban forest (2,713 ± 1,573 ions/cm^3) > suburban forest (2,147 ± 923 ions/cm^3) > downtown forest (1,130 ± 255 ions/cm^3) > urban control (531 ± 162 ions/cm^3). As mentioned by the evaluation criteria for NAIC (Table 1), the exurban forest was at Level I with extraordinarily wholesome healthcare benefits; the suburban forest was at Level II with rather wholesome healthcare benefits; the downtown forest was at Level III with averagely wholesome healthcare benefits; while urban control was at Level IV, having no healthcare benefits.

The mean value of NAIC in exurban forest was: summer (3,688 ± 2,079 ions/cm^3) > spring (2,566 ± 913 ions/cm^3) > autumn (2,195 ± 989 ions/cm^3) > winter (2,099 ± 762 ions/cm^3), suburban forest was: summer (2,852 ± 964 ions/cm^3) > spring (2,057 ± 620 ions/cm^3) > autumn (1,695 ± 490 ions/cm^3) > winter (1,480 ± 473 ions/cm^3), downtown forest was: autumn (1,298 ± 336 ions/cm^3) > winter (1,162 ± 218 ions/cm^3) > spring (1,115 ± 122 ions/cm^3) > summer (1,009 ± 159 ions/cm^3), and urban control was: autumn (646 ± 185 ions/cm^3) > winter (606 ± 108 ions/cm^3) > spring (513 ± 104 ions/cm^3) > summer (428 ± 106 ions/cm^3). In general, the seasonal variations of NAIC in exurban forest and suburban forest were summer > spring > autumn > winter, while those in downtown forest and urban control were autumn > winter > spring > summer, as illustrated in Figure 4.

3.2. Characteristics of AOC of urban forests in different geographical spaces

The AOC was corrected on the basis of Eq. 1. Based on variance analysis, the AOC of urban forests in different geographical spaces demonstrated exceedingly significant differences ($p = 0.000 < 0.01$), see Figure 5. The annual average of AOC was in the order of exurban forest (21.17 ± 0.38%) > suburban forest (21.13 ± 0.30%) > downtown forest (21.10 ± 0.16%) > urban control (20.98 ± 0.12%). As reported by the evaluation criteria for AOC (Table 2), three urban forests and an urban control were all at Level II relatively high degree, and the AOC in forest environment was markedly higher than that in urban environment.

The AOC in exurban forest was: summer (21.57 ± 0.34%) > spring (21.10 ± 0.17%) > autumn (21.03 ± 0.14%) > winter (20.81 ± 0.10%), suburban forest was: summer (21.42 ± 0.24%) > spring (21.06 ± 0.63%) > autumn (20.99 ± 0.12%) > winter (20.79 ± 0.52%), downtown forest was: summer (21.22 ± 0.17%) > spring (21.07 ± 0.31%) > autumn (21.04 ± 0.56%) > winter (20.93 ± 0.46%), and urban control was: summer (21.08 ± 0.12%) > spring (20.94 ± 0.37%) > autumn (20.92 ± 0.27%) > winter (20.85 ± 0.46%). It can also be distinctly seen that the seasonal variations of AOC in different geographical spaces revealed a consistent change rule, namely, summer > spring > autumn > winter, as shown in Figure 6.

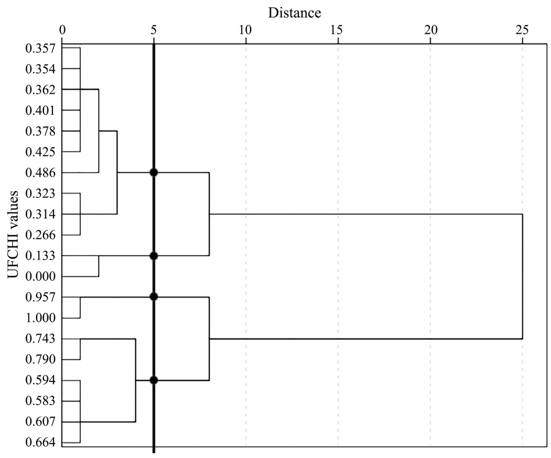

FIGURE 2
Cluster analysis using Ward's method and squared Euclidean distance.

TABLE 5 The evaluation criteria for UFCHI.

Grades	Index range	Comprehensive healthcare benefits
Level I	$0.957 \leq UFCHI \leq 1$	Extremely beneficial to human health
Level II	$0.583 \leq UFCHI \leq 0.790$	Rather beneficial to human health
Level III	$0.266 \leq UFCHI \leq 0.486$	Slightly beneficial to human health
Level IV	$0 \leq UFCHI \leq 0.133$	No benefit to human health

3.3. Characteristics of forest microclimate and HCI of urban forests In different geographical spaces

It can be seen from Figures 7, 8 that the annual average of temperature in different geographical spaces was: urban control (28.76 ± 6.54°C) > downtown forest (27.51 ± 6.21°C) > suburban forest (24.20 ± 5.12°C) > exurban forest (23.41 ± 4.41°C), and their seasonal variations were summer > spring > autumn > winter. The annual average of relative humidity in different geographical spaces was: exurban forest (79.72 ± 12.03%) > suburban forest (77.06 ± 11.26%) > downtown forest (72.42 ± 11.99%) > urban control (64.51 ± 12.82%). The relative humidity in different geographical spaces reached the maximum in spring and the minimum in autumn, and the seasonal variations of exurban forest and suburban forest were spring > summer > winter > autumn, while downtown forest and urban control were spring > winter > summer > autumn. The annual average of wind speed in different geographical spaces was as follows: suburban forest (2.05 ± 1.64 m/s) > urban control (1.22 ± 0.66 m/s) > exurban forest

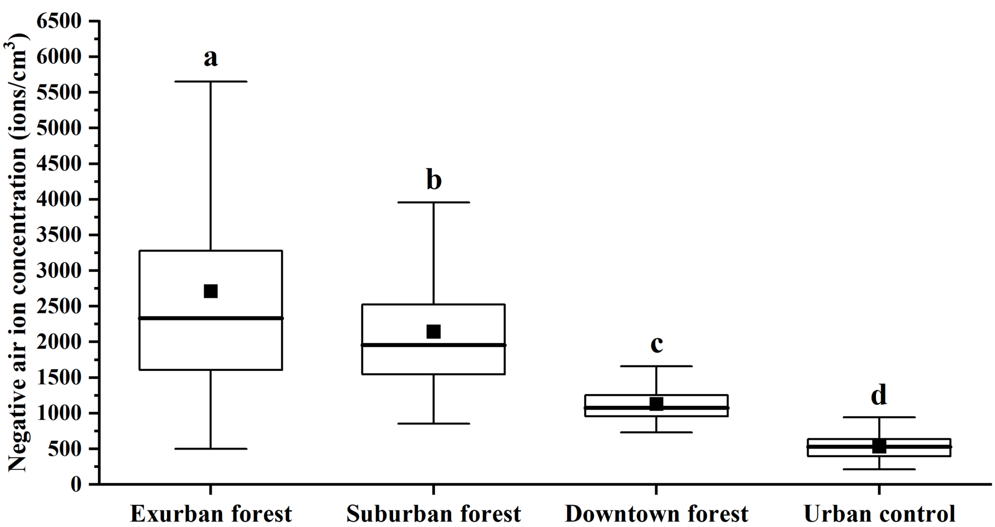

FIGURE 3
Comparison of annual average of NAIC of urban forests in different geographical spaces. The different lowercase letters indicate significant difference of urban forest in different geographical spaces (p<0.05).

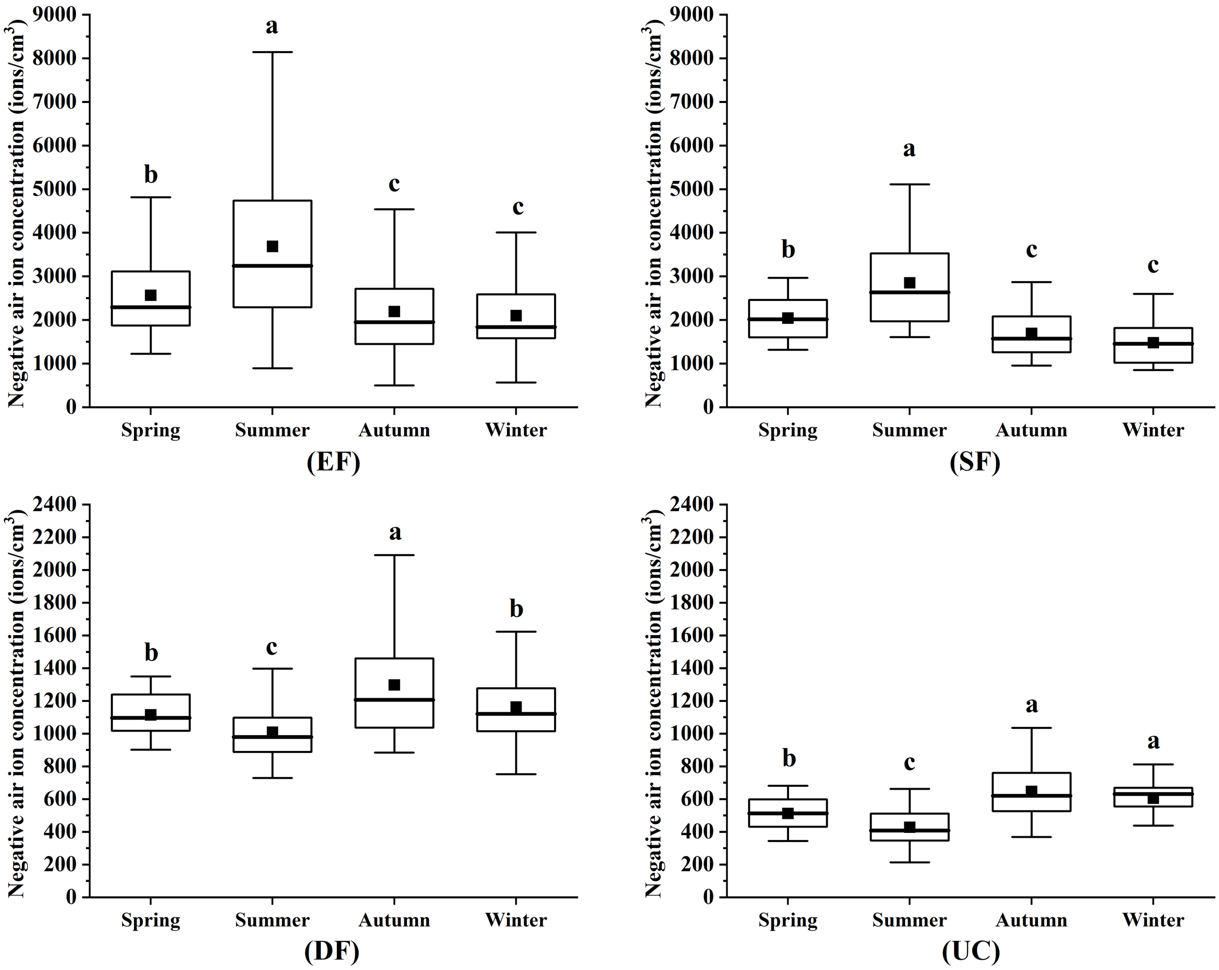

FIGURE 4
Seasonal variations of NAIC of urban forests in different geographical spaces. EF, Exurban forest; SF, Suburban forest; DF, Downtown forest; UC, Urban control. The different lowercase letters indicate significant difference of each geographical space in different seasons (p<0.05).

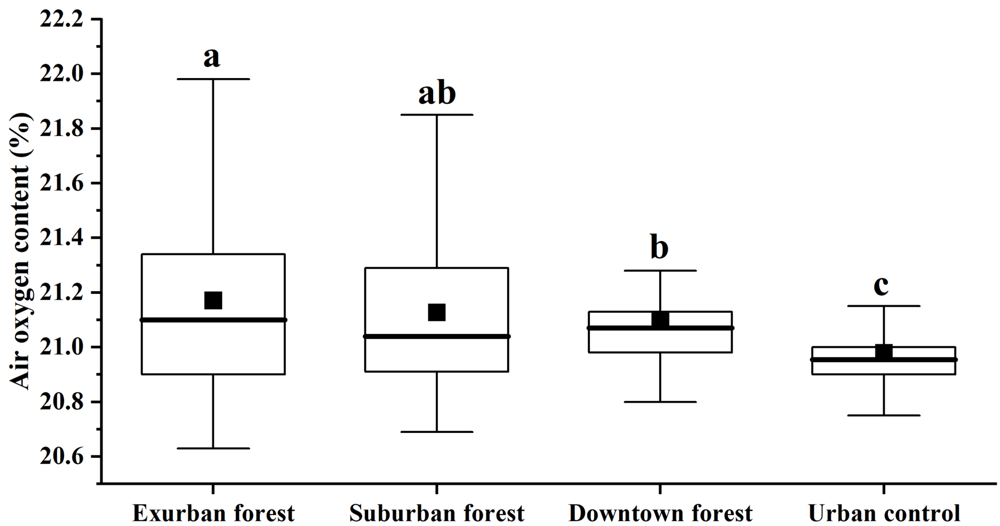

FIGURE 5
Comparison of annual average of AOC of urban forests in different geographical spaces.

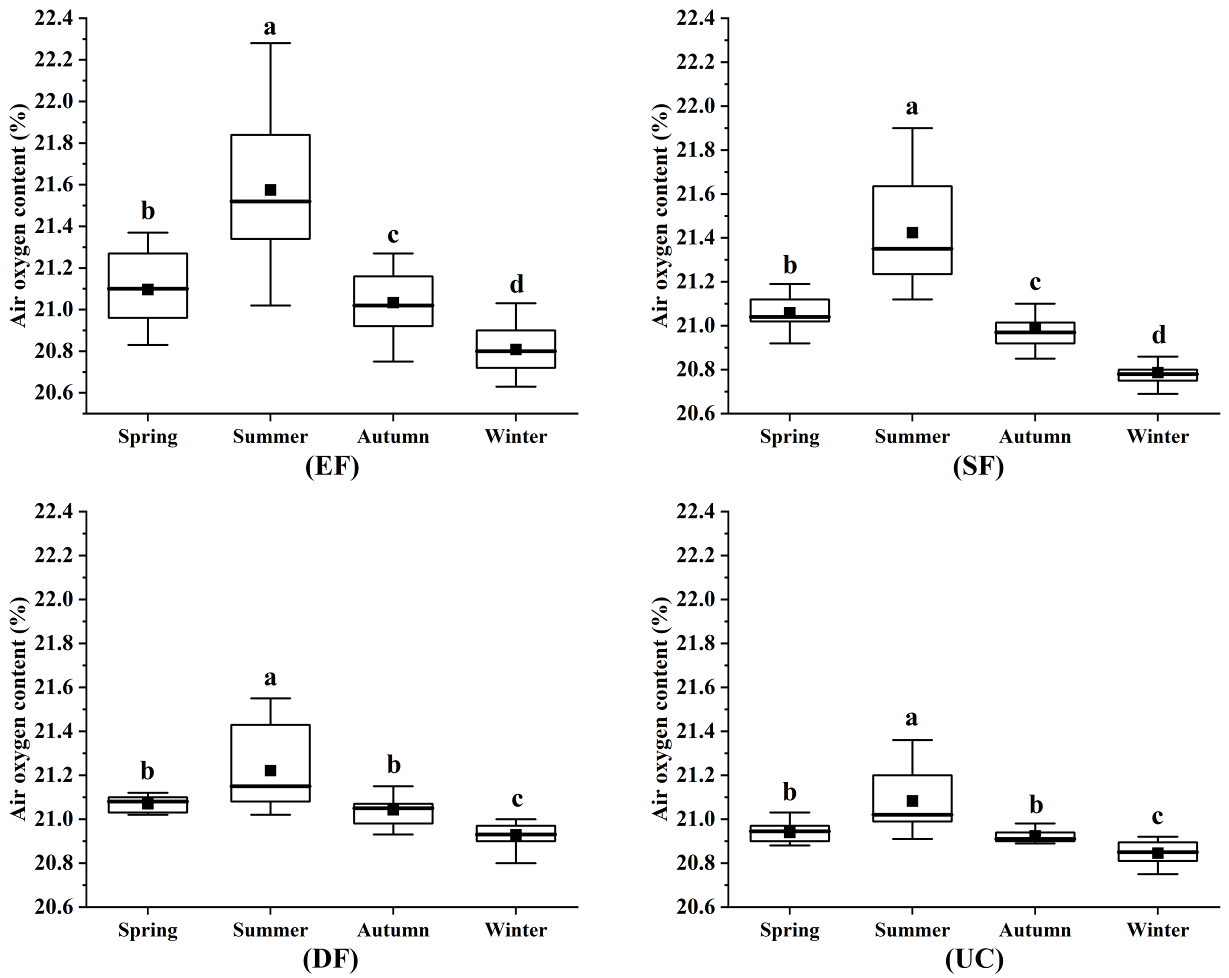

FIGURE 6
Seasonal variations of AOC of urban forests in different geographical spaces.

(0.93 ± 0.77 m/s) > downtown forest (0.83 ± 0.72 m/s). Meanwhile, there was no apparently consistent seasonal change rule of wind speed in different geographical spaces.

The HCI of urban forests in different geographical spaces was calculated by Eq. 2 mentioned above and assessed in conformity with the evaluation criteria for HCI (Table 3). Through variance analysis, the HCI indicated transparently significant difference ($p = 0.000 < 0.01$). The annual average of HCI in different geographical spaces was as follows: urban control (5.56 ± 2.32) > downtown forest (5.15 ± 1.80) > suburban forest (4.02 ± 1.53) > exurban forest (3.71 ± 1.48). HCI in exurban forest and suburban forest were at Level I very comfortable degree, while downtown forest and urban control were at Level II, with a comfortable feeling. The seasonal variations of HCI in exurban forest and suburban forest were: autumn > spring > summer > winter. Except winter was at Level II, the other three seasons were all at Level I. However, seasonal variation of HCI in downtown forest was autumn > winter > spring > summer, and in urban control was: winter > autumn > spring > summer. Moreover, HCI of downtown forest and urban control in autumn and winter were at Level I, while in spring and summer were at Level II. Overall, the HCI of urban forest environments in different geographical spaces were all the best in autumn. Among them, the exurban forest and suburban forest were the worst in winter, while downtown forest and urban control were the worst in summer, followed by spring.

3.4. Evaluation of UFCHI in different geographical spaces

As claimed by the above-mentioned Eqs. 3, 4, the normalized values of three healthcare indicators were obtained. Meanwhile, in accordance with Eq. 9 and Table 5, the annual UFCHI in different geographical spaces were calculated and evaluated (Table 6). The UFCHI in different geographical spaces was as shown: exurban forest (1.000) > suburban forest (0.790) > downtown forest (0.378) > urban control (0.000). On the basis of the evaluation criteria for UFCHI (Table 5), the exurban forest was at Level I and extremely beneficial to human health; the suburban forest was at Level II, which was rather beneficial to human health; the downtown forest was at Level III, which was slightly beneficial to human health; while urban control was at Level IV, having no benefit to human health. This reported that forest environments in exurbs and suburbs having stronger healthcare benefits were more conducive to human health and more suitable for forest therapy activities than those in central city. Compared with forest environments, the healthcare benefits of urban control were weaker, which was not good for human health.

The UFCHI in different seasons were given, as shown in Table 7. Except in winter, the UFCHI of exurban forest and suburban forest were all at Level II and above in other seasons; especially in summer, the

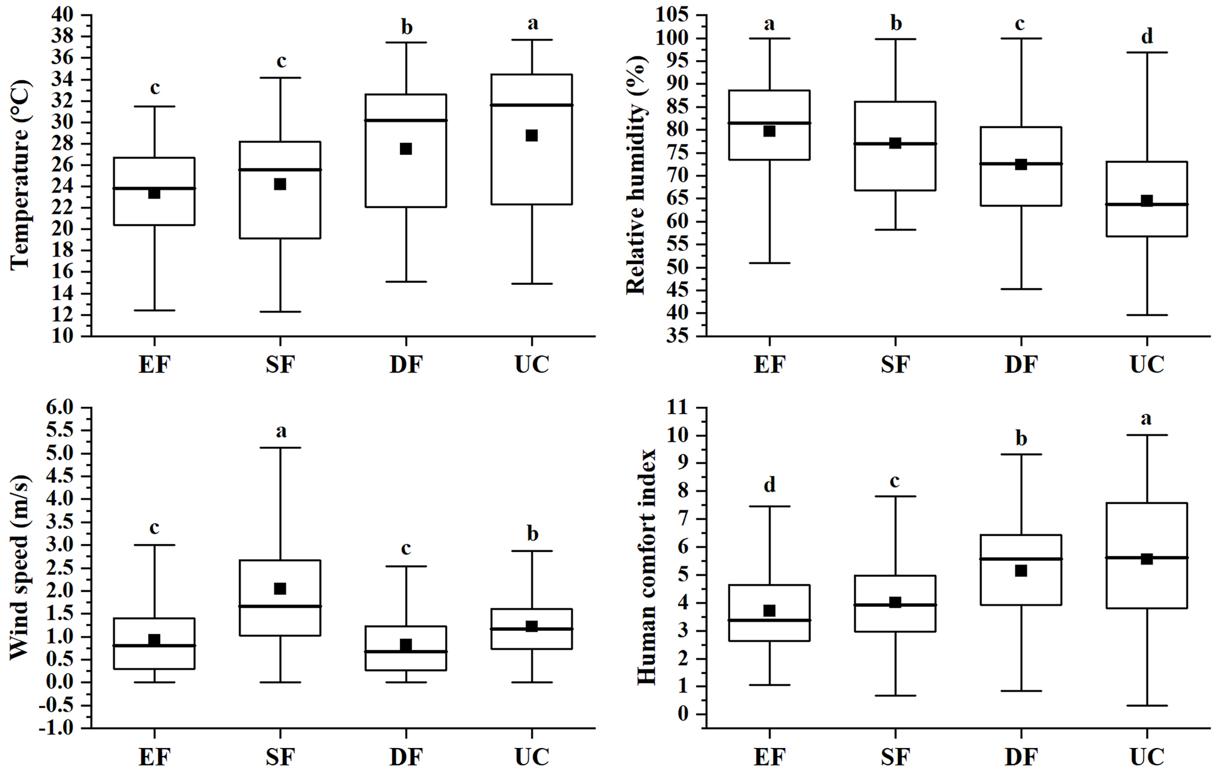

FIGURE 7
Comparison of annual average of forest microclimate and HCI of urban forests in different geographical spaces.

exurban forest was at Level I, having the superlative healthcare benefits. However, the UFCHI of downtown forest and urban control were all at Level III and below at all seasons. What's more, in summer, urban control was at Level IV, with no healthcare benefits. It advised that spring, summer, and autumn were extraordinarily suitable for people to conduct forest therapy activities in exurban forest and suburban forest.

4. Discussion

4.1. Effects of different geographical spaces on urban forest comprehensive healthcare benefits

There were significant differences in comprehensive healthcare benefits of urban forests in different geographical spaces, where exurban forest > suburban forest > downtown forest, and the healthcare benefits of three urban forest environments were all exceptionally better than those of urban control. Combining with the distance from city center, forest area, and surrounding environment of study area, we can conclude that forest environment that was away from the city center and had a concentrated and continuous forest area reaching a certain scale got superior integrated healthcare benefits. The forest area in exurbs and suburbs was large and concentrated, which was negligibly affected by the external environment (Clay et al., 2018). Furthermore, human activity was higher in the city than in the suburbs and exurbs, which steepened from rural areas toward the urban center (Meng et al., 2015). Environmental changed along a city-suburb-exurb gradient in response to urbanization, such as dense buildings, concentrated road networks, and frequent human activities, produced a gradient of forest area fragmentation (Wu et al., 2013). It was intuitive that the forest area of downtown forest was narrow and encompassed by crowded premises, forming an isolated urban forest which was more affected by the surrounding environment, which would tend to have a passive effect on healthcare benefits. The downtown forest was convenient for daily walks and exercise for the surrounding residents, but its healthcare benefits were limited. If denizens aspire to reap preferable healthcare benefits from forest setting, it is best to stay in forest environments in exurbs and suburbs to recuperate their bodies and minds. Consequently, it is advisable for forest therapy sites to be located in or adjacent to concentrated and contiguous forests, and to have a certain scale of concentrated areas that can develop an evident forest microclimate.

This finding is particularly informative. Most of the current urban parks are also isolated downtown forests, and whether their comprehensive healthcare benefits are similar requires more and deeper exploration in the future. We speculate that the area of isolated downtown forests is too small to achieve forest healthcare benefits. Future research could set up different forest area gradients for in-depth analysis and verification, so as to give scientific support for the rationality of forest therapy base site selection.

4.2. Effects of different geographical spaces on forest healthcare factors

4.2.1. Negative air ion concentration

The NAIC of three urban forests were distinctly higher than urban control, which was in line with the research conclusions of most

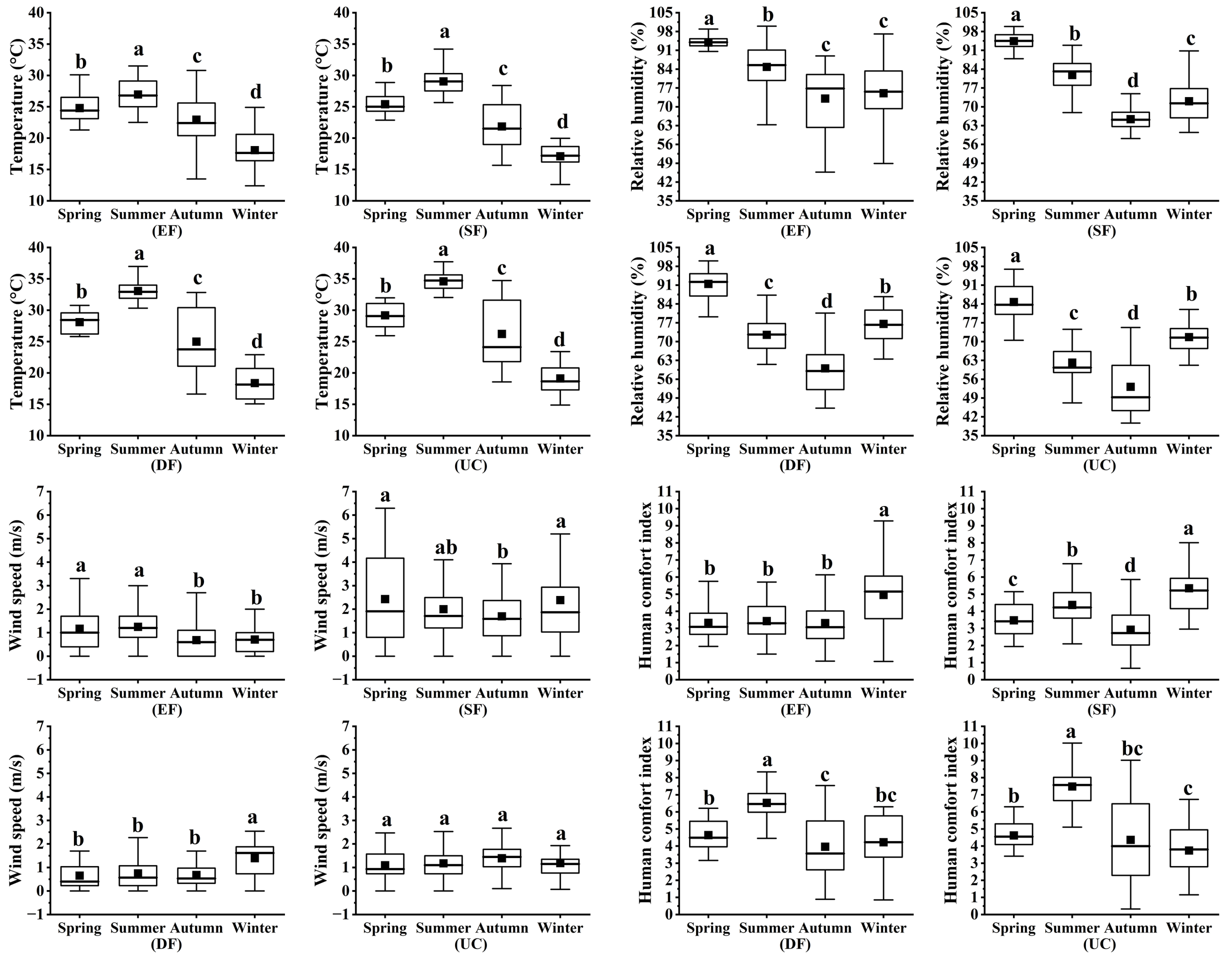

FIGURE 8
Seasonal variations of forest microclimate and HCI of urban forests in different geographical spaces.

TABLE 6 Indicators' normalized value of the whole year and their UFCHI.

Urban forest types	NAIC	AOC	HCI	UFCHI	Grades
Exurban forest	1.000	1.000	1.000	1.000	Level I
Suburban forest	0.741	0.773	0.837	0.790	Level II
Downtown forest	0.274	0.624	0.223	0.378	Level III
Urban control	0.000	0.000	0.000	0.000	Level IV

scholars: NAIC in forest areas were immensely greater than that in forestless areas (Feng et al., 2015). A possible explanation for this might be that in the forest environment, radioactive elements escaping from rocks and soil, photoelectric effects on plant branches and leaves, and volatile aromatic substances released by trees can ionize the air in the forest (Zeng et al., 2006). And the dust removal effect of forests can boost NAIC, along with extending their lifetimes. Nevertheless, the urban environment had less vegetation, dense population and heavy traffic. Previous studies have unfolded that human activity had a prominent impact on NAIC, and NAIC was negatively correlated with the flow of population and vehicles (Yuan et al., 2014; Feng et al., 2015). The dense population would consume a great deal of O_2 and generate a large amount of CO_2, and NAIC was passively linked with oxygen consumption (Pu et al., 1993). Simultaneously, CO_2 absorbed negative ions to form heavy ion deposition, leading to a further decline in NAIC. More importantly, automobile exhaust would build up the concentration of suspended particulate matter and CO_2 in near-surface air, which enormously diminished the NAIC and shortened their existence.

The average annual of NAIC in exurban forest was about 1.2 times and 2.4 times than that in suburban forest and downtown forest, respectively. The forest area and forest coverage of exurban forest and suburban forest were large and contiguous, barely influenced by the outside, and had a stable ecosystem. It was detected that NAIC was better at high forest coverage than at low forest coverage (Cui et al., 2020). In addition, exurban forest was rich in plant species, complex in community structure, large in leaf area index (LAI) of community, and relatively high in canopy density. Earlier research suggested that the higher the complexity of community structure, the greater the NAIC (Gao and Zhang, 2018), and NAIC had a positive correlation with LAI of community (Liu et al., 2011). Additionally, there was a positive correlation between NAIC and canopy density, and NAIC tended to heighten with the escalation of vegetation canopy density (Du et al., 2018; Zheng et al., 2021).

Seasonal variations of NAIC in exurban forest and suburban forest were summer > spring > autumn > winter, while downtown forest and urban control were autumn > winter > spring > summer. The reason for the difference may be closely related to the temperature. The downtown

TABLE 7 Indicators' normalized value of different seasons and their UFCHI.

Urban forest types	Seasons	NAIC	AOC	HCI	UFCHI	Grades
Exurban forest	Spring	0.656	0.393	0.913	0.664	Level II
	Summer	1.000	1.000	0.890	0.957	Level I
	Autumn	0.542	0.313	0.916	0.607	Level II
	Winter	0.513	0.027	0.555	0.357	Level III
Suburban forest	Spring	0.500	0.346	0.880	0.594	Level II
	Summer	0.744	0.808	0.683	0.743	Level II
	Autumn	0.389	0.261	1.000	0.583	Level II
	Winter	0.323	0.000	0.469	0.266	Level III
Downtown forest	Spring	0.211	0.360	0.624	0.425	Level III
	Summer	0.178	0.551	0.211	0.323	Level III
	Autumn	0.267	0.325	0.773	0.486	Level III
	Winter	0.225	0.180	0.716	0.401	Level III
Urban control	Spring	0.026	0.173	0.628	0.314	Level III
	Summer	0.000	0.375	0.000	0.133	Level IV
	Autumn	0.067	0.194	0.684	0.354	Level III
	Winter	0.054	0.075	0.822	0.362	Level III

forest was small-scale and surrounded by dense buildings, developing an isolated urban forest. In hot, muggy summer, the downtown forest had no noticeable cooling and humidifying effect, and the high temperature inside the forest lessened the stomatal conductance and photosynthetic rate of plants. Former studies have discovered that NAIC was positively correlated with stomatal conductance and photosynthetic rate (Zhao et al., 2018). Stomata was the channels for the release of negative air ions produced by plants, and the larger the stomata, the higher the NAIC (Zhang et al., 2016); the higher the photosynthetic rate, the greater the ability of plants to release oxygen, and the higher the NAIC. At the same time, the high-temperature urban environment given rise to the dispersion of pollutants (Zhang et al., 2022), and pollutants adsorbed loads of negative air ions in the process of diffusion, resulting in a lower rate of negative air ions production than consumption. Therefore, the NAIC in downtown forest and urban control were broadly lower in summer than in other seasons, which was also coherent with the seasonal variation of NAIC in Hangzhou (Qi et al., 2011) and Shenzhen (Wang et al., 2020).

4.2.2. Air oxygen content

The AOC in different geographical spaces was conspicuously different, exurban forest > suburban forest > downtown forest > urban control, and the variation of AOC in exurban forest and suburban forest were larger. It may be due to the fact that exurban forest and suburban forest were far away from the city center, having lower concentrations of air pollutants. And their forest areas were larger and concentrated, with a larger unit biomass and LAI, so the ability to release oxygen through photosynthesis was notably better than those of downtown forest and urban control. In addition, the variation of AOC was closely related to the growth and development cycle of forest communities (Wen, 2020), varying with the change of plants into the peak growing season or dormant state.

It has been established that AOC was most affected by temperature (Gu, 2013; Wang et al., 2014; Wen, 2020). The seasonal variations of AOC in different geographical spaces were summer > spring > autumn > winter, which was the same as the temperature. This illustrated that, under the impact of temperature, there was an outstanding rise in oxygen release in spring and summer, due to intense physiological activity during the peak period of plant growth. On the contrary, after entering autumn and winter, the physiological activity of plants gradually decayed and slowly entered a dormant period, which considerably reduced the oxygen release. Hence, the seasonal variations of AOC in different geographical spaces were higher in summer and spring than in autumn and winter, which was identified with the findings of Wen (2020).

4.2.3. Human comfort index

The HCI of exurban forest and suburban forest was at Level I very comfortable degree, which were one level higher than that of downtown forest and urban control. This reflected that the HCI in forest environments was superior to that in urban environments, which matched the conclusion of most scholars (Gu et al., 2019; Rahman et al., 2020; Teshnehdel et al., 2020): the function of regulating microclimate played by forest environments was strikingly better than that of non-forest area. This may have a lot to do with their altitude, mountain topography, forest area, forest coverage, surrounding environment, and their location away from urban centers. As can be seen from the study area introduction and Figure 1, the forest areas of exurban forest and suburban forest were concentrated and contiguous on a large scale with high forest coverage. Moreover, they had higher elevations, more diverse and complex terrain, and were adjacent to other forest parks, nature reserves or scenic spots. In contrast, the downtown forest had lower altitudes, less pronounced terrain variations, and smaller forest areas. Meanwhile, it was surrounded by dense buildings or the South China Expressway, and more susceptible to the effects of urban microclimates. Numerous studies have manifested that HCI was affected by altitude, vegetation cover, and terrain shading effects; HCI was positively related to altitude (Wen, 2020), and the mountainous terrain shading effect and higher vegetation cover were conducive to the HCI (Yao et al., 2019). Thus, the HCI in exurban forest and suburban forest was better than that in downtown forest and urban control. Furthermore, some scholars have claimed that HCI was positively correlated with NAIC and canopy density (Du et al., 2018). Exurban forest and suburban forest had high NAIC and canopy density, which have achieved remarkable cooling and damping effect and improved HCI. However, the lack of vegetation in urban environment resulted in large variations in temperature and humidity, and its HCI was poor.

The HCI of forest environments in different geographical spaces were all the best in autumn. In contrast, HCI was worst in winter in exurban forest and suburban forest, and in summer in downtown forest and urban control. Precedent studies have shown that all microclimate factors had a certain impact on HCI, with air temperature having the greatest impact, followed by relative humidity and wind speed (Liu C. et al., 2017; Huang et al., 2020). Forest environments can tremendously drop air temperature and rise relative humidity (Yan et al., 2012), and its ability of regulating local microclimate was relatively strong. Thus, exurban forest and suburban forest had the effect of reducing heat and improving comfort during the hot summer months, while in winter, forest environments were colder than urban environments and their HCI was poor. This was matched with the findings of Zhang (2014) that urban forest in regulating human comfort was the worst in winter. Nevertheless, temperature, relative humidity, and wind speed were all at very comfortable level in fall, so the HCI in urban forest environment in autumn was the best. It was perceived that urbanization contributed to the increase of maximum temperature in summer and minimum temperature in winter in urban areas with 57.8% and 46.1%, respectively. The HCI in urban areas moved in the direction of hot and uncomfortable in summer and warmer and more comfortable in winter (Huang et al., 2020). At the same time, downtown forest was more susceptible to urban microclimate and their ability to regulate microclimates was limited. Therefore, the downtown forest and urban control had better HCI in winter than in summer.

4.3. Limitations and future research

Admittedly, there were several limitations to this study. First, the forest healthcare factors in this study were limited to three indicators: negative air ion concentration, air oxygen content, and human comfort index. To sufficiently reflect the forest healthcare benefits, further studies can supplement the synchronous monitoring experiments of airborne bacteria content, air particulate matter concentration, phytoncide relative content, and other metrics. Second, this study primarily focused on the internal environment of urban forests. In the process of data collection, the impact of traffic exhaust and other pollutants on negative air ion concentration, air oxygen content, and human comfort index were ignored. It is true that the external environment of urban forests takes some effects on its internal environment. Future research is needed to consider how to quantify or avoid these effects. Third, the study area selection of this study was on the basis of three considerations: the distance from city center, forest area, and surrounding environment. But which of these three factors has a greater impact on the urban forest comprehensive healthcare index? It is a pity that this study did not carry out comparative experimental research on this issue. In future studies, we could set up the approximate forest area to explore the influence of the distance from city center on forest healthcare benefits; or select similar geographical locations (e.g., exurbs or suburbs) with diverse forest area gradients to discuss whether the area proportion of urban forests react greater on the UFCHI? As for the effect of surrounding environment on forest healthcare benefits, the experiment can be designed to be conducted in urban forests in suburbs or downtown which forest area is analogical, but the surroundings (such as contiguous forest environment, adjacent to a large area of water, dense buildings and population, and adjoining industrial areas) are distinguishing. Notwithstanding these limitations, this may be the first study to attempt to validate the differences in exurban-suburban-downtown gradients for urban forest comprehensive healthcare benefits using the CRITIC method.

5. Conclusion

Our results demonstrated that forests in exurbs and suburbs can make a substantial contribution to healthcare benefits than downtown forest. Although downtown forest has some healthcare benefits for daily exercise and recreation, it is inadequate for forest therapy. When choosing the site for forest therapy bases, three pivotal factors including the distance from city center, forest area, and surrounding environment should be highly valued, and priority should be given to concentrated contiguous exurban forest with a certain scale, followed by suburban forest. Furthermore, our findings identified that spring, summer, and autumn were excellent for forest therapy in both exurban forest and suburban forest.

Data availability statement

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

Author contributions

SZ, JL, and GC conceived the study. SZ, SH, FH, YS, and YG finished field investigation and laboratory experiments. SZ processed the data and analyzed the results. SZ, QQ, and QH contributed to the manuscript writing and editing. All authors contributed to the article and approved the submitted version.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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The association of park use and park perception with quality of life using structural equation modeling

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Introduction: The literature is limited on the impact of neighborhood parks on quality of life (QoL) and the mechanism linking them.

Methods: In this paper, we applied the structural equation model to data from a cross-sectional sample of 650 participants in low-income communities of New York City, we examined the associations of neighborhood park use vs. park perception and QoL, and whether these associations were mediated through self-reported perceived stress. We also examined whether park use mediated the relationship between park perception and QoL.

Results: We found that park use had a significant but weak association with QoL (standardized $\beta = 0.08$, 95% confidence interval (CI): 0.02, 0.15, $p = 0.02$), but this relationship was not mediated by self-reported stress. Park perception was more strongly associated with QoL than park use (standardized $\beta = 0.23$, 95% CI: 0.16, 0.30, $p < 0.01$), and this was partly mediated by self-reported stress (indirect effect-standardized $\beta = 0.08$, 95% CI: 0.03, 0.13, $p < 0.01$) and, to a lesser extent, by park use (indirect effect- standardized $\beta = 0.01$, 95% CI: 0.00, 0.02, $p = 0.01$).

Discussion: Having well-perceived parks appears to be an important factor for QoL independent of park use, suggesting that quality parks may benefit everyone in a community beyond park users. This strengthens the argument in favor of increasing park investment as a strategy to improve population wellbeing.

KEYWORDS
quality of life, structural equation model, perception of neighborhood park, built environment, New York City, low-income neighborhoods, perceived stress, park use

1. Introduction

Quality of life (QoL) is increasingly put forward as a key health outcome measure in its own right, as the notion of wellbeing is increasingly recognized as more than economic wealth or the absence of clinical disease (1). The European Commission has in recent years called for the inclusion of measures of QoL in the context of sustainable development (2). Other international organizations, such as the Organization for Economic Co-operation and Development has similarly produced the Better Life Index, consisting of measures of material living conditions as well as QoL (3). In public health research, there has been a rise in the use of QoL measures to evaluate policies (4–6) or compare the wellbeing of populations in different countries (7–9). However, beyond ecological comparisons, much of the research on QoL only explores associations with specific health conditions. Little research has focused on environmental correlates and determinants that might contribute to QoL.

Parks and green space are thought to play an important and positive role in health outcomes, including in QoL, especially in urban environments (10–14). While prior research on parks or green space has focused more on health behaviors such as physical activity or conditions such as obesity or depression (14), emerging research shows that frequency of park use may also be positively associated with QoL in China (13) and Turkey (11). Among United States (US) college students, frequent and active use of green space has also been positively associated with QoL (15). Another study conducted in Denmark showed that people who lived closer to green space reported better health-related QoL (16). However, the existing evidence base on QoL as an outcome remains limited and the mechanisms by which parks may exert a positive effect on QoL is still unclear.

In addition to studies that focus on the frequency of park use or proximity to parks in relation to QoL, an emerging body of research shows that subjective perceptions of parks may be an important consideration. For instance, higher QoL has been associated with more positive perceptions of neighborhood open spaces (17), area green neighborhood qualities (18), and greenway trails (19). Interestingly, a study in Hungary compared objective spatial indicators and visitors' perceptions of urban parks, and found that the two types of measures were only moderately correlated, highlighting the potential importance of both types of measures in research (20). Another study in Australia also showed that perceived greenness of the community environment did not necessarily correlate well with objectively measured greenness (21). Indeed, perceptions of parks may not directly translate into park usage (22), and the relative role of park perception vs. park use in QoL has not been well-studied.

One possible pathway linking park exposure to QoL may be perceived stress. Several studies have demonstrated that parks could play a role in reducing stress (23, 24). For example, Tyrväinen et al. (25) showed that exposure to nature areas was associated with lower stress levels compared to exposure to built-up areas. Similarly, another showed that exposure to nature vs. urban street conditions resulted in greater restorative recovery from stress even after adjusting for stress reactivity (26). However, findings on the role of stress have not always been consistent (27), and the extent to which it mediates the association of park exposure or perception with QoL is yet unclear.

In light of the fact that QoL has not been well-studied in relation to park exposure variables, and that there is lack of clarity on the relative role of park use vs. park perception and the mechanism connecting these to health outcomes, this paper sought to address these gaps through a cross-sectional structural equation modeling (SEM) study. We also tested the mediational effect of perceived stress and whether park use mediated the association between park perception and QoL. We used data from predominately low-income minority communities in New York City (NYC), a population that has been understudied in the built environment literature.

Abbreviations: QoL, Quality of Life; NYC, New York City; PARCS Study, Physical Activity and Redesigned Community Spaces Study; SEM, Structural Equation Modeling; GDP, Gross Domestic Product; US, United States; CDC, Centers for Disease Control and Prevention; ICC, intraclass correlation; CI, confidence interval; CFI, Comparative Fit Index; TLI, Tucker-Lewis Index; RMSEA, root-mean-square error of approximation; TE, Total effect; DE, Direct effect; IDE, Indirect effect; FIML, Full Information Maximum Likelihood.

2. Materials and methods

2.1. Data

We used baseline data from the Physical Activity and Redesigned Community Spaces (PARCS) Study, conducted across 54 community parks throughout NYC during 2016-18 (28). PARCS is an ongoing study examining the relationship between parks and wellbeing. Study parks were located in neighborhoods that met at least two of three criteria: high poverty ($\geq$20% population below the poverty line), high population growth (25% growth 2000–10), and high population density ($\geq$110 people/acre).

Individual-level data in the PARCS Study were obtained from residents that lived within a 0.3-mile Euclidean buffer around each neighborhood park. All participants were recruited by convenience sampling. They were over 18 years old, lived in the study neighborhoods for at least 2 years, intended to stay in the neighborhood for at least 4 years, spoke English, Spanish or Chinese, and had no mobility limitations. At baseline, participants responded to a survey on park perception and usage and psychosocial and community wellbeing. Only participants who provided consent were enrolled in the study. The study was approved by the City University of New York Institutional Review Board.

2.2. Measures

2.2.1. Outcome variable

2.2.1.1. Quality of life

QoL was operationalized using a 9-item scale with Likert response options from the public health surveillance wellbeing scale (29). It was developed and validated by the Centers for Disease Control and Prevention (CDC), with an original Cronbach's alpha of 0.87 and good construct validity. A 10th item from the original CDC scale, that asked respondents to indicate the number of days they felt very healthy and full of energy, was dropped because it was not based on Likert-type responses and the concepts of feeling healthy and energetic were already captured in other items.

The 9 items of the scale captured 3 major domains of wellbeing: mental (5 items), social (2 items), and physical health (2 items). The items related to satisfaction with life, clear sense of purpose, and feeling accomplished were rated on a 5-point Likert scale, ranging from 1 = "strongly disagree" to 5 = "strongly agree." Feelings of cheerfulness and hopelessness in the last 30 days were rated between 1 = "none of the time" to 5 = "all the time." Items on satisfaction with one's energy level, family, friends, and social life were rated on a scale of 1 (very dissatisfied) to 10 (very satisfied). Lastly, self-reported overall health was rated between 1 (excellent) to 5 (poor). The feeling of hopelessness and self-reported health status were reverse coded so that higher values meant higher QoL for all items.

2.2.2. Exposure variables

2.2.2.1. Frequency of park use

To assess the frequency of park use, we adopted 2 questions from Veitch et al. [test-retest intraclass correlation (ICC) = 0.79–0.85] (30). The original questions pertained to park use in the past 3 months; however, we modified this to the past 30 days to reduce recall bias. The two questions were: "In the past 30 days, on average, how often have you visited the study park (there was only one study park in each neighborhood)?" and "In the past 30 days, on average, how often have you visited a park other than the study park?" Response options for each question included "daily," "4–6 times/week," "2–3 times/week," "once/week," "2–3 times/month," "once/month," "less than once/month," and "have not visited in past 30 days." Based on a previously developed methodology (31), a random number was computer-generated within the range of each category as the number of days a person visited a park. The highest frequency of park use between the 2 variables was used as a proxy for park use by a given participant in his or her neighborhood.

2.2.2.2. Park perception

For individual-level park perception, we used a set of 10 survey questions developed by Veitch et al. (test-retest ICC = 0.36–0.72) (30). Items were rated on a 5-point Likert scale between 1 = "strongly disagree" and 5= "strongly agree." These items asked about the attractiveness, safety, maintenance, shade availability, and dog-walking facilities in neighborhood parks. In addition, participants rated the overall quality of parks in the neighborhood and whether children liked going to these parks.

2.2.3. Mediator

2.2.3.1. Self-reported stress

To assess stress, we used the Perceived Stress Scale (10 items) by Cohen et al. (Cronbach's alpha = 0.78) (32). The scale measured stress experienced by the participants in the past 30 days on a 5-point Likert scale (0 = "never" to 4 = "very often"). The total score ranges from 0 to 40, with higher values indicating high perceived stress.

2.2.4. Covariates

Participants self-reported age (years), sex (female vs. male), household income (below and above $20,000 per annum), and race/ethnicity (Latino, Black, White, and Other).

2.3. Statistical analysis

We conducted a multiple-mediation analysis using an SEM with complete cases. SEM provides an advantage since the models include specific and accumulative associations between different variables and evaluate multiple mediators effects simultaneously in a single model (33). Additionally, SEM tackles concerns related to measurement errors in the survey datasets better than regression models (34). We developed latent constructs for two measures, park perception, and QoL. Both measurement models were further assessed by confirmatory factor analysis. Factor loadings were used to check the association between the latent constructs and their observed variables. Observed variables with factor loadings <0.40 were excluded.

TABLE 1 Socio-demographic and health characteristics of the study participants.

	n (%)
Gender	
Male	119 (18.3)
Female	531 (81.7)
Race/ethnicity	
Latino	317 (48.8)
Non-Latino Black	247 (38.0)
Non-Latino White	33 (5.1)
Non-Latino Other	53 (8.1)
Household income per year	
≥$20,000	303 (46.6)
<$20,000	347 (53.4)
	Mean (SD)
Age (years)	38.8 (11.8)
Park use in last 30 days (# of days)	12.1 (10.3)
Perceived stress scale score	24.3 (7.5)

In addition to the direct effect of park use and park perception on QoL, we evaluated 3 mediation pathways: (35) (1) the effect of park use on QoL, as mediated by stress (park use → stress → QoL), (2) the effect of park perception on QoL, as mediated by stress (park perception → stress → QoL), and (3) the effect of park perception on QoL, as mediated by park use (park perception → park use → QoL). The bootstrap method, based on 1,000 re-samples, was used to generate standard errors and significance tests for individual parameters. All the ordinal variables were recoded so that the lowest value started from zero. Standardized total, direct and indirect path coefficients (β), along with the 95% bias-corrected percentile confidence interval (CI) and p-value were reported. To validate the fitness of the SEM, χ^2 values, the Comparative Fit Index (CFI), the Tucker-Lewis Index (TLI), and the root-mean-square error of approximation (RMSEA) were used. We considered a model acceptable when the CFI and TLI were 0.90 or greater and the RMSEA value was 0.06 or less.

Additionally, for sensitivity analysis, we used the Full Information Maximum Likelihood (FIML) approach to impute the missing values for those participants who had answered at least one but not all of the survey questions and re-ran the SEM with the larger sample ($n =$ 1,354). We chose FIML over the other imputation methods since it provides better estimates for SEM (36, 37).

R statistical software v.3.6.2 (38) and IBM SPSS AMOS v.26.0 (39) were used for analysis. Alpha was set at 0.05.

3. Results

3.1. Sample characteristics

Participants in the sample ($n = 650$) had a mean age of 38.8 ± 11.8 years, half (53.4%) had an annual household income below $20,000, and 81.7% were women. Latinos constituted 48.8% of the sample, while 38% were Black (Table 1). On an average, the participants in

TABLE 2 Confirmatory factor analysis of the latent constructs of park perception and quality of life.

Latent variable	Measured variable	Mean (SD)	Factor loading
Park perception (Cronbach's Alpha = 0.86)	• I am satisfied with overall quality of parks in my neighborhood	1.95 (1.17)	0.78
	• Parks in my neighborhood are attractive	1.88 (1.19)	0.77
	• Parks in my neighborhood are safe	1.92 (1.14)	0.78
	• Parks in my neighborhood are well maintained	1.94 (1.17)	0.76
	• Parks in my neighborhood have satisfactory shade	1.97 (1.16)	0.6
	• Parks in my neighborhood have suitable dog walking facilities	1.38 (1.21)	0.56
	• My children like going to parks in my neighborhood	2.87 (1.10)	0.44
Quality of life (Cronbach's Alpha = 0.84)	Mental health		
	• I am satisfied with my life...	2.71 (1.11)	0.61
	• My life has a clear sense of purpose...	3.08 (1.13)	0.64
	• Most days I feel a sense of accomplishment from what I do...	2.92 (1.12)	0.66
	• How much of the time during the past 30 days have you felt...? Cheerful...	2.61 (0.96)	0.68
	• How much of the time during the past 30 days have you felt...? Hopeless...	2.76 (1.13)	0.51
	Social health		
	• How satisfied you are with each of the following items, Your family life...	6.91 (2.25)	0.59
	• How satisfied you are with each of the following items, Your friends and social life...	5.64 (2.56)	0.58
	Physical health		
	• How satisfied you are with each of the following items, Your energy level...	5.68 (2.54)	0.66
	• In general, would you say your health is:	2.28 (1.04)	0.41

our study sample visited their neighborhood parks ∼12.1 ± 10.3 days in the past 30 days and they reported moderate stress (24.3 ± 7.5).

3.2. Confirmatory factor analysis of latent constructs

Means and standard deviations of underlying factors of the latent constructs of QoL and park perception are shown in Table 2. Table 2 also shows the confirmatory factor analysis results of the park perception and QoL scales, including all variables with factor loadings ≥0.40. This resulted in 0 of 9 variables excluded from QoL and 3 of 10 variables being excluded from park perception. Cronbach's alpha was 0.84 for QoL and 0.86 for park perception.

3.3. Structural equation model

The final SEM showed a good model fit with $\chi^2 = 420.87$ (187), TLI = 0.93, CFI = 0.95, and RMSEA = 0.04. The model explained 47.1% of the variance in QoL. Figure 1 shows the total, direct and indirect effects in the three mediation analyses. For Pathway #1, park use showed a significant direct association with QoL (standardized $\beta = 0.08$, 95% CI: 0.02, 0.15, $p = 0.02$), with no significant mediation through self-reported stress (standardized $\beta = 0.03$, 95% CI: −0.02, 0.07, $p = 0.28$). In Pathway #2, park perception had a direct association with QoL (standardized $\beta = 0.23$, 95%CI: 0.16, 0.30, $p < 0.01$) and a significant indirect association that was partially mediated through self-reported stress (standardized $\beta = 0.08$, 95% CI: 0.03, 0.13, $p < 0.01$). In Pathway #3, park perception also had a significant indirect association with QoL that was mediated through park use (standardized $\beta = 0.01$, 95% CI: 0.00, 0.02, $p = 0.01$). Similar results were found when SEM was performed with multiple imputations for missing values in the larger sample ($n = 1,354$; data not shown). Figure 2 shows the forest plots of the total and indirect effects.

4. Discussion

To our knowledge, this is the first study to examine the role of park use and park perception on QoL and to explore the mechanisms that may underlie these relationships. Park perception had a stronger association with QoL than park use. In addition, the association of park perception with QoL was mediated through self-reported stress to a greater extent than through park use. Although the model tested was relatively parsimonious, it explained nearly half of the variance in QoL.

The significant association between park use and QoL in our study was corroborated by prior research in urban settings showing that visits to parks or green space improved mental and physical health (40). Of note, our QoL measure also encompassed social domain of health, suggesting that the benefit of parks may be

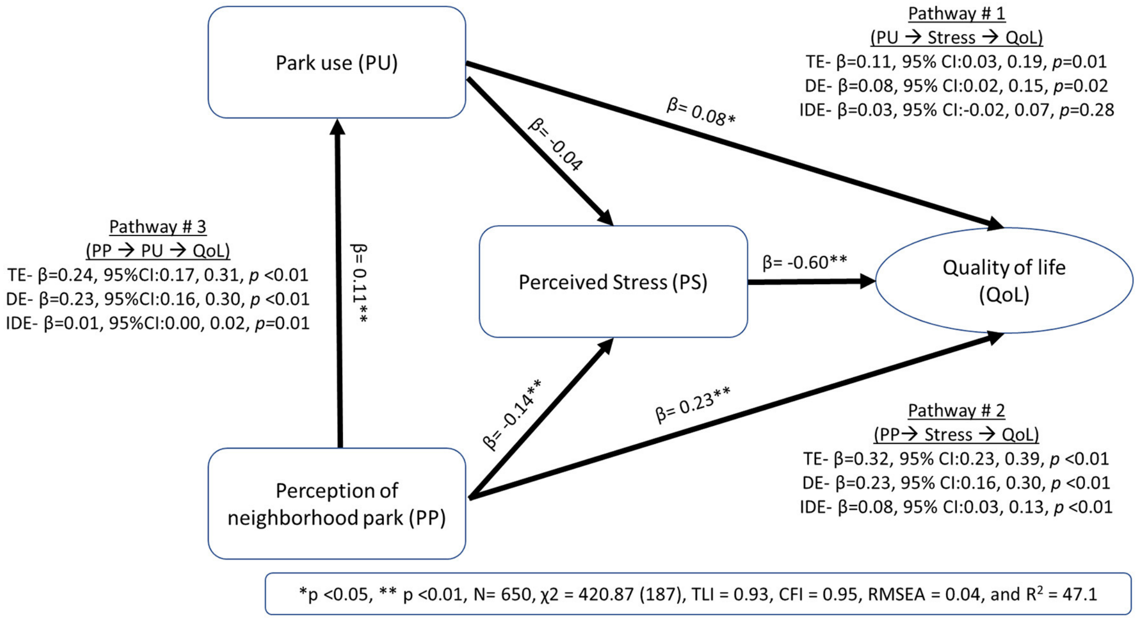

FIGURE 1
Structural equation model of park use, park perception, and self-reported stress in relation to quality of life. β, Standardized coefficient; p, p-value; CI, Confidence interval; TE, Total effect; DE, Direct effect; IDE, Indirect effect; χ^2, Chi-square value; CFI, Comparative Fit Index; TLI, Tucker-Lewis Index; RMSEA, root-mean-square error of approximation.

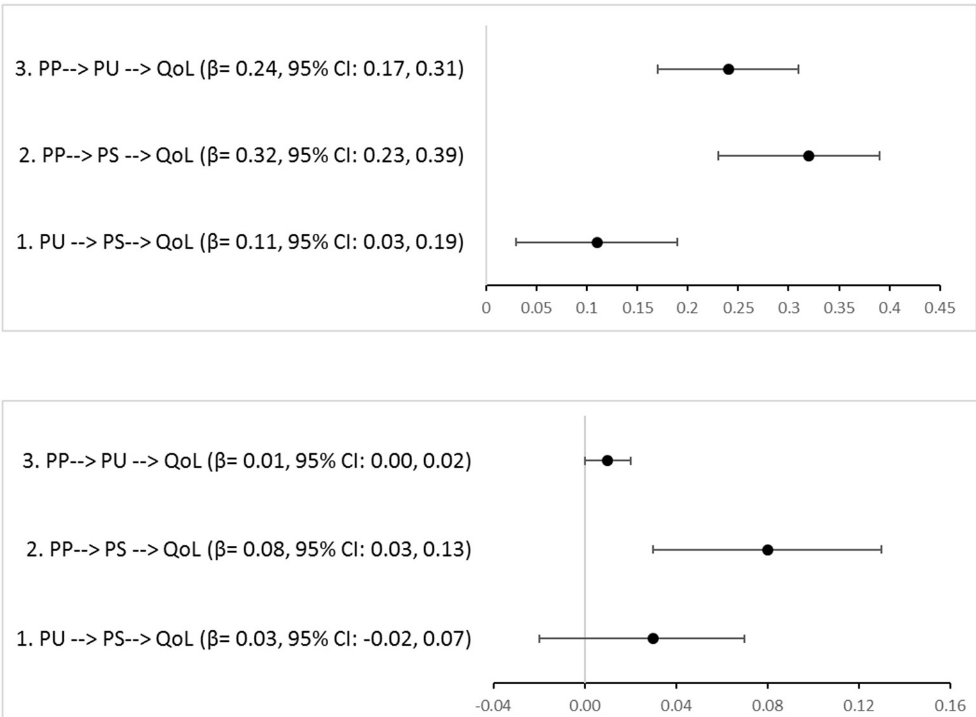

FIGURE 2
Forest plot of the total **(top)** and indirect **(bottom)** effect of park use, park perception on quality of life via self-reported stress. β, standardized coefficient; CI, confidence interval; PU, park use; PP, perception of park; PS, perceived stress; QoL, quality of life.

generalized to a broader conceptualization of wellbeing. That said, it was unexpected that the association of park use with QoL was not mediated by stress, despite the fact that stress was strongly associated with QoL. This may suggest that park use may not directly translate into a reduction in perceived stress and its effect on QoL may be due to other factors. For example, park use may increase social interaction or physical activity (10), which can have an impact on immune and endocrine functions, including the release of endorphins (41–43). Endorphins, in turn, may mitigate depressive symptoms (44, 45). In addition, there is some evidence, at least in animal studies, that chronic stress may dampen the effect of reward in the brain, suggesting that stress may moderate rather than mediate the relationship between park use and QoL (46, 47). More research on such alternative pathways is warranted. It is also possible that the effect of park use on stress can only be observed following long term use of park, which our study was not able to examine.

That perception of parks may play a larger role in QoL than actual park use, as indicated from the SEM. This suggests that having quality parks in a neighborhood may confer benefits to the wellbeing of local residents even if they do not engage in frequent park use. Although this is a new finding, the National Recreation and Park Association previously conducted a survey on the perception and use of local recreation and park services among Americans and showed that even non-users of parks believed that having a local park, playground, or open space in their neighborhood was important to their personal and community wellbeing (48). In another study of Switzerland adults, higher satisfaction with the living environment and perception of access to green spaces were associated with higher health-related QoL (49).

To our knowledge, there have been no studies that specifically examined the role of park perception on QoL *via* the mediation of stress. However, in a virtual reality experiment, it was reported that parks and urban green space reduced stress levels through olfactory, audio, and visual sensory stimulation (50). Studies indicate that exposure to (without necessarily requiring interaction with) urban green space could help reduce stress and improve mental wellbeing or QoL (51–55). Of note, in our study, there was a potential effect of park perception on QoL beyond the mediating role of stress, suggesting that there are likely other mechanisms that need further research.

While we found an association of park perception with QoL, which was partially mediated by park use, it was notable that this mediation was weak. On one hand, some research has shown that park perception is correlated with park use (56). On the other hand, a study of young people in three cities in China found that while a perception of green space accommodating health promotion activities was associated with an increased willingness to use the park, it had less of an effect on actual park usage (22).

QoL is an increasingly important and recognized population outcome globally. For decades, countries have used economic indicators such as gross domestic product (GDP) to measure progress and prosperity. However, GDP does not capture environmental and social wellbeing or the degree to which people are satisfied with their living conditions (2, 57–61). In 2020, New Zealand released a "wellbeing budget," with spending and policy decisions based on citizens' health and wellbeing rather than GDP or economic growth (59). Our study uses a robust yet simple measure of QoL that was previously validated by the CDC. Our findings contribute to the growing body of literature on the importance of QoL and what cities and countries can do to improve such an outcome.

In general, urban green space shares a complex relationship with health. It is inversely associated with the prevalence of non-communicable diseases related morbidity, and mortality (14, 62–64), premature death (65, 66), and stress (23, 24). It is also positively associated with improved pregnancy outcomes (67), mental health (68, 69), and life expectancy (70). In a broader sense, green space may influence health through five major pathways: physical, mental, social, environmental, and economic. It provides space for physical activity, which reduces the burden of various non-communicable diseases (14, 62, 63). Exposure to green space reduces stress, anxiety, depression, and various mental health issues (71). It also promotes social interaction and cohesion and improves social capital (72). Green space also reduces heat and air pollution, impacting environmental health (73). Last but not least, the presence of green space improves real estate values (74) and provides opportunities for jobs and small businesses (72). All these outcomes interact to contribute to individual and community QoL, but research is warranted to examine these different pathways in a synergistic and systems framework.

This study could be beneficial to urban planners and policymakers looking to revitalize or future-proof urban environments. Currently, there is a rise in investment in urban green space to create more equitable parks, with special attention paid to building new parks or renovating existing parks in low-income neighborhoods (75). It is essential to understand a community's perception of parks during redesign and renovation. For instance, in recent years, the City of Chicago has also invested more than US$44 million to repair over 300 playgrounds. Interestingly, the Chicago experience showed that the renovation led to increased park use in higher-income neighborhoods, suggesting the impact might not have been equitable and those future efforts would need to do better in aligning park redesign with community preferences and participation (76). These lessons were shared in New York City, where since 2014, the NYC Department of Parks and Recreation has been implementing the Community Parks Initiative, investing over US$300 million to redesign and renovate 67 small parks in underserved neighborhoods (77). As part of the process, the city organized community input meetings to understand the needs of diverse potential park users. Building on this effort, our team is now deepening the engagement with select communities to co-design park-based strategies to further enhance the social environment of neighborhoods that have recently experienced park renovation.

The primary limitation of our study is that it was cross-sectional. Therefore, caution should be taken in inferring causality. Future longitudinal studies could be helpful to examine cause-and-effect and to determine if our findings hold over time. Second, our study did not examine the multiple pathways that parks could influence QoL. However, this paper sets the stage for future research that can account for the diverse synergistic framework described by the World Health Organization (72). In addition, our study was conducted in NYC, which can be quite different than other cities in the US and globally. Thus, the generalization of our findings to other locales may be limited. Lastly, we would like to acknowledge that our study population was mostly female (∼82%). Future research will need to examine whether there are gender differences in the relationship between parks and QoL.

Nevertheless, our study also has many strengths. First, in light of the issue of environmental and health equity, we specifically undertook our study in low-income, minoritized communities, making an important contribution to the limited literature on the topics of parks and QoL in underserved populations. In addition, the use of SEM in this area of inquiry was novel and allowed us to test the effect of multiple pathways involving latent constructs simultaneously (33, 35). Last but not least, our paper makes an important contribution by establishing the important role of park perception in health beyond park access or use.

5. Conclusions

In conclusion, we showed that both the perception and frequency of use of parks are important to QoL. However, our findings also suggest that having quality parks in a neighborhood could be broadly beneficial to community residents, even beyond frequency of use. This finding strongly supports the investment in community parks, as all residents may benefit from such investment, not just regular park users. In addition, our study showed that stress reduction may be an important mechanism for the effect of park perception on QoL, but that it may not play a role in associations between park use and QoL. Nonetheless, our model suggests that this explanation may be incomplete, and more research is needed to further elucidate the ways in which park perception and park use contribute to QoL. With parks and QoL both at the forefront of policy discussions in the US and around the world, this study demonstrates that these two factors are indeed connected and suggests that strategic investment in public parks can play a critical role in reducing inequities and improving the wellbeing of all residents.

Data availability statement

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

Ethics statement

The studies involving human participants were reviewed and approved by City University of New York Institutional Review Board (#2016-0248). The patients/participants provided their written informed consent to participate in this study.

Author contributions

HK: methodology, software, formal analysis, data curation, writing—original draft, and visualization. EF: writing—original draft. KW: supervision. KE and JD: writing—review and editing. LT: writing—review and editing and funding acquisition. TH: conceptualization, methodology, writing—review and editing, supervision, and funding acquisition. All authors contributed to the article and approved the submitted version.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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The built environment's nonlinear effects on the elderly's propensity to walk

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The increased ageing of the population is a vital and upcoming challenge for China. Walking is one of the easiest and most common forms of exercise for older people, and promoting walking among older people is important for reducing medical stress. Streetscape green visibility and the normalised difference vegetation index (NDVI) are perceptible architectural elements, both of which promote walking behaviour. Methodologically we used Baidu Street View images and extracted NDVI from streetscape green visibility and remote sensing to scrutinize the nonlinear effects of streetscape green visibility and NDVI on older people's walking behaviour. The study adopted a random forest machine learning model. The findings indicate that the impact of streetscape green visibility on elderly walking is superior to NDVI, while both have a favourable influence on senior walking propensity within a particular range but a negative effect on elderly walking inside that range. Overall the built environment had a non-linear effect on the propensity to walk of older people. Therefore, this study allows the calculation of optimal thresholds for the physical environment, which can be used by governments and planners to formulate policies and select appropriate environmental thresholds as indicators to update or build a community walking environment that meets the needs of local older people, depending on their own economic situation.

KEYWORDS

green visibility, built environment, walking, random forest, older people

1. Introduction

According to the results of China's seventh national census compared to 2010, the population aged 60 and over rose by 5.44 percentage points (Statistics NBo, 2021). These figures indicate that the proportion of the population aged 60 and over is increasing and that more and more middle-aged people are entering old age with the expectation of a longer life expectancy. The ageing of the population is becoming a growing problem and there is an urgent need to increase the independence and self-care of older people, as otherwise, the burden on society and healthcare will continue to increase.

The World Health Organization recommends that older people get at least 150 min of appropriate physical activity per week; walking is the simplest form of low-intensity physical activity for humans, and increasing the amount of time older people spend walking is beneficial for improving their own health status (Nordbakke and Schwanen, 2014). Encouraging older people to be active in walking for travel is an important means of keeping them fit and ensuring a better quality of life (Moniruzzaman and Páez, 2016; Curl and Mason, 2019). Also walking is a common mode of travel. Walking can also help people access their destinations in some situations that are not accessible by cars and transit (Cheng et al., 2019; Chen et al., 2021; Yang et al., 2022a, 2023a,b). Walking can also increase older people's sense of well-being and happiness by maintaining their independence through social participation (Nordbakke and Schwanen, 2014).

Research has shown that urban greenery plays a positive role in the walking time and propensity of elders (Lu et al., 2018). Assessing urban greening has been an important topic, and in the past urban greening assessments have tended to be flat, site surveys, aerial photography and satellite remote sensing images. These data images are often presented as bird's eye views and top views; however, these methods are too traditional and are not perceived by the population, ignoring the perceptions of the people themselves (Kang et al., 2020). Image analysis of urban street scenes is rapidly developing rapidly in new research; street images have been rapidly developed in recent years in the field of public health care, with results indicating that street images are more easily perceived by the population and can provide a more objective image of the greenery of the street (Zang et al., 2020). However, in cases where there are missing data in the street view images, an objective and comprehensive assessment can be made together with the remote sensing images.

According to extant research on the effect of socioeconomic and demographic factors and built environment features on older adults' walking behavior, environmental factors such as density, land use mix, and street connectivity are the most significant. Relatively few studies have explored the effect of greening on older adults' walking behavior, and those that do exist have assumed a linear connection between walking behavior and other environmental parameters (Yang et al., 2019, 2022b; Zang et al., 2020). Nevertheless, it has been demonstrated that the link between the built environment and the walking behavior of older adults may also be nonlinear (Ding et al., 2019; Liu et al., 2021). Peer effects may be used to explain the link between nonlinearity and walking. The main focus in the most recent studies has been on nonlinearity, where the nonlinear association between the built environment and the walking behavior of older people is analyzed. Only one of these studies has been conducted on the nonlinearity of green views on walking behavior, however. With a proper understanding of the substantive implications of the nonlinear benefits, there is a need for a more in-depth study of the nonlinearity between the built environment and walking behavior.

To investigate the above issues in more depth, we used 597 valid data from our research group's March 2021 survey of older people aged 65 and above in Guangzhou using the International Physical Ability Questionnaire (IPAQ), Baidu Street View (BSV) images and 2021 NDVI images to assess older people's willingness to walk and the propensity to green their environment, respectively. A random forest model was used to evaluate the effect of urban greening and street greening on older people's willingness to walk, while a binary logistic regression model was used and compared with the random forest model.

The main research objectives of this paper are as follows:

1. To fill the gap in the study of non-linear comparison between streetscape green visibility and NDVI.
2. To examine the nonlinear and threshold impacts of urban and streetscape vegetation on walking behavior.
3. To investigate the nonlinear and threshold impacts of internal environmental characteristics (e.g., Density, Design, Diversity etc. "3Ds") on older adults' walking behavior.

2. Literature review

Numerous experts have conducted studies on the built environment's effect on older adults. A search of the relevant literature in the Web of Science to retrieve nearly 17 relevant articles from 2005 to 2022. The papers were first filtered by topic and then manually filtered by the relevance of the abstract content to this study. Table 1 summarizes the screened research on the association between the built environment and older adults' walking behavior. The table does not present sociodemographic characteristics, but rather primarily reflects the built environment as the subject of subjective versus objective measures and as the variable that has received the most research attention to date.

Certain characteristics of the built environment (e.g., population density, land street connectivity, etc.) generally have consistent impacts. However, the results from practice (e.g., the effect of pedestrian facilities on walking) need more investigation due to disparities in prediction, control variables and study techniques.

Most of the research methods are geographically weighted regression models and are dominated by traditional linear regression and binary logistic regression, which have limitations. In a recent paper, Cheng et al. used a random forest model for modelling (Cheng et al., 2020). Compared to traditional geographically weighted regression models, this model is more accurate in predicting and confirming that the built environment influences older people to walk in a nonlinear way, but more research is needed to validate and add to the theory.

In the regions studied, North American cities have received more academic attention than South American cities, probably because the economies of North America are more developed. The European cities studied have been mainly in Belgium and the Netherlands, where ageing is relatively high, and to a lesser extent in Australia, probably because ageing is less of an issue in Australia. Over the recent decade, Asian cities (e.g., Harbin, Hong Kong, Nanjing, Zhongshan, and Guangzhou) have progressively migrated into the primary research area. The majority of Asian research was completed after 2010. Consequently, as a characteristic of the built environment, Zang et al. (2020) and have only recently focused on streetscape greenery. This is largely due to advances in greenery measurement techniques that enable accurate and efficient estimation of perceived greenery at eye height, as well as the provision of street view image data that is available for free from the map website. Most notably, such nonlinear impacts of the built environment on older adults' walking behavior have received less attention. Additionally, Cheng et al. (2020) and Van Cauwenberg et al. (2011) conducted a comprehensive review of prior studies on the influence of the built environment on older adults' walking behavior.

Through the above literature review and in the context of the medical pressures of ageing that China is facing, it is important to identify the nonlinear effect of greening on the propensity of older people in China to walk for 10 min, which will help to verify whether the findings of previous studies are applicable in China and to fill in the research gap on the correlation between greening and the propensity to walk.

3. Data and method

3.1. Research program

This research is based on a random intercept around the community that was chosen to reflect the various population density zonings of Guangzhou City Planning zones in the surrounding community. Density zones 1, 2, and 3 correspond to low-, medium-, and high-density regions in this article. According to the March 2021 price sample, there are six groups: low socioeconomic status (SES), high SES, low SES, >30,000 RMB/m2 and high SES. Ages 65–74, 74–84, and 85 and above were considered. To eliminate seasonal impacts, respondents were questioned in the spring. The survey took into account sociodemographic variables (e.g., employment, age, and level of

TABLE 1 Summary of studies on the built environment's effect on walking for older adults.

Reference	Context/ Walking behaviour measure(s)	Sample	Built environment measures	Modelling approach	Conclusion
Mendes de Leon et al. (2009)	Chicago, U. S./ Walking time	4,317 people aged ≥65	Disorder in the neighbourhood (e.g., litter, trash, vandalism, and broken sidewalks)	Multilevel linear regression model	The neighbourhood level was disordered (all $p > 0.10$) and was significantly associated with walking, independent of other correlates of neighbourhood perceptions and walking at the individual level ($\beta = -1.46$, $p = 0.08$). Further adjustment for ethnicity weakened this association to a marginally significant level. Neighbourhood conditions may influence older people's walking behaviour ($\beta = -2.35$, $p = 0.01$), particularly conditions reflecting physical neglect or social threat. Promoting walking behaviour in older people may require improvements in the safety and maintenance of the neighbourhood environment.
Procter-Gray et al. (2015)	Boston, U.S./ Transport walking time and recreational walking time	745 people aged ≥70	Access to the bus, hospital, etc.	Logistic regression model	Across the 16 communities in the study area, the prevalence of recreational walking was relatively uniform, while the prevalence of utilitarian walking varied. Both types of walking were associated with personal health and physical ability (AREA = 0.56, $p < 0.001$). However, utilitarian walking was also strongly associated with community socio-economic status and several measures of access to amenities, whereas recreational walking was not. Utilitarian walking is strongly influenced by the community environment, but intrinsic factors may be more important for recreational walking.
Shigematsu et al. (2009)	King County/ Seattle, U.S./ Transport walking propensity and recreational walking propensity	360 people aged ≥66	Population density, street connectivity, etc.	Partial correlation analysis	Walking for transportation was significantly associated with a wide range of perceived neighbourhood attributes in all age groups, but not walking for recreation. In the youngest age group, walking for transport was significantly related to almost all neighbourhood environmental variables. In contrast, in the two oldest groups, only two environmental attributes, proximity to non-residential uses (e.g., shops) and recreational facilities, were moderately associated with walking for transport. The availability of non-residential destinations and recreational facilities within walking distance may be among the most important attributes supporting physical activity among older people.
Maisel (2016)	New York, U.S./ Walking time	121 people aged ≥65	Population density, land use mix, street connection, and so forth.	Spearman rank correlation analysis	Perceptions of street connectivity, crime and traffic safety, and overall satisfaction were associated with specific types of walking behaviour, and the strength of this relationship varied by community type. Sociodemographic variables, such as age and gender, were associated with certain types and amounts of walking behaviour among older people, including in each community type. The importance of perceived street connectivity, regardless of community type, and the impact of perceived crime safety in rural communities on older people's walking behaviour.
Barnes et al. (2016)	British Columbia, Canada/Transport walking propensity	3,860 people aged ≥45	Access to public transportation and walkability	Logistic regression model	The 34% increase in odds of walking to travel (OR = 1.34; 95% CI: 1.23, 1.47) and the 28% increase in odds of using public transport (OR = 1.28; 95% CI: 1.17, 1.40) were associated. People in communities with excellent transit/passenger haven were more than three and a half times more likely to walk to transit and three and a half times more likely to use public transportation compared to communities with minimal transit/partial transit ($p < 0.005$). Stronger associations were observed between transit scores and active transportation in the older population and between walking scores and transit walking in the non-retired population.
Moniruzzaman and Páez (2016)	Montreal, Canada/ Walking propensity	31,631 one-way home-based trips made by people aged ≥55	Population density, employment density, etc.	Logistic regression model	Twenty-nine items were tabulated and tested. 13 items negated the original assumption of independence at $p < 0.05$. These locations were then targeted for walkability audits. A walkability audit of 403 streets was used to demonstrate this concept. The items audited were summarised in a contingency table and independent chi-square tests were used to identify streetscape elements associated with pedestrian traffic.
Neves et al. (2021)	São Paulo, Brazil/ Walking options	12,000 people aged ≥60 years	Population density, origins, and accessibility to destinations, etc.	Logistic regression model	Applying a traditional logit model, the results are that for the city of São Paulo, the built environment variable is more relevant to the place of departure $p < 0.05$, and the dimension most relevant to the choice of walking is diversity, probably due to socio-economic reasons. Individual characteristics also had a significant effect, along with age, gender and income, which must be taken into account when developing local public policy to encourage walking.

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Reference	Context/ Walking behaviour measure(s)	Sample	Built environment measures	Modelling approach	Conclusion
Etman et al. (2014)	Spijkenisse, Rotterdam, the Netherlands/ Walking time	408 people aged ≥65	Access to functional characteristics, aesthetics, and destination accessibility, etc.	Linear regression model	Increases in infrastructure (e.g., presence of pavements and benches) in the 400 m buffer, urban tidiness (e.g., absence of litter and graffiti) in the 800 and 1,200 m buffers, and an additional destination in the 400 and 800 m buffers were associated with more transit-oriented walking (CI 1.07–7.32; $p < 0.05$). No differences were found between frail and non-frail older people.
Van Holle et al. (2016)	Ghent, Belgium/ Transport walking time	438 people aged ≥65	Land use mix, street connection, and walkability, etc.	Multilevel linear regression model	Neighbourhood walkability did not moderate the association between physical function and MVPA. In low-income neighbourhoods, the relationship between physical functioning and MVPA was not moderated ($p = 0.769$); there was a strong overall positive association between physical functioning and accelerometer-based MVPA ($p < 0.001$), and only in high-income, high-walking neighbourhoods were higher physical functioning scores associated with higher levels of MVPA ($p < 0.001$).
Böcker et al. (2017)	Greater Rotterdam, the Netherlands/ Walking propensity	147 people aged ≥65	Diversification of buildings, coverage of green space, etc.	Logistic regression model	The transport needs of older people are crucial. Recognise the mobility needs of older people. As older people increasingly As older people increasingly use cars, encourage older people to use more physically active and environmentally friendly modes of transport, such as cycling. Due to the increasing use of cars by older people.
Nguyen and Mertens (2021)	Belgium/Transport walking time	503 people aged ≥65	Park density, public transport density, intersection density, etc.	Negative binomial regression model	Older people living in environments with higher residential density, higher park density, lower public transport density and higher entropy index have higher levels of active transport ($p = 0.046$). In addition, the different types of neighbourhoods in which older people live lead to different moderating factors that play a decisive role in increasing active transport behaviour among older people ($p = 0.015$).
Boruff et al. (2012)	Perth, Australia/ Walking trip frequency	325 people living in 32 retirement villages	Land-use exposure	Logistic regression model	Differences in built environment characteristics were found within the newly created 'neighbourhoods' ($p = 0.024$). Exposure measures derived from alternative buffering techniques provided a better fit when examining the relationship between land use and walking for transit or recreation ($p = 0.024$). The size and orientation of buffers influenced the relationship between built environment measures and recreational walking for older people ($p = 0.066$).
Ghani et al. (2018)	Brisbane, Australia/ Transport walking duration	11,035 people aged 58 to 65	Population density, connection of streets, etc.	Multilevel binary logistic regression model	A relatively limited role was played in terms of neighbourhood differences in the relationship between age and walking. Residential density and street connectivity explained 13 and 9% of the inter-neighbourhood variation in WfT for each age group, respectively. Older people were more sensitive to their neighbourhood environment. Age differences in WfT were smaller in areas with higher residential density and street connectivity.
Cheng et al. (2020)	Nanjing, China/ Walking time	702 people aged ≥60	Population density, land use mix, street connectivity, the total number of bus stations, the total number of bike-sharing stations, the distance to the closest square/park, the distance to the closest card/chess room.	Random Forest Model	All the built environment attributes analysed tend to have prominent non-linear and threshold effects on walking times. The combination of population density and land use can only increase walking by older people to a certain extent. Areas with too high a population density and an excessive mix of land uses can even lead to a reduction in walking. Thus, interventions in the built environment are only effective up to a certain point.

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TABLE 1 (Continued)

Reference	Context/ Walking behaviour measure(s)	Sample	Built environment measures	Modelling approach	Conclusion
Yang et al. (2021)	Hong Kong, China/Walking propensity	101,385 people aged ≥60	Population density, land use mix, intersection density, the proximity of bus stations, availability of recreational amenities greenery in public spaces.	Random Forest Model	Streetscape greenery has the second highest relative importance (12.82%), surpassed only by age (16.65%). Streetscape greenery has a positive effect on propensity to walk within a certain range, but outside of that range the positive association no longer holds. Non-linear associations were also investigated for other built environment attributes.
Cheng et al. (2021)	Nanjing, China/ Walking time	702 people aged ≥60	Population density, land use mix, connection of streets the quantity of bus stations, the number of stations for bike sharing, the distance to the closest square/ park, the distance to the closest card/ chess room	Global Moran's I test model	There is spatial heterogeneity in built environment effects across the study area. It affects all relationships, with subtle differences in significance levels, parameter sizes or sign reversals, depending on location. As a result, policy interventions will only be effective in certain areas for certain built environment attributes. Spatial heterogeneity stems from contextual effects, i.e., the specificity of places with a discriminatory composition of individual and/or environmental characteristics.
Wu et al. (2021)	Zhong shan, China/Walking frequency	4,784 people aged ≥60	Population density, residential density, density of sidewalks, density of road network, density of bus stations, accessibility for commercial purposes, distance from the centre, mixture, greenspace.	The Semiparametric GAMM as penalized generalised linear models	Non-linear relationships exist for five of the six built environment characteristics. Within certain thresholds, population density, pavement density, bus stop density, land use mix and percentage of green space were positively correlated with walking trips by older people. In addition, land use mix and percentage of green space showed an inverse 'V' shaped relationship. Built environment features can support or hinder the frequency of walking by older people. This is a good guide to cost effectiveness.
Zang et al. (2021)	Guang zhou China/Walking time	597 people aged ≥60	population density, land use mix, street connection.	Global Moran's I test model	Land use mix and NDVI were positively correlated with traffic walking in low density areas, and traffic walking was negatively correlated with road intermediary centrality (BtE) and point of interest (PoI) density. In addition, recreational walking in medium density areas was negatively correlated with self-rated health, road intersection density and PoI density. Street connectivity, road intersection density, DNVI and recreational walking in high density areas showed negative correlations.

education) as well as travel information (e.g., frequency of walking trips, broad questions related to walking time). We pooled the collected data of 600 older adults to increase the sample size, and after eliminating incomplete data records, we obtained a random group of 597 older adults in Guangzhou (see Figure 1).

The preliminary analysis of the 12 sample regions revealed considerable disparities in the built environment between low and high socioeconomic status districts in Guangzhou. To achieve appropriate impartiality and to avoid the model that ignores specific environmental factors from the computations, we simulated and computed the low- and high-SES regions evenly. The chosen sample locations are summarized in Figure 1.

The International Physical Activity Questionnaire-Long Version (IPAQ-LC) was used to categorize respondents' desire to walk in the questionnaire according to the purpose of the interview. All respondents were divided into two groups: those who had some willingness to walk within 24 h (whether walking = 1) and those who did not (whether walking = 0), with the willingness to walk per person as the predictor variable. Additionally, areas beyond the residential context (greater than 1,000 m) were omitted.

3.2. Streetscape greenery and NDVI

The static 360° street-view picture covers a larger geographic area, has fewer data mistakes, is more cost- and time-efficient, and is sampled by humans more than standard data sources (Kang et al., 2020). In comparison to Google Street-view (GSV), Baidu Street-view (BSV) is more China-centric, with picture data spanning all major cities in the country and gathered by sensor automobiles equipped with GPS devices assuring both accuracy and timeliness.

Using BSV images, a streetscape greenery index with a highly similar perspective to the human eye was obtained, which reflects the degree of greenery directly acquired by the human eye. The method is as follows. First, the coordinates are geocoded into ArcGIS software based on the subdivisions of the sampled elderly sample areas. A 1,000 m buffer zone is drawn based on the boundaries of the sample, and all primary to tertiary streets within the 1,000 m range are sampled and recorded, after which a fixed 50 m spacing is taken to generate sampling points in all streets within the buffer zone. A total of 40,000 BSV images are downloaded from the Baidu Maps developer platform for static map API download. For each location point, four images were sampled at 90, 180, 270, and 360° each to represent the 360° panorama image (Long et al., 2015; Zang et al., 2020; see Figure 2). The BSV-generated streetscape greening was calculated as follows:

$$Green\ view\ index = \frac{\sum_{i=1}^{4} Greenery\ pixels_i}{\sum_{i=1}^{4} Total\ pixels_i}$$

The NDVI normalized difference vegetation index (Tucker, 1979) can be used as a complement to green plant visibility where streetscape map coverage is incomplete to represent the chlorophyll content of the area in which it is located (Helbich, 2019). In secondary and tertiary roads relatively far from the main urban area, streetscape data are missing; in green sight assessment, NDVI, although not the most direct reflection of human vision to the same extent as streetscape, is the best data supplement in the absence of data. To provide a more objective assessment of the environment in the sample area, we used a map of Guangzhou city with an accuracy of 10 m extracted from remote sensing in August 2021 as a base map and calculated the pigment absorption of chlorophyll in the red band and the high reflection of vegetation in the near-infrared (NIR) band (see Figure 3). The formula for calculating NDVI is as follows:

$$NDVI = \frac{(NIR - R)}{(NIR + R)}$$

3.3. Variables

The prediction variables used were two minimal sociodemographic characteristics and nine variables relating to the built environment, with the exception of the streetscape and greenery variables, where we focused on seven environmental variables developed under the '3D' built environment assessment framework (Zang et al., 2019). All environmental variables were measured within ArcGIS software using geographic data from the national geographic information service platform SkyMap.[1]

Table 2 presents descriptive statistics for the predictor and predictive variables, from which it can be seen that 75% of the older adults did at least some walking in the 24-h period. The other 25% of older people did not walk.

3.4. Methodology

Random forests (a.k.a., random decision forests) are currently one of the most popular and effective computer learning algorithms in international competitions (Sagi and Rokach, 2020) and can perform data mining, classification and regression tasks and explain finer correlations between variables. This excellent machine learning algorithm was first proposed in 1995 by Tin (1995), and the "Stochastic Decision Forest" (Tin, 1998) constructed a forest comprised of several decision trees for classification and regression.

The random forest approach shown in Figure 4 combines the ease of a decision tree with the restriction to a subset of the sample's test and predictor variables. Random forests algorithmically reduce the variance and coordinate multiple decision trees together to optimize the model (Breiman, 2001), thus solving the overfitting challenge. The objective is to minimize the loss function and verify the accuracy of the findings by iteratively assessing the test and prediction sets using their own method until the loss function achieves a minimal value or stays stable. The random forest is made up of an infinite number of decision trees and works, as shown in Figure 4. To ensure the variety of the decision trees, two randomness tree treatments are applied. First, the training data are structured in such a way that each tree develops with a unique subsample. Second, features are randomly chosen to produce distinct groups of explanatory variables from which to divide the tree's nodes. Splitting continues in a single decision tree until the maximum tree depth is achieved. Based on the average answer of each location, a

1 https://www.tianditu.gov.cn/

single forecast is created. By averaging the predictions of all individual decision trees, the ultimate result is achieved.

Three factors significantly affect the forecasting effectiveness of random forest algorithms (Cheng et al., 2019); first, improving the accuracy of individual trees and second, reducing the similarity of each tree. Finally, we need to parameterize the whole model, most notably three parameters (Claesen and Moor, 2015): the tree's greatest depth, its total number of trees, and the number of splits. Random forest parameters are manually and continually checked to determine the optimal values. Most other machine learning approaches, including random forests, do not yield t statistics, *p* values, or other markers of statistical significance. However, the random forest can calculate the relative importance of variables and then visualize it with the following formula for the importance of variable x.

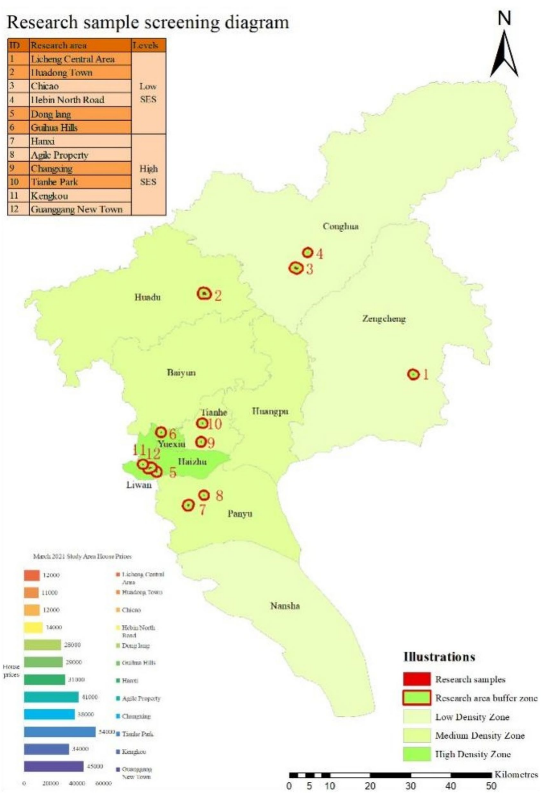

FIGURE 1
Research sample screening diagram.

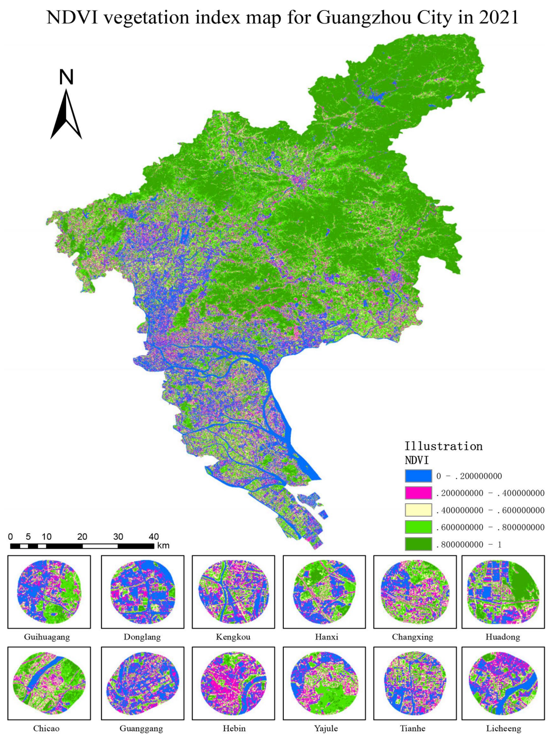

FIGURE 3
NDVI normalized difference vegetation index (NDVI) map for Guangzhou in 2021.

FIGURE 2
A random forest technique example.

TABLE 2 Summary statistics and descriptions of the predicted and predictor factors.

Variable	Description	Mean/Percentage	Std. Dev.
Predicted variable			
Walking propensity	Indicator variable = 1 if you walked on the reference day; = 0 otherwise.	0.75	0.43
Predictor variables: sociodemographics			
Age	Older people aged 65–74 (0: No; 1: Yes)	0.87	0.34
	Older people aged 74–84 (0: No; 1: Yes)	0.12	0.32
	Older people aged >85(0: No; 1: Yes)	0.02	0.12
Education level	Higher-educated respondents (0: No; 1: Yes)	0.13	0.34
	Secondary education respondents (0: No; 1: Yes)	0.77	0.42
	Less-educated respondents (0: No; 1: Yes)	0.1	0.30
Predictor variables: built environment			
Population density	Within the neighbourhood, population density is measured in terms of 100 persons per km^2.	1.24	1.04
Land-use density	Entropy for local land uses $H = -\left[\sum_{I=1}^{N} P_I * \ln(P_I)\right] / \ln(N)$, where pi represents the percentage of the i -th land use and N represents the total number of land use categories. Three land uses are studied in this research (N = 7): residential, office, commercial, medical, entertainment, public services, and education.	0.46	0.17
Street connectivity	Total sidewalk length/Total built-up area in a buffer zone (km/km^2)	1.74	0.18
Road intersection density	Within a density community at a street intersection (Unit: 1 km^2)	106.33	52.00
Number of bus stations	The total number of bus stations inside a 1Km buffer zone.	20.07	13.55
Bus stop distance	The shortest distance from the sample plot to the bus stop	229.56	186.404
NDVI	Difference between the NIR and red areas in terms of reflectance/Sum of the NIR and red regions in terms of reflection.	0.41	0.08
Streetscape green visibility	The green view index is determined by dividing the total number of pixels by the fraction of greenery pixels.	0.20	0.06
Sample size	597		

$$VI_{xi} = \frac{1}{N}\sum_{t}\left(OOB_{MSE}^{t} - OOB_{MSE,perm_i}^{t}\right)$$

where VI_{xi} is the importance of the variable, the total number of decision trees in a random forest model is denoted by N , OOB_{MSE}^{t} denotes the mean squared error t before the variables are ranked in the decision tree, and t , $OOB_{MSE,perm_i}^{t}$ denotes the mean squared error x_i after the variables are ranked (Breiman, 2001).

In contrast to standard regression-based statistical studies, which predetermine the (often linear) connections between predictor and predictor variables, random forest does not make these assumptions. Additionally, depending on the degree of the predictor variable, hypothetical random forest modelling generates partial dependency plots (PDPs) to illustrate the link between the test and predictor factors (Pedregosa et al., 2011). The equation for partial dependence is as follows:

$$\hat{f}_s(x_s) = \frac{1}{N}\sum_{i=1}^{N}\hat{f}(x_s, x_{ic})$$

where x_{ic} is the x_c value of the variable for the modelled dataset and N denotes the number of occurrences. The graph demonstrates how the built environment's influence on walking time is constant over a variety of nonlinear connections (Buitinck et al., 2013).

Prior to modelling, the independent variables were first checked for multicollinearity analysis, with all sociodemographic and environmental variables satisfying VIF < 5, ensuring that all variables were free of multicollinearity. For the purpose of random forest model pair optimization, a range of these three parameters was first determined (maximum tree depth is between 1 and 20, the number of features per tree is between 2 and 6, and between 10 and 1,000, and there is one interval per 10 trees). Second, we estimated a total of 8,000 (=20 × 4 × 100) potential combinations and used Area Under Curve (AUC) to evaluate model performance (Lee, 2019). After 900,000 tests, we discovered that the model stopped developing quarterly at a maximum tree depth of 8, a feature count of 4, and a tree count of 830, even though the root mean square deviation values were low and the model functioned well. Finally, the model was applied for further analysis.

3.5. Comparative analysis of random forest and binary logistic modelling

We evaluated the performance of random forest and binary logic modelling using tenfold cross-validation. Three common

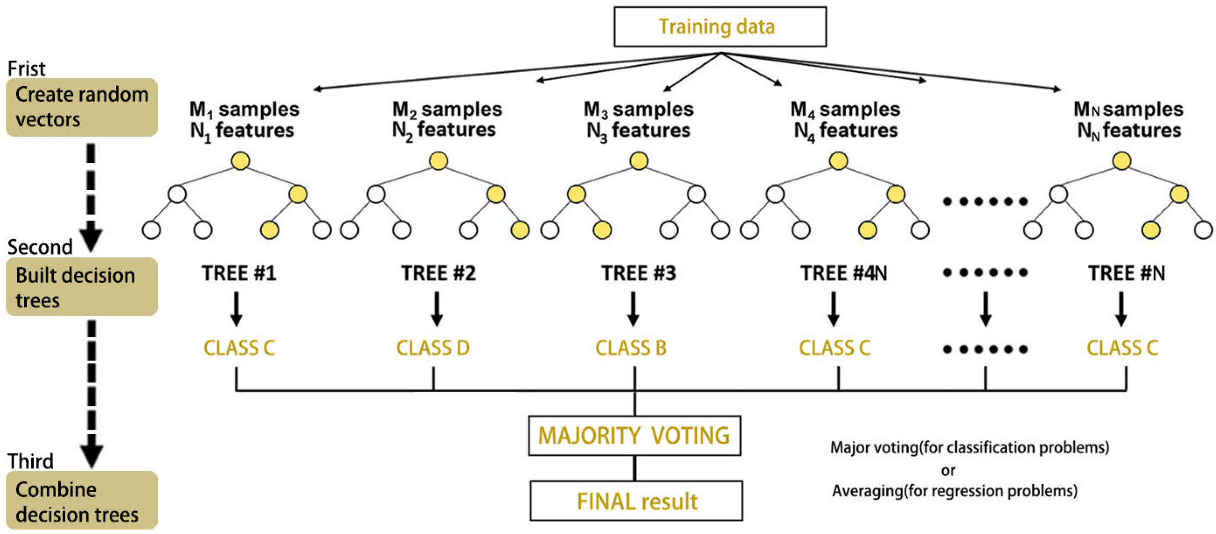

FIGURE 4
Depiction of the BSV-based method for estimating streetscape greenery at eye level.

classification metrics were used, namely, model accuracy, mean squared error and mean squared error. These three metrics were calculated as follows:

$$Accuracy = \frac{\sum_{i=1}^{N} TP_i + TN_i}{\sum_{i=1}^{N} TP_i + FN_i + FP_i + FPN_i}$$

$$MAE = \frac{1}{N}\sum_{I=1}^{N}\left(\hat{y}_i - y_i\right)^2$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(\hat{y}_i - y_i\right)^2}$$

where Accuracy denotes the ratio of properly predicted samples to total predicted samples, *N* is the number of samples in the validation set, *TPi* denotes the number of correctly predicted samples (predicted walking tendency is True and actual walking tendency is also True), *TNi* is interpreted as (predicted walking tendency is False and actual walking tendency is also False), *FPi* is interpreted as (predicted walking tendency is True but predicted walking tendency is False), and *FNi* is interpreted as (predicted walking tendency is True 1 but actual walking tendency is Ture).

In the MAE and RMSE equations, N denotes the total number of respondents in the validation set, yi denotes the sample's projected propensity to walk, and y_i is the sample's actual propensity to walk; the lower the values of these two equations are, the more evidence of a more accurate model. The results of 10 cross-validations of the two models are shown in Table 3. All three metrics demonstrate that the random forest model beats the classic binary logistic regression equation and is more adaptable in its nonlinear performance (Zang et al., 2022).

TABLE 3 Comparison of random forest versus binary logistic regression results.

Model	Accuracy	MAE	RMSE
Random forest	0.67	0.23	0.41
Model logistico-binary	0.60	0.37	0.44

4. Result

4.1. Predictor variables' relative relevance

The relative relevance of the predictor factors is shown in Table 4, and their ordering is shown in Figure 5. The other '3DS' environmental factors are similarly extremely highly placed in the top five in terms of overall relative significance, ranging from (9.80–12.65%); it is worth noting that NDVI is ranked relatively low at number seven, with a value of (8.83%), suggesting that streetscape greenery has more influence on the propensity to walk than NDVI.

Environmental variables accounted for 82.92% of the total importance, while sociodemographic variables accounted for only 17.08%. This indicates that built environment characteristics significantly influence older persons' proclivity to walk, which is consistent with the results of Cheng et al. (2020) and Yang et al. (2021), who also studied the relationship between older adults and walking in Nanjing, China and Hong Kong, China, where built environment factors dominated in a nonlinear model. This result also complements the findings in the European and North American samples, where built environment variables had a greater impact on walking than sociodemographic variables (Gim, 2013; Wang and Ozbilen, 2020; Yu et al., 2021).

4.2. Nonlinear effect of streetscape green visibility and NDVI

As illustrated visually in Figures 6A,B, the random forest results for the predictor variables used to calculate PDPs illustrate the nonlinear

TABLE 4 The random forest algorithm calculates the relative relevance of predictor variables.

Variable category	Variable	Rank	Relative importance (%)	Total (%)
Sociodemographics				17.08
	Age	10	6.51	
	Education level	4	10.57	
Built environment				82.92
	Population density	5	9.80	
	Land-use density	2	12.65	
	Street connectivity	8	8.23	
	Road intersection density	3	10.70	
	Number of bus stations	6	8.97	
	Bus stop distance	9	7.99	
	NDVI	7	8.83	
	Streetscape green visibility	1	15.74	
Total relative importance				100

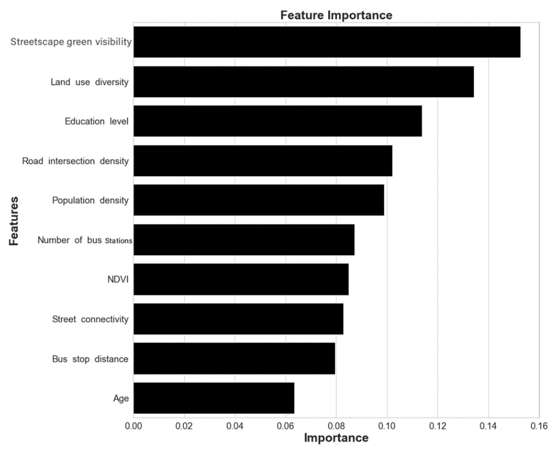

FIGURE 5
Predictor variables' relative relevance.

relationship between streetscape greenness and propensity to walk, where the x-axis represents the distribution of the predictor variables, the y-axis represents propensity to walk, the black line represents the predicted outcome, and the red line represents the smoothed curve of the predicted outcome. The smoothed curve may be used to more intuitively represent the trend of the expected outcomes (Tao et al., 2020).

The impact of streetscape green visibility on older adults' proclivity to walk is seen in Figure 6A. As the first environmental factor to influence the propensity to walk, its predictive index peaks at less than 0.24 and is positively correlated with the propensity to walk, with a decreasing trend line when green visibility exceeds 0.24, a finding consistent with related research findings (Yang et al., 2021). The impact of the streetscape green visibility is relatively limited, and when it reaches 0.24, a further increase in the streetscape green visibility does not increase the propensity of older people to walk.

Figure 6B shows the effect of NDVI on the propensity to walk of older people, peaking at an NDVI of 0.45, which is positively correlated with propensity to walk when the predicted index is less than 0.45 and negatively correlated with propensity to walk when the predicted index is above 0.45. One interpretation is that vegetation cover is already high when the NDVI is 0.45, and when the vegetation index increases further, its walkability visibility and environmental confinement also increase, and walkability decreases. Although the NDVI is not as important as the streetscape green visibility, it is a good guide to the propensity to walk.

4.3. Nonlinear effects of other built-environment variables

Figures 6C–H represent PDPs for other built environment variables. 5c shows a negative correlation between the population density predictive index and propensity to walk at less than 3.6, with population density having a negative effect on the propensity to walk, possibly indicating that more developed places with higher population density in the sample area are becoming less attractive to older people. This result is not very consistent with existing studies (Cheng et al., 2020; Yang et al., 2021). The shaky curve decreases faster when the walking index is 2, which may be due to older people disliking densely populated areas and preferring to walk in sparsely populated, quiet places.

The impact of land use mix on the inclination to walk is seen in Figure 6D, with a positive effect when the projected index of land use mix is smaller than 0.45, a result that is consistent with some of the literature results (Cerin et al., 2017; Cheng et al., 2020; Yang et al., 2021), where an appropriate land use mix of 0.45 provides a richer functional need and a stimulus for walking. A predictive index greater than 0.45 is negatively correlated with the propensity to walk, i.e., a high land use mix does not create a positive environment for walking.

Figures 6E,F show the nonlinear effects of road intersection density as well as street connectivity on the propensity to walk. Figure 6E predicts a positive correlation with the propensity to walk from 0 km–200 km, consistent with existing studies (Cheng et al., 2020). 在 For the time being no adverse effects on walking were found within the study area, which may be related to the urban infrastructure development. The sample area does not have a higher

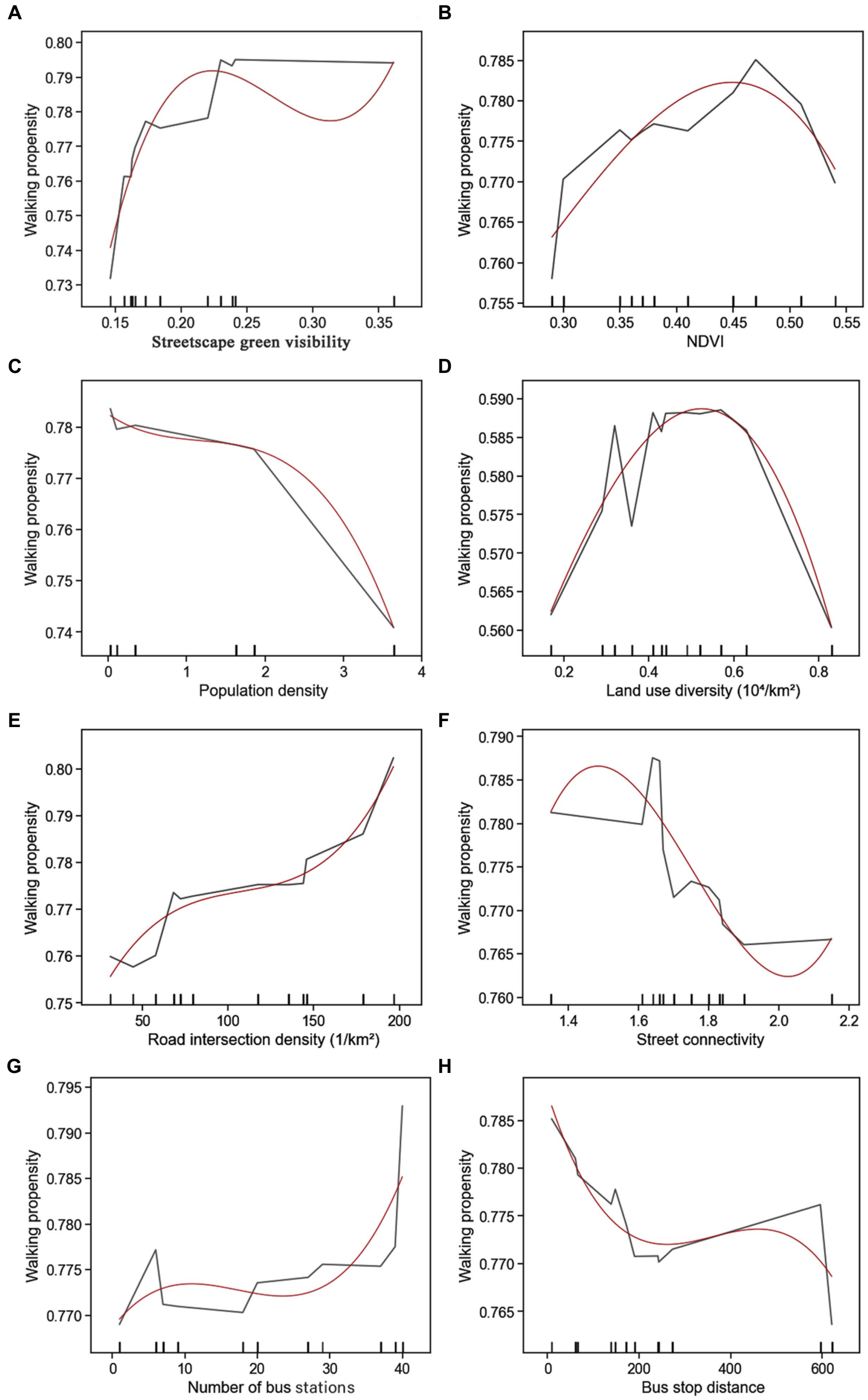

FIGURE 6
(A–H) The nonlinear effect of built-environment characteristics on walking proclivity.

denser road network to predict the effect of higher density road intersections on the propensity to walk, and it is not possible to confirm the research theory of Yang et al. (2021). The nonlinear effect of Figure 6F is more apparent when the predicted value of street connectivity is less than 0.15 and is positively correlated with propensity to walk and negatively correlated with propensity to walk in the range of 0.15–2.0. This may be because when connectivity is too high, it means that road junctions become complex and the elderly are less safe crossing the road, resulting in less walkability. Thus, while contemplating the addition of more road junctions, it is critical to examine the complexity of the intersections to create a more pleasant walking environment.

The nonlinear impacts of the number of bus stations and the shortest distance to the bus stop are shown in Figures 6G,H, as predicted from both the findings and Cheng and Yang's research. All of the projected outcomes are positively associated with a proclivity to walk.

5. Discussion and conclusion

In the context of China's growing ageing problem, it is important to build more walkable community environments. Walking allows older people to maintain their health status better, and it is necessary to promote walking frequency among older people through the environment. This study uses machine learning to calculate streetscape greenness and greenness indices through non-linear modelling to fill a gap in the non-linear influence of the Normalized Vegetation Variance Index (NDVI) on propensity to walk, complementing observations of the threshold influence of streetscape vegetation and internal features of the built environment on the propensity to walk of older people. Such comparisons have rarely been studied in the non-linear modelling literature. As a result (Statistics NBo, 2021), Streetscape Green Visibility is more perceived by older people than NDVI, and Streetscape Green Visibility is the most important (Nordbakke and Schwanen, 2014). Both Streetscape Green Visibility and NDVI have a nonlinear effect on walking propensity (Curl and Mason, 2019). When the predictive index of Green Streetscape Visibility is less than 0.24, it is favorably connected with walking propensity; however, when the predictive index is greater than 0.24, it has a negligible influence on walking propensity (Moniruzzaman and Páez, 2016). The built environment, such as 3Ds, also showed an effect on walking propensity in the nonlinear model.

In practice, it is more difficult to control the NDVI to a value of 0.45, as it is more macroscopic than the street-level green vision, whereas it is relatively easy to control the streetscape green visibility, with green pixels occupying 1/4 of the human eye's visual range to maximize the propensity for older people to walk. While it is important to use the NDVI as a criterion for assessment, it is also important to assess the streetscape greenness and walkability of a community from the perspective of the people themselves by taking photographs of the actual environment in a sample of the planned area. This will enable poorer neighborhoods to be optimized and avoid the unnecessary waste of human and material resources by overinvesting in greenery in existing good environments.

This research adopts a more scientific approach and relevance, and its findings will provide a scientific basis for policy-makers. Researchers can quantify the space, and previous research illustrates the existence of nonlinear effects of the built environment on human behavior. Research should focus on both linear research and nonlinear research. The use of machine learning helps researchers construct more complex models of the link between the built environment and behavior and to dig deeper into the results and conclusions. Additionally, this study is also a practice of a new approach, as the traditional linear system can only prove the link between two variables, but it is not easy to reflect the true complexity of the impact of the environment on the walking behavior of older adults. This study uses a nonlinear model to provide an optimal index of the physical environment, which avoids wasting resources. The Government can use these environmental thresholds to develop policies to regulate the use of green infrastructure, especially in less economically developed cities where the environmental thresholds have been shown to be lower than in developed cities, and should choose the appropriate environmental thresholds as indicators to update or build a community walking environment that meets the needs of the local elderly according to their own economic situation. The construction of a nature-centric green city is currently a significant trend in international urban planning, but due to the limitations of each city's position and its own economic development more research is urgently needed to help different cities tailor their own green-friendly city standards to maximize the efficiency of economic resource use, and this study provides a green construction indicator solution for other scholars to consider.

This study provides relatively new findings and proof of previous theories, offering new vivid ideas for future research. However, there are still limitations. First, Guangzhou is a first-tier city in China, a city with a relatively high mix of population and land use, and similar studies are currently available in Nanjing and Hong Kong; however, the nonlinear effects of the built environment on older people's propensity to walk need to be studied in more regions to confirm the applicability of the generalizations and transferability of the findings. Second, the built environment (streetscape green views and NDVI) has a good synergistic effect on promoting walking propensity. Third, as a data-driven approach, the random forest method used in this study relies on the relative importance of orthogonal decision edges and predictor variables, which may not find optimal partitioning. Therefore, the choice of independent variables should be reversed in that all factors of the dependent variable cannot be controlled for in the decision tree; therefore, the results are still biased. Fourth, in the actual walk, the elderly are experiencing a richer experience through the greenery, based on the streetscape green visibility not capturing all the perceptions of the elderly, with the development of science and technology and the relative maturity of the Unreal 5 engine, a relatively realistic scenario can be built and combined with wearable devices to assess the environmental conditions more deeply. Fifth, the study's nonlinearity and threshold effects provide critical insights for land use and transportation strategies aimed at encouraging older adults to walk.

Data availability statement

The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding author.

Ethics statement

Ethical approval was not required for the study involving human participants in accordance with the local legislation and institutional requirements.

Author contributions

PZ: conceptualization. HZ and FX: resources. KC and JM: supervision. HQ and YQ: validation. PZ and HQ: writing—original draft. KL and HG: writing—review and editing. All authors contributed to the article and approved the submitted version.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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Understanding the motivational mechanisms behind the usage frequency of ride-hailing during COVID-19 pandemic

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Introduction: This study aimed to explore the factors influencing people's utilization of ride-hailing services, particularly in the context of the COVID-19 pandemic.

Methods: A two-stage survey was conducted among the same group of passengers pre and post COVID-19 pandemic, resulting in a total of 670 valid samples. Exploratory factor analysis (EFA) was applied to the data, followed by the ordered probit and ordered logit models to identify the motivational factors behind passengers' frequency of using ride-hailing.

Results: The findings indicated that trust and loyalty were the most influential factors in determining passengers' frequency of using ride-hailing services. However, passengers' perception of the COVID-19 pandemic did not have a significant effect on the frequency of using ride-hailing.

Discussion: This research provides empirical evidence and policy implications for understanding people's usage of the ride-hailing services in the context of public-health emergency.

KEYWORDS

ride-hailing service, passengers' trust and loyalty, usage frequency, exploratory factor analysis, COVID-19 pandemic

1. Introduction

The utilization of mobile technology has had a considerable impact on the form of transportation services and the way passengers travel (1, 2). For instance, passengers can now use ride-hailing services to request a driver to pick them up at a specified location (3–6). This type of service is beneficial as it can save time for both passengers and drivers, as well as increase vehicle efficiency. Consequently, ride-hailing services have been adopted by many companies globally, such as Uber and Lyft (USA), Didi Chuxing (China), Ola (India), and Grab (Southeast Asia). Statistics indicate that ∼3.2 billion passengers have used ride-hailing services, which is comparable to the number of people using urban bus and rail systems (7). However, there are also divergent findings. For example, Pew Research Center (8) revealed that only 3% of their sample data (N = 4,787) used ride-hailing services on a daily basis, while the remaining 12% used these services once a week.

Studies found numerous factors influence passengers' ride-hailing frequency, for example: psychological factors. Septiani et al. (9) found factors of internal perception and innovation characteristic influence the behavioral intention of online transportation service. Similarly, Huynh et al. (10) found attitude and subjective norms influence passengers' intention to use Uber/Grab services.

1.1. Social factors

Nguyen-Phuoc et al. (11) found trust fully mediate the relationships between perceived booking app-related risks and satisfaction and loyalty.

1.2. Demographics factors

The female passengers are 28.51% higher than that of male passengers who use ride-hailing services (10). Older ride-hailing passengers make more transit trips than others (12). Alemi et al. (13) found that passengers with higher educational and income levels were more likely to utilize these services, due to their familiarity with new technologies and other attributes of vehicle ownership. Murphy and Feigon (14) showed that the most frequent users of on-demand ride-hailing services were those from middle-income families with annual incomes between 50,000 USD and 75,000 USD. Those who have a strong inclination toward using their own vehicle tend to use ride-hailing services less frequently (15).

1.3. Environment factors

There is a close relationship between different building environments and passengers' ride-hailing frequency. For example, building density has a significant inhibitory effect on ride-hailing trips (16). Moreover, environmental consciousness plays an important role in ride-hailing frequency of use (17).

However, so far, there have been limited studies on the factors affecting the usage frequency of ride-hailing services in developing countries, especially the quantitative analysis of the potential impact of these factors. In addition, the continuous success of ride-hailing services is accompanied by various challenges, such as passengers' trust and loyalty, which are essential for these companies in terms of market share and profits. The concept of customer loyalty was first proposed by Guest (18), referring to customers' long-term psychological attachment to the company's products. Later, Boulding et al. (19) showed that loyalty is expressed in customers' higher willingness to recommend the company's supplies. Ride-hailing services have the potential to reduce traffic and emissions by reducing car ownership (20, 21). However, the impact of passengers' trust and loyalty on the frequency of ride-hailing usage has not been fully explored (22). Studies have shown that trust can increase people's intention to use such services (23, 24). Previous research has mainly focused on passengers' trust and loyalty prior to adoption (25). There are discrepancies between passengers' initial adoption and their actual usage frequency (26–28). For example, passengers' initial adoption can be altered over time (28). Thus, it is essential for ride-hailing companies to understand the influence of trust and loyalty on the frequency of using ride-hailing services in order to meet passengers' needs.

Additionally, due to the COVID-19 pandemic, another new challenge arises for ride-hailing: the social environment changed dramatically. After the outbreak of the COVID-19 pandemic, the World Health Organization (WHO) encourages people to maintain physical distance to avoid the epidemic spreading. In December 2019, after the outbreak of COVID-19, the Chinese government encouraged residents to minimize travel, for security reasons. The transportation services market has shrunk significantly, and ride-hailing is inevitably affected (29). In addition, safety concerns during the pandemic become the key consideration of transportation services (30). Passengers' behavioral patterns including the usage frequency of ride-hailing changed under the influence of COVID-19 pandemic (31). Therefore, to better understand the passengers' behavioral change, this study conducted a two-stage survey among the same group of passengers in pre and post COVID-19 pandemic.

Overall, this study attempts to addresses the following questions:

(1) Do the passengers' trust and loyalty significantly affect the usage frequency of ride-hailing?
(2) What is the effect of COVID-19 pandemic on passengers' usage of ride-hailing?
(3) What other factors will affect how often people use ride-hailing?

In order to answer these questions, this research proposes a theoretical model (as shown in Figure 1) based on Kotler (32) in order to construct and validate a conceptual framework to explain the usage frequency of ride-hailing. Specifically, the exploratory factor analysis (EFA) is conducted to develop the ordered probit and ordered logit models to study the affecting factors of the usage frequency of ride-hailing. Methods section introduces the data and methods. Results section introduces the models' construction details and analysis results. Discussion section discusses the findings. Finally, Conclusion section draws the conclusions.

2. Methods

2.1. Data collection and descriptive statistics

The questionnaire survey was conducted through Sojump, a popular online survey platform in China, following a pre-test with 30 respondents to ensure its applicability. The survey was divided into two phases: the pre-epidemic phase (from December 2019 to January 2020, Phase-1), where COVID-19 was not yet widespread in China, and the post-epidemic phase (from August 2020 to September 2020, Phase-2), where the number of new cases per day was less than 20 and mostly imported from abroad, indicating the effective control of the epidemic. Figure 2 shows the newly confirmed cases of COVID-19 during the survey period in China.

This two-stage survey was conducted among the same group of participants. Initially, 800 questionnaires were collected in the Phase-1 survey. When the epidemic was under control, the Phase-2 survey was conducted, resulting in 694 questionnaires. After eliminating 24 ineffective questionnaires, 670 valid samples were recruited. The participants were asked to answer questions related to the usage of ride-hailing, including whether they had used ride-hailing, followed by social factors, psychological factors, personal factors and perception of the epidemic. The psychological factors and perception of the epidemic were measured using a five-level Likert scale, with "1" indicating "strongly disagree," "3" indicating "neutral," and "5" indicating "strongly agree".

The descriptive statistics about the sample are presented in Table 1. Participants included both students and the working population, which accounted for 39.48 and 57.49%, respectively. Males constitute 61.38% and females represent 38.62%. According to the report released by Aurora Big Data, in China, most of the

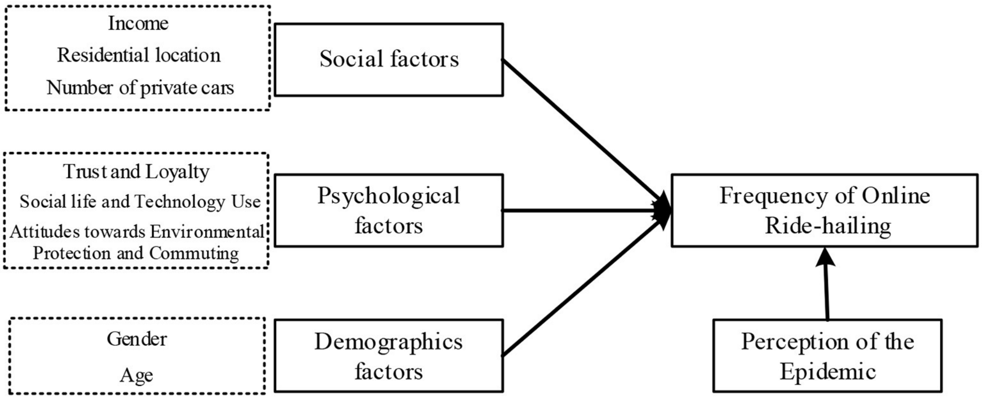

FIGURE 1
Typical factors selected in this research.

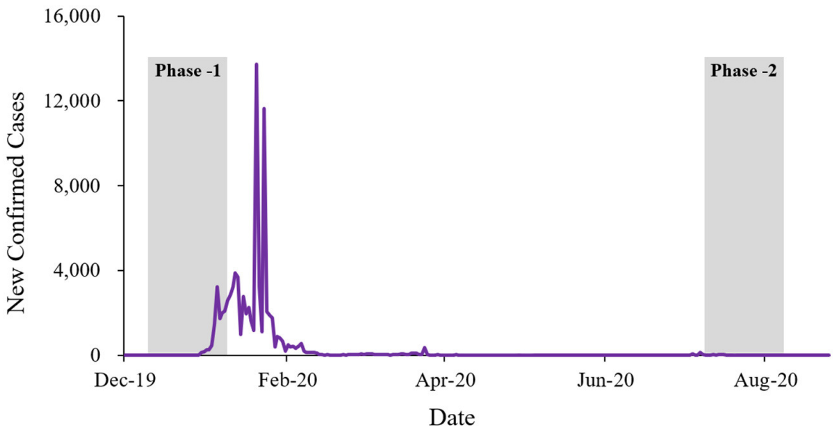

FIGURE 2
The new confirmed cases of COVID-19.

users of independent ride-hailing apps were male, and the proportion of male users of Shenzhou Special Car and Shouqi's ride-hailing apps has been close to 70%. Didi Chuxing has a relatively high proportion of female users of 41.1%. In addition, according to the report released by Aurora Big Data, Beijing, Hangzhou, Wuhan, Guangzhou, Dalian, Tianjin, Chengdu, Shenyang, Shenzhen, and Hefei have been the top ten most popular cities for ride-hailing in China. In our survey, participants from these ten cities accounting for 67% which indicate that the participants in our survey have a certain degree of representativeness.

2.2. Model development

2.2.1. Exploratory factor analysis

The use of Exploratory Factor Analysis (EFA) was employed to reduce the dimensions of the collected data. Studies have demonstrated that when multiple measurement variables are used to represent a common factor, EFA can provide more accurate results (33, 34). EFA is a method used to gain a better understanding of the relationships between a set of measured variables by determining the number and type of common factors that explain the correlation patterns. Thus, EFA can integrate variables with complex relationships into a few core factors.

2.2.2. Ordered probit model and ordered logit model

In regression models, the dependent variable is usually measured by a ratio scale. However, when the dependent variable is binary, sequence, or identifier, the ordinary least square method is no longer the best-unbiased estimator. Therefore, the ordered logit and ordered probit models in the discrete choice model are used to estimate the regression model of multiple ordered variables. These models are based on maximum likelihood estimation and assume that the random disturbance follows either a logistic or a multivariate normal distribution. Although the ordered probit model is more attractive in theory, it is difficult to prove that the dependent variable follows a normal logit distribution function or a standardized normal distribution function strictly. Thus, two regression methods are applied to the collected data to obtain a more reliable conclusion by comparing their results.

The basic principle of the ordered logit and ordered probit models is that there is an unobserved continuous variable Y^* that

TABLE 1 Demographics and socioeconomics of the sample.

Categorical variable	Category	Frequency	Percent (%)
Gender	Male	414	61.79
	Female	256	38.21
Age	Under 18	12	1.79
	18–24	338	50.45
	25–34	278	41.49
	35–41	33	4.93
	42 and above	9	1.34
State of life	Student	264	39.40
	Worker	391	58.36
	Else	15	2.24
Income per month (Yuan)	<3,000	208	31.04
	3,000–6,000	176	26.27
	6,000–10,000	208	31.04
	10,000–20,000	61	9.10
	>20,000	17	2.54
Education	Junior High school and below	18	2.69
	High School	147	21.94
	Bachelor's degree and junior college	335	50.00
	Post-graduate and above	170	25.37
Number of private cars	0	165	24.63
	1	435	64.93
	2 and above	70	10.45
Have Children (under 14 years old)	Yes	342	51.04
	No	328	48.96

satisfies the following relation:

$$Y^* = \sum \beta_j X_j + \varepsilon, \tag{1}$$

where Y denotes the latent variable indicating the frequency of people using the ride-hailing; X_j denotes the factor score of the impact factor obtained by the EFA; β_j denotes the unknown parameter that needs to be estimated; and ε represents the random error term. In this work, it was assumed that the mean of all error terms was zero and the error terms of different subjects were irrelevant. The relationship between the observed ordered variable Y and Y^* is as follows:

$$Y = \begin{cases} 1 \; if & -\infty < Y^* < k_1 \\ 2 \; if & k_1 < Y^* < k_2 \\ 3 \; if & k_2 < Y^* < k_3 \\ 4 \; if & k_3 < Y^* < k_4 \\ 5 \; if & k_4 < Y^* < \infty \end{cases}. \tag{2}$$

3. Results

3.1. Reliability test and EFA results

In order to reduce the influence of individual choice differences on the results, subjects whose current city and urban residential location remained constant between the two phases of the study were chosen. It was also determined that the time gap between the two questionnaires was too short for personal preferences to change significantly. Additionally, Cronbach's alpha coefficient of the questionnaires was calculated to be 0.953 and 0.954 for the first and second phases respectively, indicating a high reliability. Furthermore, the KMO values of the first and second phases were 0.949 and 0.950 respectively, both of which were larger than 0.7, thus demonstrating the suitability of the questionnaires for further analysis using EFA.

Subsequently, EFA was employed to identify independent regression variables and calculate factor scores. After data cleaning and preprocessing, the number of factors influencing personal attitudes before the epidemic was reduced from 49 to 23, which were organized into three groups: Attitudes to Environmental Protection and Commuting (ATT), Social Life and Technology

Use (SOC), and Passenger Trust and Loyalty (TRU). The latter refers to the passengers' loyalty to the ride-hailing service, not the third-party platforms providing the service. Similarly, the number of factors influencing personal attitudes after the epidemic was reduced from 53 to 29, which were organized into four groups: Attitudes to Environmental Protection and Commuting (ATT), Social Life and Technology Use (SOC), Passenger Trust and Loyalty (TRU), and Epidemic Impact (EPI). The results of the rotated component matrix before and after the epidemic are presented in Supplementary Tables A2, A3 in the Appendix, respectively, with factor loading coefficient values all greater than 0.5.

3.2. Results of ordered probit and ordered logit models

The ordered probit regression and an ordered logit regression were conducted on all the factors in the above analysis that affected the usage frequency of ride-hailing services in the pre-epidemic and post-epidemic stages. The regression results showed that in the pre-epidemic and post-epidemic stages, seven factors had significant effects on the frequency of use of the dependent variable. It is worth noting that in the post-epidemic stage, the EPI factor did not have a significant effect on the dependent variable. The comparison results of regression models before and after the epidemic are presented in Table 4.

The regression model can be explained based on the results of the ordered logit and ordered probit regression, which are shown in Table 2. The results showed that people's usage frequency of ride-hailing services was significantly affected by the following seven independent variables: ATT, SOC, TRU, AGE, INC, CAR, and LOC. The comparison of the regression coefficients before and after the epidemic shows that the influences of various factors on the dependent variable before and after the epidemic did not change significantly in the coefficients. However, after the epidemic, the influence of passengers' trust and loyalty on the usage frequency of ride-hailing significantly increased, while the influences of social life and technology significantly decreased.

The main reason why individuals' perception of the epidemic was not a significant affecting factor was that, in the second stage of the questionnaire, the epidemic situation in China had been effectively controlled, work and production had been resumed in an orderly manner in various regions, and travel restrictions had gradually weakened. In the long run, the authors believe that the usage frequency of ride-hailing services may no longer be affected by the epidemic in the future. However, the emergence of the epidemic has brought higher requirements for the safety of ride-hailing services, such as requiring daily disinfection and requiring passengers and drivers to wear masks. Therefore, in the second phase of the questionnaire, the influence of passengers' trust and loyalty on the usage frequency of ride-hailing increased significantly. Due to restrictions on travel during the epidemic, people's social and entertainment activities were reduced during the investigation phase, so the impact of social life and technology use on the usage frequency of ride-hailing in the post-epidemic phase was significantly weakened.

TABLE 2 Comparison of the regression model coefficients before and after the epidemic.

Factor	Ordered logit		Ordered probit	
	Before	After	Before	After
ATT	0.8884*** [0.0899]	0.9427*** [0.0938]	0.5041*** [0.0502]	0.5337*** [0.0518]
SOC	0.2205*** [0.0801]	0.1722** [0.0798]	0.1174** [0.0463]	0.0925** [0.0459]
TRU	0.5366*** [0.0876]	0.5991*** [0.0886]	0.3058*** [0.0508]	0.3464*** [0.0504]
EPI		0.0616 [0.0892]		0.0266 [0.0510]
AGE	−0.2379** [0.1180]	−0.2344** [0.1185]	−0.1161* [0.0685]	−0.1206* [0.0689]
GEN	−0.2290 [0.1600]	−0.1906 [0.1602]	−0.1425 [0.0930]	−0.1239 [0.0932]
INC	0.7955*** [0.0891]	0.7672*** [0.0887]	0.4332*** [0.0496]	0.4187*** [0.0493]
CAR	0.2482** [0.1244]	0.2440** [0.1247]	0.1427* [0.0731]	0.1386* [0.0733]
LOC	−0.5005*** [0.1631]	−0.5172*** [0.1643]	−0.2818*** [0.0945]	−0.2975*** [0.0948]
k1	−2.4205 [0.5301]	−2.5024 [0.5308]	−1.3433 [0.3059]	−1.4213 [0.3071]
k2	−0.5853 [0.5223]	−0.6179 [0.5228]	−0.3187 [0.3037]	−0.3713 [0.3044]
k3	0.9922 [0.5216]	0.9752 [0.5219]	0.5915 [0.3036]	0.5484 [0.3041]
k4	2.5018 [0.5275]	2.4795 [0.5276]	1.4691 [0.3056]	1.4258 [0.3059]

Std.Err is in the brackets. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

3.3. Model verification

The goodness of fit of the model was tested. The test results of the two models before and after the epidemic are presented in Table 3. The result of the chi-square test shows that P(Sig.) was less than 0.001, which was statistically significant, illustrating that our model was meaningful as a whole. The values of R^2 and Log likelihood of the two models were similar, indicating that there was no obvious difference between the advantages and disadvantages of the two models.

3.4. Marginal effect analysis

The marginal effect of a previously fitted model was calculated by fixing the values of certain covariates and integrating over the remaining covariates. This effect demonstrated how the dependent variable would alter when a particular independent variable changed, with all other covariates held constant (35). To calculate the Average Marginal Effect (AME), the marginal effect of each variable was calculated for each observation, whilst taking into consideration any covariates, and then the average was determined. Based on the introduction to the regression model method given in results of ordered probit and ordered logit models section, the coefficient estimation of a variable in the regression-result table reflects the

TABLE 3 Model fit of research models.

Stage	Model	LR chi^2	Pseudo R^2	Log likelihood	Sample size
Before	Ordered logit	380.09***	0.1787	−873.1602	670
	Ordered probit	392.15***	0.1844	−867.1308	670
After	Ordered logit	370.34***	0.1742	−878.0359	670
	Ordered probit	383.67***	0.1804	−871.3674	670

***$p < 0.01$.

impact of the variable on the explained variables. However, the regression models considered in this study are non-linear. The line graphs of the marginal effects of all the factors are presented in Figures 3, 4. The predicted marginal values of seven independent variables before and after the epidemic are presented in Tables 4, 5. These values can be used to explore the influence of changes in independent variables on the changes in dependent variables and analyze and compare the size of the predicted marginal value of the dependent variable in different situations.

The positive marginal effect indicates that as the value of a factor increases, the possibility of consumers choosing to use the ride-hailing will also increase, and the greater the value is, the greater the possibility will be. As shown in Table 5 before the epidemic, the factor TRU "passengers' trust and loyalty" had a negative marginal effect on the frequency of use, i.e., less than once a month, 1–3 times a month, and 1–2 times a week, and had a positive marginal effect on the usage frequency, i.e., 3–4 times a week and more than five times a week, and the marginal effect for more than five times a week was the largest at 0.0647, indicating that when the other factors remained unchanged, for a one-unit increase in the passengers' trust, the possibility of consumers choosing to use the ride-hailing five or more times a week increased by 6.47%, and the possibility of choosing less than once a month decreased by 4.76%. After the epidemic, when other factors remained unchanged, for a one-unit increase in the passengers' trust, the probability that consumers would choose to use the ride-hailing five or more times a week increased by 7.12%, while the probability to use it less than once a month decreased by 5.07%. Thus, the more passengers trusted the service, the more frequently it was used, and vice versa.

Similarly, before and after the epidemic, the four factors, including the ATT, SOC, INC, and CAR, had a negative marginal effect on the frequency of use, i.e., less than once a month, 1–3 per month, and 1–2 times a week, and had a positive marginal effect on the usage frequency, i.e., 3–4 times a week and more than five times a week, and the factor "attitudes to environmental protection and commuting" after the epidemic had the largest marginal effect at 0.1093, indicating that when the other factors remained unchanged, for a one-unit increase in the attitudes to environmental protection and commuting, the possibility of consumers choosing to use the ride-hailing five times or more per week increased by 10.93%. The results also show that the more private cars people owned, the higher the usage frequency of ride-hailing would be. This may be due to the fact that people who own private cars are more inclined to travel by cars, and thus they have a higher acceptance of ride-hailing services. Also, when it is not possible to use a private car to travel, they are more willing to choose ride-hailing services rather than other traveling methods, such as public transportation.

Contrary to the above factors, both before and after the epidemic, the marginal effect of the age and residential location in the urban area on the frequency of use, i.e., less than once a month, 1–3 times a month, and 1–2 times a week, was positive, the marginal effect on the usage frequency, i.e., 3–4 times a week and more than five times a week, was negative. When the other factors remained unchanged, for a one-unit increase in the residential location in the urban area before the epidemic, the possibility of consumers choosing to use the ride-hailing five or more times a week decreased by 5.50%, and the possibility of choosing it less than once a month increased by 4.05%.

After the epidemic, when the other factors remained unchanged, for a one-unit increase in the location and convenience of car usage before the epidemic, the probability that consumers would choose to use the ride-hailing five or more times per week decreased by 5.87%, and the probability of choosing it once a month increased by 4.18%. This result shows that people who live outside the urban area and are farther away from the urban area use ride-hailing services less frequently.

The possible reason for this result can be that the farther away from the urban area people are, the less the supply of ride-hailing services may be. Also, compared to the urban areas, the convenience of obtaining the ride-hailing services in rural and suburban areas can be slightly worse, which can make people in that areas be more inclined not to use the ride-hailing or to use them less often. Furthermore, the older the person is, the lower the usage frequency of ride-hailing will be. Based on the descriptive statistics, users who had used ride-hailing services were mainly between the ages of 18 and 34, and the younger generation was the majority. This age group also accounted for the highest proportion of participants who had used the ride-hailing services. The authors believe that there are two possible reasons for this result: (1) people in this age group have higher travel needs, and (2) they are highly adaptable to technological changes and are more likely to accept new technologies.

4. Discussion

In this study, the data obtained from the online questionnaires are used to investigate the factors affecting the usage frequency of ride-hailing services in China. Many studies have found the impact of the COVID-19 pandemic on passengers' ride-hailing frequency. It has been established by Morshed et al. (31) that the COVID-19 pandemic has had a significant impact on the ride-hailing market, leading to a decrease in its popularity as a transportation option. The recent COVID-19 pandemic has caused a significant decrease in the revenue of on-demand ride-hailing services due to the fear of infection in shared vehicles (36, 37). A study conducted

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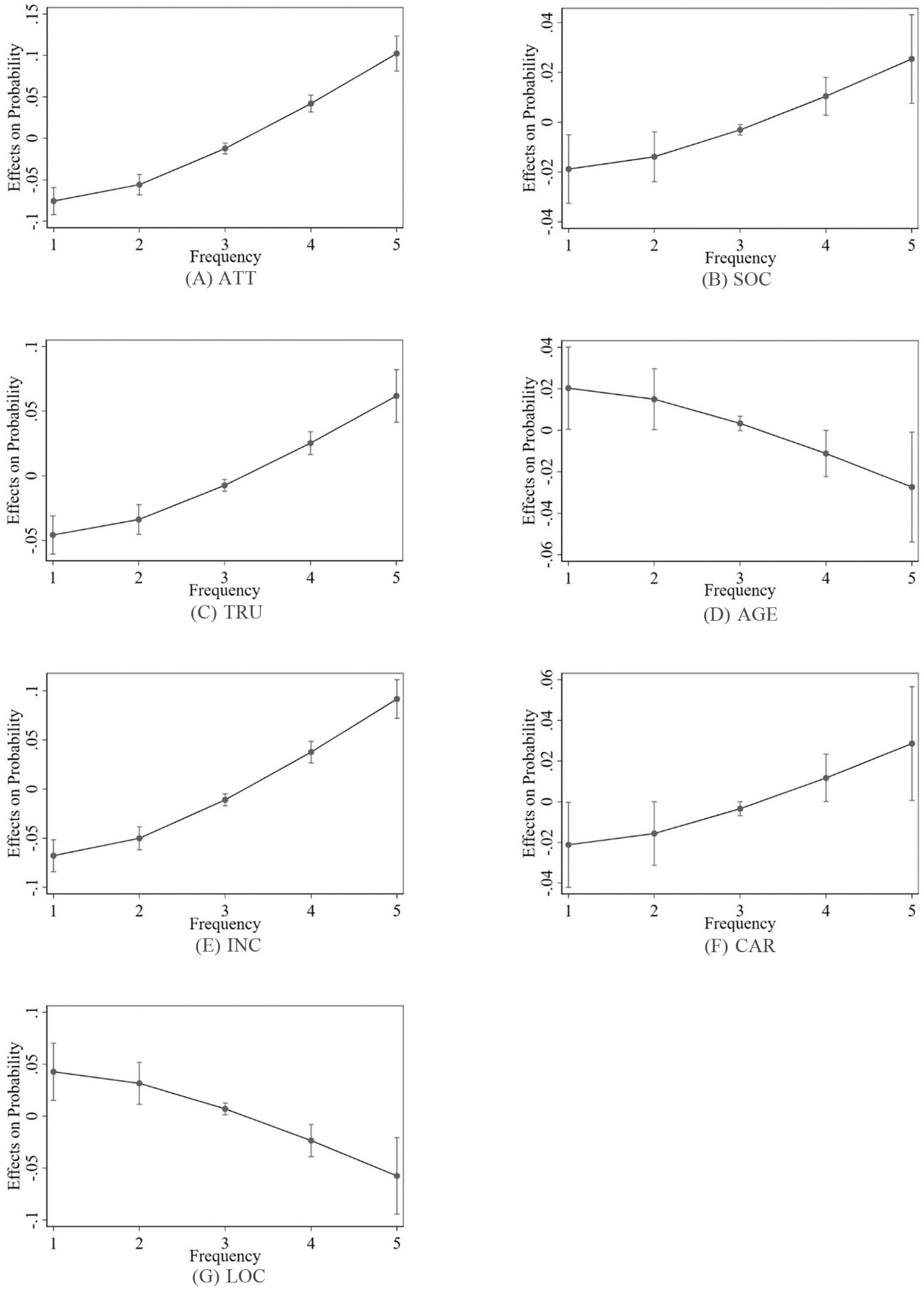

FIGURE 3
Average marginal effects at 95% confidence intervals before the epidemic.

in Chicago revealed a substantial decline in the number of ride-hailing trips when compared to those using private cars during the COVID-19 pandemic (36). Nguyen-Phuoc et al. (38) concluded that self-efficacy has the most significant influence on self-protective behaviors among ride-hailing passengers during the COVID-19 pandemic. According to the regression results of this study, it can be

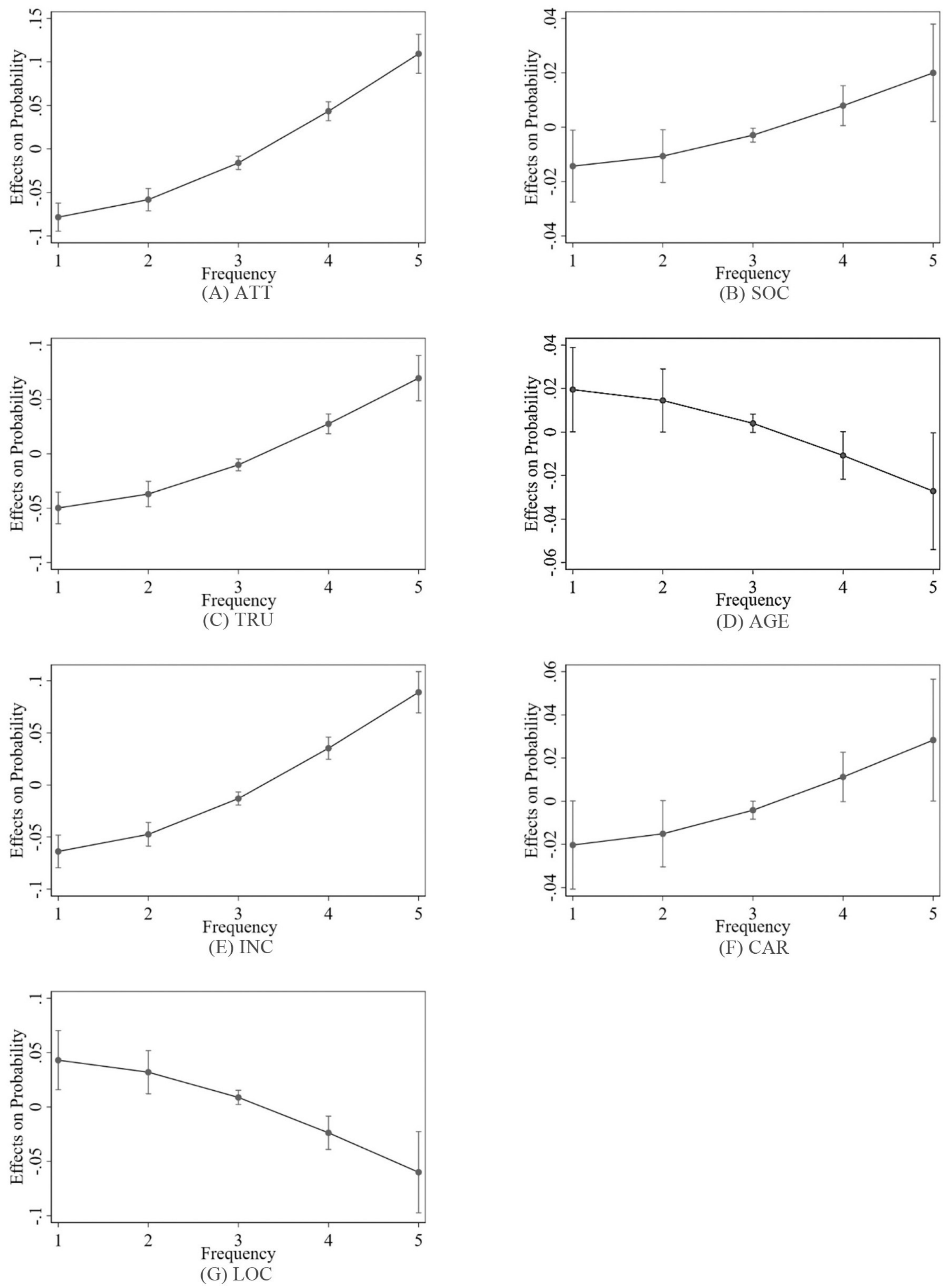

FIGURE 4
Average marginal effects at 95% confidence intervals after the epidemic.

concluded that the travelers' usage frequency of ride-hailing services is highly correlated with the following seven factors: ATT, SOC, TRU, AGE, INC, PRIVATE, and LOC. Besides, based on the result comparison of different models, the individual's perception of the EPI does not have a significant impact on the usage frequency of ride-hailing services.

Specifically, the factor passenger trust and loyalty are positively related to the frequency of use of ride-hailing services. The marginal

TABLE 4 Marginal effects of different factors before the epidemic.

		Margin	Std.Err	z	$P>\|z\|$	[95% Conf. Interval]	
ATT	1	−0.0755***	0.0083	−9.11	0.000	−0.0917	−0.0592
	2	−0.0559***	0.0062	−8.96	0.000	−0.0682	−0.0437
	3	−0.0128***	0.0034	−3.75	0.000	−0.0195	−0.0061
	4	0.0417***	0.0052	8.06	0.000	0.0316	0.0518
	5	0.1025***	0.0109	9.42	0.000	0.0812	0.1238
SOC	1	−0.0204***	0.0070	−2.90	0.004	−0.0341	−0.0066
	2	−0.0151***	0.0051	−2.95	0.003	−0.0251	−0.0051
	3	−0.0035***	0.0011	−3.04	0.002	−0.0057	−0.0012
	4	0.0113***	0.0039	2.90	0.004	0.0037	0.0189
	5	0.0277***	0.0091	3.04	0.002	0.0098	0.0455
TRU	1	−0.0476***	0.0076	−6.28	0.000	−0.0625	−0.0328
	2	−0.0353***	0.0059	−5.95	0.000	−0.0469	−0.0237
	3	−0.0081***	0.0024	−3.32	0.001	−0.0128	−0.0033
	4	0.0263***	0.0046	5.78	0.000	0.0174	0.0352
	5	0.0647***	0.0105	6.17	0.000	0.0441	0.0852
AGE	1	0.0196*	0.0101	1.95	0.052	−0.0001	0.0394
	2	0.0145*	0.0075	1.94	0.053	−0.0002	0.0293
	3	0.0033*	0.0018	1.83	0.068	−0.0002	0.0069
	4	−0.0108*	0.0057	−1.92	0.055	−0.0219	0.0003
	5	−0.0267**	0.0136	−1.96	0.050	−0.0533	−0.0001
INC	1	−0.0662***	0.0082	−8.03	0.000	−0.0824	−0.0501
	2	−0.0491***	0.0060	−8.17	0.000	−0.0609	−0.0373
	3	−0.0112***	0.0031	−3.67	0.000	−0.0172	−0.0052
	4	0.0366***	0.0056	6.59	0.000	0.0257	0.0475
	5	0.0899***	0.0101	8.94	0.000	0.0702	0.1096
CAR	1	−0.0223**	0.0106	−2.10	0.036	−0.0431	−0.0014
	2	−0.0165**	0.0080	−2.07	0.039	−0.0321	−0.0009
	3	−0.0038**	0.0018	−2.06	0.039	−0.0074	−0.0002
	4	0.0123**	0.0059	2.07	0.038	0.0007	0.0239
	5	0.0302**	0.0143	2.12	0.034	0.0022	0.0582
LOC	1	0.0405***	0.0140	2.88	0.004	0.0129	0.0680
	2	0.0300***	0.0103	2.91	0.004	0.0098	0.0502
	3	0.0069**	0.0029	2.38	0.017	0.0012	0.0125
	4	−0.0224***	0.0079	−2.84	0.004	−0.0378	−0.0069
	5	−0.0550***	0.0189	−2.91	0.004	−0.0919	−0.0180

*$p < 0.1$; **$p < 0.05$; ***$p < 0.01$.

effect diagram in marginal effect analysis section shows that the more passengers trust the service, the higher the frequency of use of ride-hailing services will be, and vice versa. Similarly, consistent with our findings, Nguyen-Phuoc et al. (39) demonstrate that perceived benefits, perceived sales promotion and perceived service quality are all direct contributors to passenger satisfaction and loyalty, with perceived service quality being the most influential factor (39). Nguyen-Phuoc et al. (11) examined the direct and indirect effects of elements impacting the loyalty of ride-hailing and conventional taxi users. Ma et al. (40) found that trust in drivers has a positive influence on users' trust and attitude toward the platform. Trust and implicit cost have been found to have a positive influence on e-loyalty relate to ride-hailing (41). Chinese passengers view ride-hailing services as less secure than traditional taxis, and women are more likely to be affected by the perceived lack of security than men (42).

TABLE 5 Marginal effects of different factors after the epidemic.

		Margin	Std.Err	z	P>|z|	[95% Conf. Interval]	
ATT	1	−0.0778***	0.0082	−9.53	0.000	−0.0938	−0.0618
	2	−0.0582***	0.0065	−8.91	0.000	−0.0710	−0.0454
	3	−0.0166***	0.0040	−4.16	0.000	−0.0244	−0.0088
	4	0.0433***	0.0056	7.77	0.000	0.0324	0.0542
	5	0.1093***	0.0116	9.46	0.000	0.0867	0.1320
SOC	1	−0.0145**	0.0067	−2.15	0.031	−0.0277	−0.0013
	2	−0.0108**	0.0050	−2.18	0.029	−0.0206	−0.0011
	3	−0.0031**	0.0013	−2.29	0.022	−0.0057	−0.0004
	4	0.0081**	0.0038	2.15	0.032	0.0007	0.0154
	5	0.0204**	0.0092	2.22	0.026	0.0024	0.0383
TRU	1	−0.0507***	0.0074	−6.86	0.000	−0.0651	−0.0362
	2	−0.0379***	0.0060	−6.30	0.000	−0.0497	−0.0261
	3	−0.0108***	0.0029	−3.75	0.000	−0.0165	−0.0052
	4	0.0282***	0.0047	5.99	0.000	0.0190	0.0374
	5	0.0712***	0.0107	6.63	0.000	0.0501	0.0922
AGE	1	0.0192*	0.0099	1.94	0.052	−0.0002	0.0385
	2	0.0143*	0.0074	1.93	0.053	−0.0002	0.0289
	3	0.0041*	0.0022	1.85	0.064	−0.0002	0.0084
	4	−0.0107*	0.0056	−1.91	0.057	−0.0216	0.0003
	5	−0.0269**	0.0138	−1.96	0.050	−0.0539	0.0000
INC	1	−0.0626***	0.0080	−7.85	0.000	−0.0782	−0.0470
	2	−0.0468***	0.0058	−8.06	0.000	−0.0582	−0.0354
	3	−0.0134***	0.0032	−4.17	0.000	−0.0196	−0.0071
	4	0.0348***	0.0054	6.42	0.000	0.0242	0.0455
	5	0.0879***	0.0102	8.66	0.000	0.0680	0.1078
CAR	1	−0.0208**	0.0104	−2.00	0.045	−0.0411	−0.0005
	2	−0.0155**	0.0078	−1.98	0.047	−0.0309	−0.0002
	3	−0.0044**	0.0022	−1.99	0.046	−0.0088	−0.0001
	4	0.0116**	0.0058	1.98	0.048	0.0001	0.0230
	5	0.0292**	0.0144	2.02	0.043	0.0009	0.0575
LOC	1	0.0418***	0.0138	3.02	0.002	0.0147	0.0689
	2	0.0313***	0.0102	3.08	0.002	0.0114	0.0512
	3	0.0089***	0.0034	2.63	0.008	0.0023	0.0156
	4	−0.0233***	0.0078	−2.98	0.003	−0.0385	−0.0080
	5	−0.0587***	0.0191	−3.07	0.002	−0.0962	−0.0213

Std.Err is in the brackets.
*$p < 0.1$; **$p < 0.05$; ***$p < 0.01$.

It is imperative to increase the convenience, security, and popularity of ride-hailing services in order to build trust and loyalty among passengers and thus, increase the number of people using the service. To this end, it is necessary to promote complaints and feedback mechanisms for improvement; improve online payment methods; implement practical measures to ensure the safety of passengers; and provide transparent information to enhance corporate image and value, so that passengers can continue to choose ride-hailing services and recommend them to others.

Studies have shown a positive correlation between social life and technology usage and the frequency of use of ride-hailing services, which is in line with the findings of prior studies. Additionally, attitudes toward environmental protection and commuting are positively associated with the frequency of use of ride-hailing services.

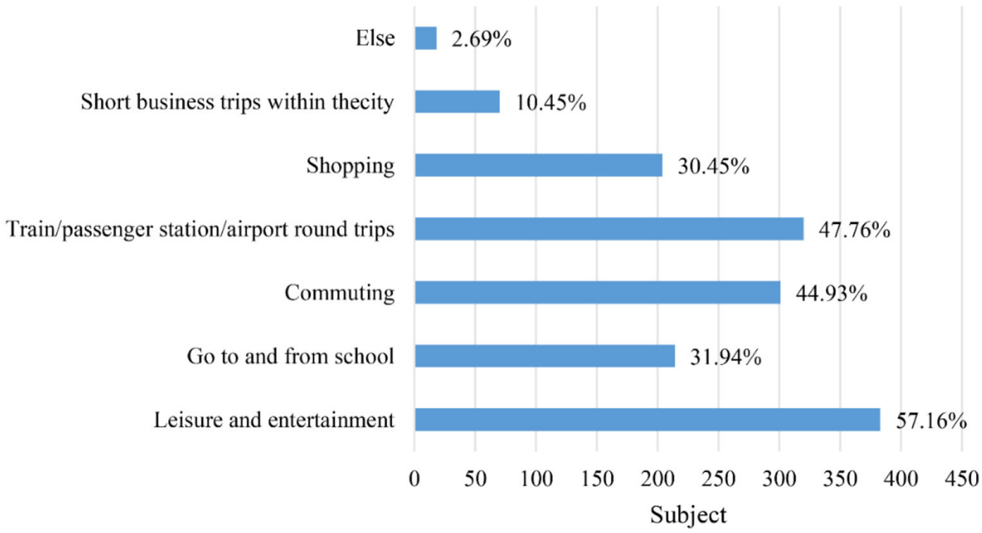

FIGURE 5
Purpose of travel before the epidemic.

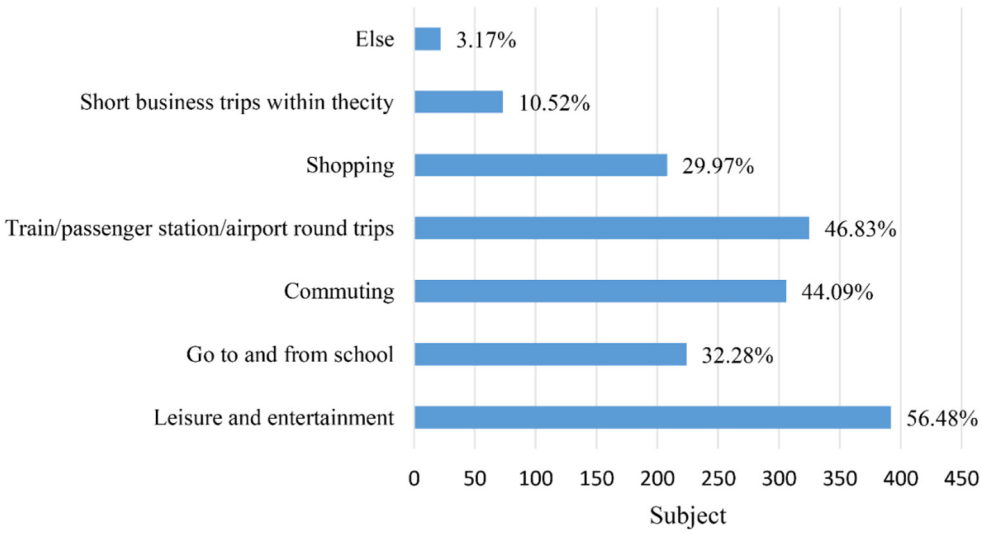

FIGURE 6
Purpose of travel after the epidemic.

Urban residential location, however, is negatively correlated with the frequency of use of ride-hailing services, which may be due to the lower availability of ride-hailing services in these areas. Age and frequency of use of ride-hailing services are also negatively correlated, indicating that young people are the main demographic using ride-hailing. Finally, the number of private cars is positively correlated with the frequency of use of ride-hailing services, as those who own private cars are more likely to use ride-hailing services when they cannot use their own vehicles.

The survey results revealed that the majority of ride-hailing trips (about 60%) were for leisure and entertainment. This was followed by trips to/from train/passenger station/airport (about 50%) and commuting (about 45%). The figures in Figures 5, 6 illustrate the trip purpose in the two questionnaires. Ride-hailing services offer a convenient solution to the problems associated with personal driving (e.g., parking and drinking) and public transportation (e.g., time control and comfort). This could explain why ride-hailing is so popular for leisure and entertainment. Figures 7, 8 show the usage frequency and age range of ride-hailing users, respectively. It can be seen that the majority of users choose ride-hailing 1–3 times a month and 1–2 times a week. The highest usage frequency of ride-hailing was among the 18–34 age group, which is in line with the previous conclusion.

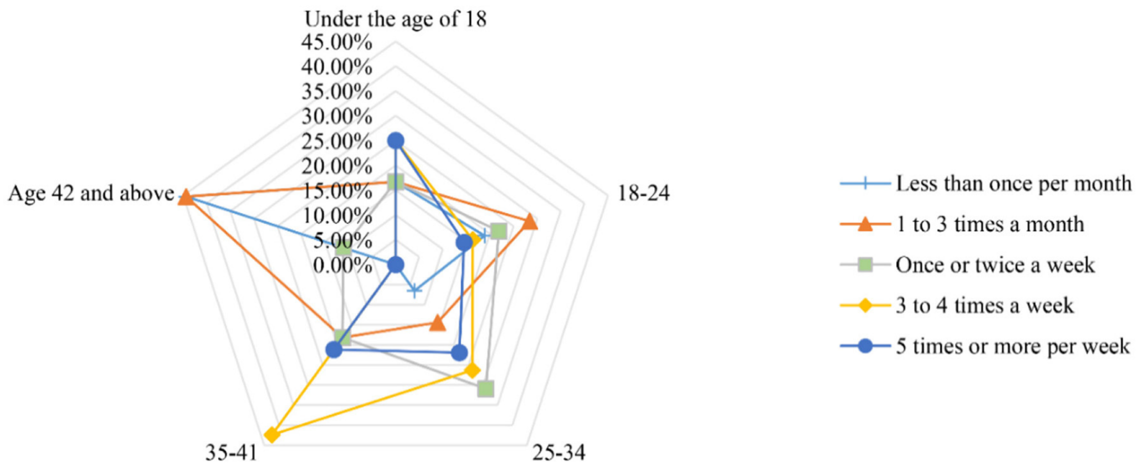

FIGURE 7
Radar charts of the age group and frequency of use of ride-hailing services before the epidemic.

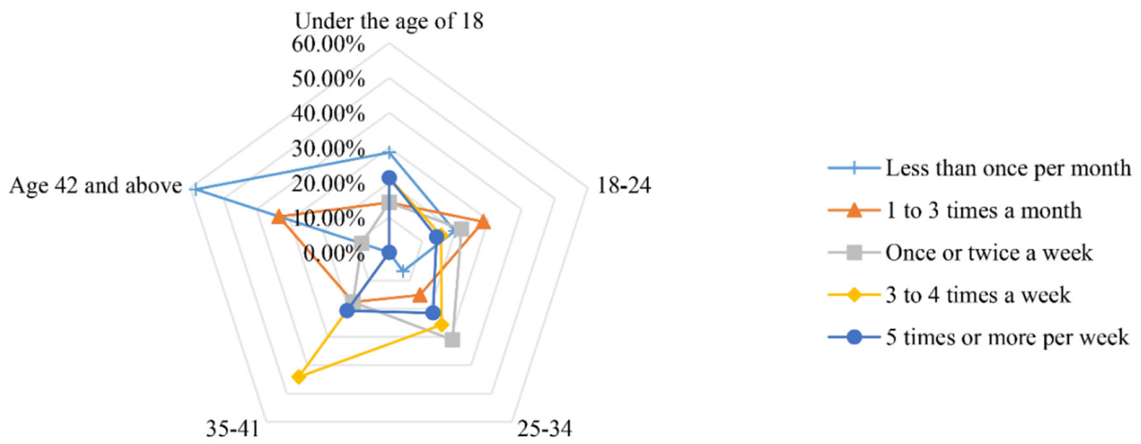

FIGURE 8
Radar charts of the age group and frequency of use of ride-hailing services after the epidemic.

5. Conclusion

This study conducted a two-stage survey among the same group of passengers to investigate the factors influencing people's usage of ride-hailing services in the pre-epidemic and post-epidemic phases. This research was distinct from existing literature in that it included discussions on two additional factors: the epidemics and the passenger trust, and their impacts on the frequency of use of ride-hailing services were quantitatively studied. The survey acquired information on participants, including their geographic area, lifestyle, technology use, personal attitudes, and social economy, which was then subjected to an Exploratory Factor Analysis to develop a usage frequency model of ride-hailing. Model estimation results revealed that the passenger trust and loyalty, social life and technology use, attitudes to environmental protection and commuting, age, personal income, number of private cars, and residential location in the urban area had a significant impact on the usage frequency of ride-hailing services. The results indicated that in the long run, the epidemic would have a slight impact on the usage frequency of ride-hailing.

This study provides beneficial information for firms and executives when analyzing ride-hailing models. To guarantee passenger security during the pandemic, enterprises and platforms should execute practical safeguards, such as mandating drivers to don face masks, measure and transmit body temperature data, frequently disinfect vehicles, and open windows for ventilation. The reliable statistical models used in this research are also beneficial for future research and provide useful advice for regulators, managers, and enterprises.

This initial study was limited by sample size, encompassing only 670 valid cases. Future research should aim to expand the scope of the study by increasing the sample size and collecting data from a more diverse geographical area, employing various techniques such as machine learning. Future research should extend this study by assessing different causal relationship structures, and contrasting the magnitude of each endogenous variable's effect on ride-hailing and other behaviors. Moreover, to address the limitations of the current analyses, preference heterogeneity should be incorporated in the model estimation, thereby allowing us to gain insight into the individual decision-making process.

Data availability statement

The original contributions presented in the study are included in the article/Supplementary material, further inquiries can be directed to the corresponding authors.

Author contributions

SL: writing—original draft and supervision. YJ: software and writing—original draft. XY: data curation, validation, and methodology. HD: conceptualization. TZ: language polishing and data analysis. All authors contributed to the article and approved the submitted version.

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Conflict of interest

TZ was employed by TOEC Technology Co., Ltd.

The remaining authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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Supplementary material

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/fpubh.2022.1097885/full#supplementary-material

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Spatial effects of environmental regulation on high-quality economic development: From the perspective of industrial upgrading

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Studying the spatiotemporal heterogeneity of environmental regulations on high-quality regional economic development is of enormous practical value in the context of sustainable economic, social, and environmental development. Only a few studies, however, examined the regional heterogeneity of environmental regulation affecting economic development from the standpoint of upgrading the industrial structure. This research investigated the spatial distribution traits of high-quality regional development based on the construction of a comprehensive assessment index system for high-quality economic development. The economic geography-nested spatial Durbin model is then used to perform an empirical test. The findings demonstrate that (1) high-quality economic development has visible spatial heterogeneity, with strong local spatial agglomeration between regions; (2) environmental regulation and the modernization of the industrial structure are significant variables influencing high-quality economic development, but their development is not balanced; and (3) environmental policies promote high-quality regional development through a distinct channel. Formal environmental regulation promotes economic development through rationalizing industrial structure, while informal environmental regulation does so through upgrading the industrial structure. Further, both kinds of environmental regulation have positive spatial spillover effects on adjacent areas. Therefore, the regional heterogeneity of environmental regulation and industrial structure is of great significance in promoting the high-quality and sustainable development of regional economies.

KEYWORDS

environmental regulation, industrial structure upgrading, spatial heterogeneity, regional economy high-quality development, sustainable development

1. Introduction

The Chinese economy has experienced extraordinary growth during the last few decades (1). However, over time, the extensive growth model has led to significant energy waste and progressively worse environmental issues. This is incompatible with the new socialist development paradigm and has become a major impediment to China's sustained growth (2–4). The report of the 20th National Congress of the Communist Party of China has clearly stated that China should adhere to the theme of promoting high-quality development, organically combine the implementation of the strategy of expanding domestic demand with deepening supply-side structural reforms, accelerate the establishment of a new development pattern, and promote the effective improvement of quality and reasonable growth of the economy. The upgrading of the industrial structure can deepen the structural reform of the supply side through the spontaneous force of the market and adjust the industrial structure, which is an important force in promoting stable economic growth (5, 6). Environmental regulation (ER) is a crucial instrument for businesses to execute environmental protection measures, as it serves as a critical measure for environmental governance and an institutional guarantee for fostering economic development (7, 8).

Additionally, it is also a key path to coordinate industrial structure upgrading and high-quality economic development (EDQ). Reasonable ER can promote EDQ while promoting industrial modernization and lowering pollutants. However, different ER have various paths for acting on industrial structures, and the effects of solving environmental problems are also different. Therefore, developing effective environmental policies and reversing the conventional dependency on the growth of pollution-intensive firms will help to increase the ability of businesses to regulate pollution and the effectiveness of resource allocation, thereby encouraging sustainable economic and social development in harmony with the environment (9–11). Clarifying the mechanisms of ER, industrial upgrading, and EDQ is a key measure to achieve high-quality economic development against the realistic background of comprehensively deepening reforms and promoting EDQ in China. In addition, this is a crucial step in creating a regional economic structure and land-use system with complementary advantages and high-quality development.

Research on EDQ mainly focuses on three aspects. The first is connotation. Ren Baoping pointed out that high-quality development is the advanced and optimal state of the EDQ (12). Wang Xicheng proposed that the core connotation of EDQ is high-quality, high-efficiency, and high-stability supply systems (13). Gao Peiyong believed that EDQ lies in shifting from focusing on "speed advantage" to pursuing "quality advantage" (14). The second is the evaluation system. Shifu measured the level of EDQ from the three perspectives of development fundamentals, social achievements, and ecological achievements. Ou Jinfeng and Gao Zhigang have combined the five major development concepts in building an index system for EDQ from the five dimensions of innovation, coordination, green, openness, and sharing (15, 16). The third is the realization path. Li Mengxin and Ren Baoping believed that the path chosen for EDQ in the new era was to reconstruct the driving force of technological innovation and deeply embed green productivity (17). Jin Pei proposed that, in the process of achieving EDQ, we should focus on alleviating or even curbing the ecological and environmental problems brought about by economic development (18).

Environmental regulations are environmental standards or actions created by the government to directly or indirectly regulate economic activity and to address the issue of harmful externalities from environmental pollution (19). There are primarily two perspectives in the current research on ER and EDQ. The first view is that the improvement of ER has inhibited enterprises from implementing emission reduction actions. Strict ER leads enterprises to expand output and increase pollution emissions to maximize profits, which is detrimental to the growth of EDQ (20). The second point is that appropriate regulatory measures can encourage enterprises to reduce pollution emissions through green innovation (21, 22), promoting EDQ (23). According to the different types of ER, some scholars divide it into command-and-control, market-type, and informal-type (24), and two types are also sometimes used: formal regulation (FER) and informal regulation (IER) (25). The formal type, which primarily includes the command-and-control and market incentive types (26), belongs to government conduct. It dominates in coordinating environmental protection and economic development (27, 28). The informal type is a non-governmental organization or individual behavior, including public participation and voluntary regulation. When facing higher environmental pollution control needs, IER automatically completes environmental protection agreements through negotiation and so on. It regulates environmental pollution behaviors, achieving higher environmental benefits (29, 30). Different types of ER have varying effects on EDQ due to variations in implementation strategies. Ignoring this difference will lead to deviations in the results of relevant environmental policy evaluations (31, 32). Therefore, we should carefully evaluate how different policies will affect economic development to coordinate ER and EDQ (33).

Industrial upgrading is an important driving force for optimizing resource allocation, promoting kinetic energy conversion, and reducing pollutant emissions. Appropriate ER can encourage enterprises to carry out R&D innovation, optimize resource allocation, and effectively alleviate the contradiction between the economic and ecological systems (34). ER's effects on industrial modernization have always been a vital scholarly concern (35–38), but no unified conclusion has been reached yet. Some scholars believe that ER can promote industrial restructuring (39, 40). Driven by ER, social production materials flow to low-pollution and high-efficiency industries, stimulating high-pollution and low-efficiency enterprises to carry out technological innovation. This process has effectively promoted energy savings and efficiency improvements in enterprises as well as industrial upgrading while reducing emissions (41). For example, Li Hong et al. found that ER can force industrial optimization, thus promoting industrialization's upgrading (42). Kivimaa and Kern discovered that environmental policies encourage technical innovation among businesses, which helps to upgrade the industrial structure (43). Some scholars hold the opposite view, arguing that the cost effect caused by the implementation of ER has inhibited the upgrading of industrial structures (44–46). For example, Liu Jianhua believed that ER had significantly increased the pollution control costs of enterprises, reduced productive investment, and hindered the upgrading and transformation of industrial structures (47). Meng Hao found that ER is not conducive to industrial structure upgrading by constructing the spatial Durbin model (48). It should be emphasized that, while the empirical test for this research produced some results, the conclusions are inconsistent across countries due to variations in environmental laws, sample sizes, and research methodologies. More research needs to be done on ER and modernizing industrial structures.

The relationship between ER, industrial upgrading, and EDQ has been covered in earlier research and has achieved considerable research results, but there are still some deficiencies. First, most of the relevant discussions on promoting EDQ through ER focus on the level of FER while ignoring the contribution of IER. Although some scholars in recent years have proposed that IER is an essential factor affecting EDQ, relevant research has not yet formed a consensus and lacks systematic analysis. Second, the existing literature explores the connection between ER and EDQ from many angles. However, little research was done on the synergistic effects of multiple ERs on EDQ. Most studies are only conducted from one perspective, failing to consider potential mutual limitations across policies. Finally, ER and EDQ, as well as ER and industrial upgrading, are frequently studied in isolation in previous literature, making it hard to reflect on the relationship between them. Few studies link these three items to explore their relationship and spatial spillover effects.

The following are the primary contributions of the article in comparison to previous research: First, this study quantitatively analyzes the comprehensive evaluation index system of EDQ and its spatial distribution and further studies the systemic effect of ER from the perspective of industrial upgrading on this basis. This can provide more targeted suggestions for formulating China's macroeconomic and environmental policies. Second, the article divides environmental regulations into formal and informal environmental regulations to examine their independent and interactive effects on EDQ. Third, this article puts dual ER, industrial upgrading, and EDQ in the same research framework and explores the relationship between them and their temporal and spatial characteristics. Therefore, it can provide a reference for promoting environmental governance, facilitating the change of industrial structure, and realizing coordinated EDQ. Fourth, this study discusses how the industrial transformation paths of FER and IER affect EDQ and provides a valuable reference for formulating and implementing ER policies in the future. Finally, this study divides regions according to spatial geographic location for heterogeneity and replaces the spatial weight matrix for robustness testing, which provides an empirical basis for policymakers to improve the quality of economic development.

The remainder of the essay is organized in the following manner. The theoretical analysis and research assumptions are covered in theoretical analysis and research assumptions section. The resources and procedures are described in materials and methods section. Results and discussion section contains the empirical findings as well as the analysis. Robustness and endogeneity test section is the robustness test and the endogeneity test. The conclusions and their consequences for policy are provided in conclusions and policy implications section.

2. Theoretical analysis and research assumptions

Due to the influence of numerous elements, including regulation type, regulation intensity, and policy execution, the effect of ER on EDQ is ambiguous (49, 50). This influence is primarily accomplished by combining the "cost offset effect" and the "innovation compensation effect" as the transmission method. On the one hand, increased environmental legislation has forced businesses to pay a premium to reduce pollution. Enterprise innovation's cost effect cannot now be balanced out by its compensation effect (51, 52). In particular, the increased cost of environmental pollution control will reduce the initial investment in the productive output of businesses, skew resource allocation to businesses, impede the development of green technologies, and subtly impede EDQ. As opposed to this, when the innovation compensation impact outweighs the cost offset effect, the company will reduce pollution emissions through the invention of green technology, increase its production efficiency, and balance the cost effect, occupying a favorable position in the market competition and driving EDQ. The effect of ER on the EDQ is thus ambiguous. ER is divided into two categories in this study: FER and IER. Compared to IER, the cost-effectiveness of FER is more visible, but the innovation compensation effect is less clear and even has a negative impact. FER describes the restrictions put in place by the government to force polluting companies to reduce emissions through administrative action and market incentives. Therefore, polluting businesses will incur a disproportionately high cost when they succeed in maximizing profits. Due to the informal and non-mandatory nature of IER, its influence on resource allocation distortion is frequently subtle. Therefore, it will not have a significant effect on business expenses. More businesses will embrace an environmentally friendly company philosophy as the idea of green and sustainable development becomes more widely accepted in society. Companies will increase their social impact and brand awareness through this technique. Thus, informal environmental control will effectively encourage the "innovation compensation" effect of businesses and realize the "win-win" of environmental protection and productivity improvements. The following hypotheses are put forth in this study based on the analysis shown above:

H1: Varying ER has different degrees of impact on EDQ; FER has a negative effect, and IER has a positive effect.

Industrial upgrading is the reallocation of production factors among distinct economic sectors and industries (53), that is, the process of promoting industrial structure rationalization (TR) and advanced development (TS). Industrial upgrading can encourage the coordinated growth of different industries within the national economy, enabling those industries to flourish in ways compatible with EDQ. The TR reflects the degree of coordination among industries and the effective use of resources. It gauges how closely each region's factor input structure and industrial structure are coupled (54). By optimizing the proportion of the industrial structure, the TR adjustment can accomplish complete resource protection, lower energy consumption, minimize pollutant emissions, and foster EDQ. Factors of production, including labor force, capital, and natural resources, move freely between industries due to the shift in the force that drives economic development. The industrial structure is constantly shifting from the secondary to the tertiary industry, thereby driving the structural adjustment of various production factors (55–57). TS describes the process of changing the regional industrial structure from a low-level structure dominated by labor-intensive industries to a high-level structure dominated by technology-intensive industries. The advanced industrial system promotes the transfer of factor resources from high-consumption to low-consumption industries, which helps store energy and reduce pollution. At the same time, the continuous development of knowledge-intensive industries can drive technological progress, thereby driving the upgrading of traditional production methods and the use of advanced production methods. This is conducive to achieving EDQ. On the basis of the analysis above, the following premises are advanced:

H2: TR and TS can both promote the regional EDQ.

Environmental regulation has a mandatory restraint force on an enterprise's production and pollution discharge behavior and intends to safeguard the environment. Microscopically, it can encourage companies to implement pollution control and green innovation. Macroscopically, it can direct the conversion of polluting businesses into clean ones and realize an important step from the secondary industry to the tertiary industry. ER affects the direction of industrial structure transformation through various means, affecting EDQ (32). FER controls pollution emissions at the source by clarifying each market entity's pollution reduction and corporate responsibilities, thereby affecting EDQ. This impact can be divided into two aspects. First, the "environmental compliance costs" of different types of industries are different. Pollution-intensive industries need to bear higher environmental costs and have weak technical research capabilities, making it difficult to offset costs through innovation effects. Clean industries have green competitive advantages and tend to increase R&D investment to cope with rising environmental costs. Strict ER leads to the reconfiguration of market shares, which promotes the continuous improvement of the level of coordination among various industries, thus promoting the process of rationalizing industrial structure. Second, moderate ER will stimulate businesses to innovate. Driven by technological progress, low-productivity sectors have gradually withdrawn from the market, and high-productivity sectors have continued refining their labor division. This will drive the transformation of the industrial structure to an advanced level, move the frontier of social production forward, and promote EDQ. IER refers to the spontaneous completion of environmental protection agreements by the public, the media, or other environmental protection organizations through negotiations and consultations to standardize environmental pollution control behaviors when faced with higher environmental pollution control needs. The incentive effect of IER on industrial structure adjustment is mainly reflected in two aspects. First, IER can directly exert pressure on polluting industries by acting on productive demand, prompting enterprises to reform the industrial structure (58) and advance the regional EDQ. The second is that the demand for environmentally friendly goods and services is growing along with public awareness of environmental protection. These factors encourage enterprises to increase research and application of green technologies, which helps to upgrade the industrial structure and raise the standard of EDQ. The following assumptions are therefore outlined in this paper:

H3: Dual ER can effectively force industrial transformation and upgrading, promoting EDQ.

Environmental regulation policies are multifield and complex, so it is unreasonable to only emphasize the impact of a single policy (59). Ignoring the heterogeneity of ER might result in deviations throughout policy evaluation results that are not favorable for regional EDQ. Therefore, coordinating multiple policies has become an inevitable choice to encourage EDQ. Specifically, one is that local governments can still not eliminate the influence of the GDP-only theory. They typically make a trade-off between ER and economic performance. At this time, informal environmental regulation organizations such as the public, media, and environmental protection associations are required to supervise the implementation of FER. The strength of IER is used to supervise the effective implementation of FER. Therefore, dual ER work together to promote EDQ. The other is that the promulgation of FER represents the government's determination to control environmental pollution. Its extensive influence in society is conducive to raising the public's awareness of environmental protection and enhancing social groups' understanding of pollution control. That is, FER can encourage the formation of IER, which will then support EDQ under the influence of consumption and industrial structure adjustment effects. Thus, FER and IER can interact with each other to promote EDQ. In light of the previous analysis, the following assumptions are proposed in this paper:

H4: The interaction between FER and IER promotes regional EDQ.

3. Materials and methods

3.1. Design of research

The empirical analysis presented in this research uses the Spatial Durbin Model (SDM) to investigate the effects of ER and industrial upgrading on EDQ and its spatial impact. This study uses the two components of industrialization advancement (TS) and rationalization (TR) to measure industrial upgrading. Based on this measurement, the interaction between ER and industrial transformation and modernization is introduced. The specific model settings are as follows:

$$\begin{aligned} \ln EDQ_{it} = {} & \rho W_{ij} \ln EDQ_{it} + \beta_1 \ln FER_{it} + \beta_2 \ln TS_{it} + \beta_3 \ln TR_{it} \\ & + \beta_4 \ln FER_{it} \times TS_{it} + \beta_5 \ln FER_{it} \times TR_{it} + \beta_6 X_{it} \\ & + \delta_1 W_{ij} \ln FER_{it} + \delta_2 W_{ij} \ln TS_{it} + \delta_3 W_{ij} \ln TR_{it} \\ & + \delta_4 W_{ij} \ln FER_{it} \times TS_{it} + \delta_5 W_{ij} \ln FER_{it} \times TR_{it} \\ & + \delta_6 W_{ij} X_{it} + \mu_i + \gamma_t + \varepsilon_{it} \end{aligned} \quad (1)$$

$$\begin{aligned} \ln EDQ_{it} = {} & \rho W_{ij} \ln EDQ_{it} + \beta_1 \ln IER_{it} + \beta_2 \ln TS_{it} + \beta_3 \ln TR_{it} \\ & + \beta_4 \ln IER_{it} \times TS_{it} + \beta_5 \ln IER_{it} \times TR_{it} + \beta_6 X_{it} \\ & + \delta_1 W_{ij} \ln IER_{it} + \delta_2 W_{ij} \ln TS_{it} + \delta_3 W_{ij} \ln TR_{it} \\ & + \delta_4 W_{ij} \ln IER_{it} \times TS_{it} + \delta_5 W_{ij} \ln IER_{it} \times TR_{it} \\ & + \delta_6 W_{ij} X_{it} + \mu_i + \gamma_t + \varepsilon_{it} \end{aligned} \quad (2)$$

Equations (1) and (2) represent the spatial panel Durbin model of formal and informal environmental regulation, respectively. Among them, ρ represents the spatial correlation coefficient of the dependent variable; i demonstrates the region; t shows time; W_{ij} reflects the geographic economic nesting spatial weight matrix; EDQ_{it} represents high-quality economic development; FER_{it} and IER_{it} represent formal and informal environmental regulations, respectively; TS_{it} and TR_{it} represent the industrial structure's advancement and rationalization, respectively; and Xit displays the control variable array. The space and time control variables are symbolized by μ_i and γ_i, including both. ε_{it} denotes the random error term.

Researching the combined regulatory impact of FER and IER is necessary to be more likely with the realistic background. Therefore, the interaction terms FER and IER are introduced into the aforementioned spatial Durbin model. Following is the model for such a corresponding panel expansion:

$$\begin{aligned} \ln EDQ_{it} = {} & \rho W_{ij} \ln EDQ_{it} + \beta_1 \ln FER_{it} + \beta_2 \ln IER_{it} + \beta_3 \ln FER_{it} \\ & \times \ln INER_{it} + \beta_4 \ln TS_{it} + \beta_5 \ln TR_{it} + \beta_6 \ln FER_{it} \times TS_{it} \\ & + \beta_7 \ln FER_{it} \times TR_{it} + \beta_8 \ln IER_{it} \times TS_{it} + \beta_9 \ln IER_{it} \\ & \times TR_{it} + \beta_{10} X_{it} + \delta_1 W_{ij} \ln FER_{it} + \delta_2 W_{ij} \ln IER_{it} \\ & + \delta_3 W_{ij} \ln FER_{it} \times \ln IER_{it} + \delta_4 W_{ij} \ln TS_{it} + \delta_5 W_{ij} \ln TR_{it} \\ & + \delta_6 W_{ij} \ln FER_{it} \times TS_{it} + \delta_7 W_{ij} \ln FER_{it} \\ & \times TR_{it} + \delta_8 W_{ij} \ln IER_{it} \times TS_{it} + \delta_9 W_{ij} \ln IER_{it} \times TR_{it} \\ & + \delta_{10} W_{ij} X_{it} + \mu_i + \gamma_t + \varepsilon_{it} \end{aligned} \quad (3)$$

Among them, the meanings of the symbols are the same as in the above formulas (1) and (2).

3.2. Variable choice

3.2.1. Explained variable

The explained variable is high-quality economic development (EDQ). EDQ is a shift in the economic growth model, moving from high-speed growth's quantitative change to its qualitative change. This improvement makes the economy run more effectively, the industrial structure more sensible, the services and goods better, the economy healthier and more sustainable, the society more egalitarian and harmonious, and the ecosystem greener (12). EDQ stands for high-level economic development. The degree of EDQ can only be effectively quantified by building an efficient method for measuring it (13). The majority of the current literature is based on the five development concepts of innovation, coordination, greenness, openness, and sharing to create a high-quality development index evaluation system. However, the EDQ index system should not only reflect the current condition of economic development but also pay attention to the operating status of economic development (60). The indicator system created by the five development concepts may fail to pay attention to the operational efficiency of economic development, and it will invariably have issues such as complex indicators that result in poor indicator selection efficiency (61). This study builds an index system from six dimensions: economic efficiency, economic structure, economic stability, innovation level, green environmental protection, and public welfare, combining existing research and integrating it with the concept of EDQ (15–18, 62). The specific indicators are shown in Table 1, and index weights are calculated using the entropy method.

3.2.2. Independent variables

Formal environmental regulation (FER): This study selects the completed investment in industrial pollution control to measure the intensity of FER. This investment in business environmental protection reflects the government's attention to environmental pollution and its determination to control it, which is suitable for FER.

Informal environmental regulation (IER): In accordance with the measurement method by Pargal and Wheeler (63), the indicators of economic status, population size, educational attainment, and age distribution are selected to be measured by the entropy method, representing IER.

Industrial upgrading includes rationalizing industrial structure (TR) and advancing industrial structure (TS).

Rationalizing industrial structure (TR): With reference to the study by Cheng et al. (64), we assessed TR using the inverse of the Theil index. The Theil index maintains the theoretical basis and economic meaning of the degree of structural deviation while also considering the relative significance of sectors and avoiding absolute value computation. The specific formula is as follows:

$$TR = 1/\sum_{i=1}^{n}\left(\frac{Y_i}{Y}\right)\ln\left(\frac{Y_i}{L_i}/\frac{Y}{L}\right) \quad (4)$$

Here, Y represents the gross regional product. L symbolizes the employed population. Yi/Y symbolizes the employed population as a symbol for the output structure. Y/L represents productivity. The industrial structure is more logical and sensible as the TR increases and is more out of equilibrium as the TR decreases.

Advanced industrial structure (TS): TS reflects the service-oriented tendency of the economic structure and the transformation process of the industrial structure from a lower-level form to a higher-level form. Therefore, the ratio of secondary sector production quality to the tertiary sector is measured in this study.

Control variables: This research includes control factors to decrease the forecast error caused by omitted regressors and to provide an objective evaluation of the policy effect. Specifically, it considers economic development (Vgdp), which is measured by per capita GDP; marketization (Vmark), which is expressed by the total marketization index proposed in the "China Marketization Index"; financial development level (Vfin) is represented by the balance of various deposits of financial institutions as a percentage of the regional GDP; and technological innovation (Vrd), the ratio of R&D expenditure to GDP, is known as the technological innovation metric.

3.3. Data sources

We used the provincial panel data from 30 provinces (municipalities, autonomous regions) in China from 2002 to 2020 (excluding Hong Kong, Macau, Taiwan, and Tibet) for empirical analysis. The primary sources are the "China Statistical Yearbook," "China Financial Yearbook," "China Environmental Yearbook," and the EPS database. Some missing data were provided by linear interpolation. The variables, as mentioned earlier, are taken logarithmically to eliminate possible heteroskedasticity issues in the data. Table 2 displays the summary statistics for the variables.

4. Results and discussion

4.1. Calculation results of high-quality economic development

The entropy method was employed to calculate the degree of EDQ in 30 Chinese provinces in accordance with the research methods discussed above. To more intuitively show the spatial correlation between EDQ in various regions, this study draws a spatial distribution map of EDQ. Figure 1 shows the regional distribution of EDQ at the provincial level in 2020. Economic development is divided into three levels. The darker the color, the higher the level of EDQ. From the perspective of space, the high-value agglomeration areas for EDQ are mainly coastal, economically developed areas. In contrast, the northeast, northwest, and underdeveloped areas in the interior are primarily low-value agglomerations. This shows that the EDQ between regions has a strong local spatial agglomeration effect: high–high (H–H) or low–low (L–L) agglomeration.

4.2. Spatial correlation test

4.2.1. Moran's index test

This study used the exploratory spatial data analysis method to test the global spatial correlation of the EDQ level of each province according to the global Moran's index (GMI). Considering the combined effect of economic and geographical factors, this paper employs that spatial matrix of geographic socioeconomic nesting to

TABLE 1 Comprehensive indicator system for high-quality economic development.

Primary indicators	Secondary indicators	Calculation method	Attributes
Economic efficiency	Labor efficiency	GDP/number of employees	Positive
	Land efficiency	Grain production/sown area of grain crops	Positive
	Capital efficiency	GDP/social fixed asset investment	Positive
	Energy efficiency	GDP/10,000 tons of standard coal	Positive
	Full factors production rate	Full factors production rate	Positive
Economic structure	Advanced industrial structure	Advanced index	Positive
	Rationalization of industrial structure	Rationalization index	Negative
	Urbanization rate	Urban population/total population	Positive
	Consumption rate	Consumption expenditure/GDP	Positive
	Binary gamma	Binary gamma	Negative
	Binary contrast coefficient	Binary contrast coefficient	Positive
	Investment rate	Gross capital formation/GDP	Positive
	Deposit balance/GDP	Deposit balance/GDP	Positive
	Loan balance/GDP	Loan balance/GDP	Positive
	Foreign trade openness	Total import and export trade/GDP	Positive
	Openness to foreign investment	Outward direct investment/GDP	Positive
Economic stability	Consumption index	Consumer price index	Negative
	Economic growth rate	Regional real economic growth rate	Negative
	Production index	Producer price index	Negative
	Unemployment rate	Urban registered unemployment rate	Negative
	Retail index	Commodity retail price index	Negative
Innovation level	Technological innovation output	The number of granted patent applications	Positive
	R&D investment intensity	Internal expenditure of R&D funds/GDP	Positive
	Technical turnover	Technology market turnover/GDP	Positive
	Technology investment intensity	Science-technology expenditure/financial expenditure	Positive
	Market index	Market index	Positive
Green development	Energy consumption	Total energy consumption/GDP	Negative
	Exhaust emissions	Total SO_2 emissions/GDP	Negative
	Wastewater discharge	Total industrial wastewater discharge/GDP	Negative
	Power consumption	Electricity consumption/GDP	Negative
	Solid waste discharge	Industrial solid waste generation/GDP	Negative
	Intensity of environmental governance	Environmental protection expenditure/financial expenditure	Positive
	Green area	Green coverage	Positive
Public welfare	GDP per capita	GDP per capita	Positive
	Workers' Compensation Proportion	Workers' compensation/real GDP	Positive
	Population mortality	Population mortality	Negative
	Years of education per capita	Average years of education for people	Positive
	Per capita education expenditure	Education expenditure/total population	Positive
	Health technicians per 1,000 population	Number of health technicians/total resident population∗1,000	Positive
	Old-age insurance coverage	Number of people participating in basic pension insurance/total population	Positive
	Health insurance coverage	Urban medical insurance participants/total urban population	Positive

TABLE 2 Variables' descriptive statistics.

Variables	Mean	Std.Dev	Min	Max	Observations
lnEDQ	−1.650	0.390	−2.380	−0.280	570
lnFER	2.400	1.140	−3.040	4.950	570
lnIER	−1.760	0.430	−2.670	−0.130	570
lnTS	−0.040	0.390	−0.700	1.670	570
lnTR	1.740	0.820	0.130	4.840	570
lnVgdp	1.090	0.790	−1.120	2.800	570
lnVmark	1.830	0.320	0.850	2.480	570
lnVfin	0.440	0.330	−0.290	1.720	570
lnVrd	−4.480	0.670	−6.350	−2.740	570

FIGURE 1
Regional distribution of high-quality development.

examine regional EDQ's spatial autocorrelation. Table 3 displays the test results.

The EDQ index's GMI values all passed the test at a significance level of 1% and were significantly positive. This demonstrates that EDQ is significantly spatially correlated positively. The EDQ index has an apparent spatial agglomeration effect among regions. High (low) adjacent interprovincial units are relatively agglomerated, showing a relatively spatial solid agglomeration pattern.

This study draws a partial Moran index scatter plot of EDQ for 2002, 2008, 2014, and 2020, depicted in Figures 2A–D, to investigate further if there are variations in the spatial correlation of EDQ in various regions. The EDQ Moran scatter plot shows that most provinces are clustered among the first and third quadrants, presenting the characteristics of "H–H" or "L–L" agglomeration. This demonstrates that EDQ has an apparent spatial agglomeration tendency. Specifically, comparing those figures in 2002 and 2020, we can see that the percentage in regions with "L–L" agglomerations expanded significantly. The first and third quadrants included 24, 25, 24, and 25 provinces in 2002, 2008, 2014, and 2020, respectively. The spatial distribution of EDQ is mainly characterized by high-high or low-low aggregation, which means that provinces with high quality are usually adjacent to other regions with high-quality economic development, and vice versa.

4.2.2. Spatial model selection test

There are three common spatial econometric models, namely the spatial lag model (SAR), the spatial error model (SEM), and the spatial Durbin model (SDM). The analysis model was selected according to the spatial econometric model selection method proposed by Elhorst (65), and the results are shown in Table 4. It is appropriate to choose SDM among SAR, SEM, and SDM by the LM test. The Hausman test results are significant at the 1% level, so this study chooses the fixed effect model. The Wald and LR tests rejected the hypothesis that the SDM model can be simplified to SAR and SEM. Therefore, the fixed-effect spatial Durbin model is this study's optimal spatial econometric model.

TABLE 3 Moran's index testing.

Year	GMI	Z	Year	GMI	Z
2002	0.524***	5.359	2012	0.506***	5.328
2003	0.481***	4.934	2013	0.514***	5.420
2004	0.503***	5.156	2014	0.505***	5.348
2005	0.538***	5.533	2015	0.500***	5.344
2006	0.534***	5.490	2016	0.480***	5.183
2007	0.529***	5.457	2017	0.487***	5.375
2008	0.527***	5.480	2018	0.466***	5.158
2009	0.523***	5.494	2019	0.474***	5.198
2010	0.524***	5.510	2020	0.469***	5.126
2011	0.516***	5.415			

***, **, *represent the 1, 5, and 10% levels of significance, respectively.

4.3. Empirical results

This study built a spatial Durbin model in accordance with the previous test to investigate the implications of dual ER and industrial upgrading on EDQ. Table 5 presents the outcomes. The model's capacity to fit data well and the reliability of the regression findings are both demonstrated by the sigma2_e and R^2 statistics. The spatial lag term's coefficients ρ are all significantly positive, which confirms that the local EDQ has a positive externality to the surrounding areas. It shows that the influence of spatial

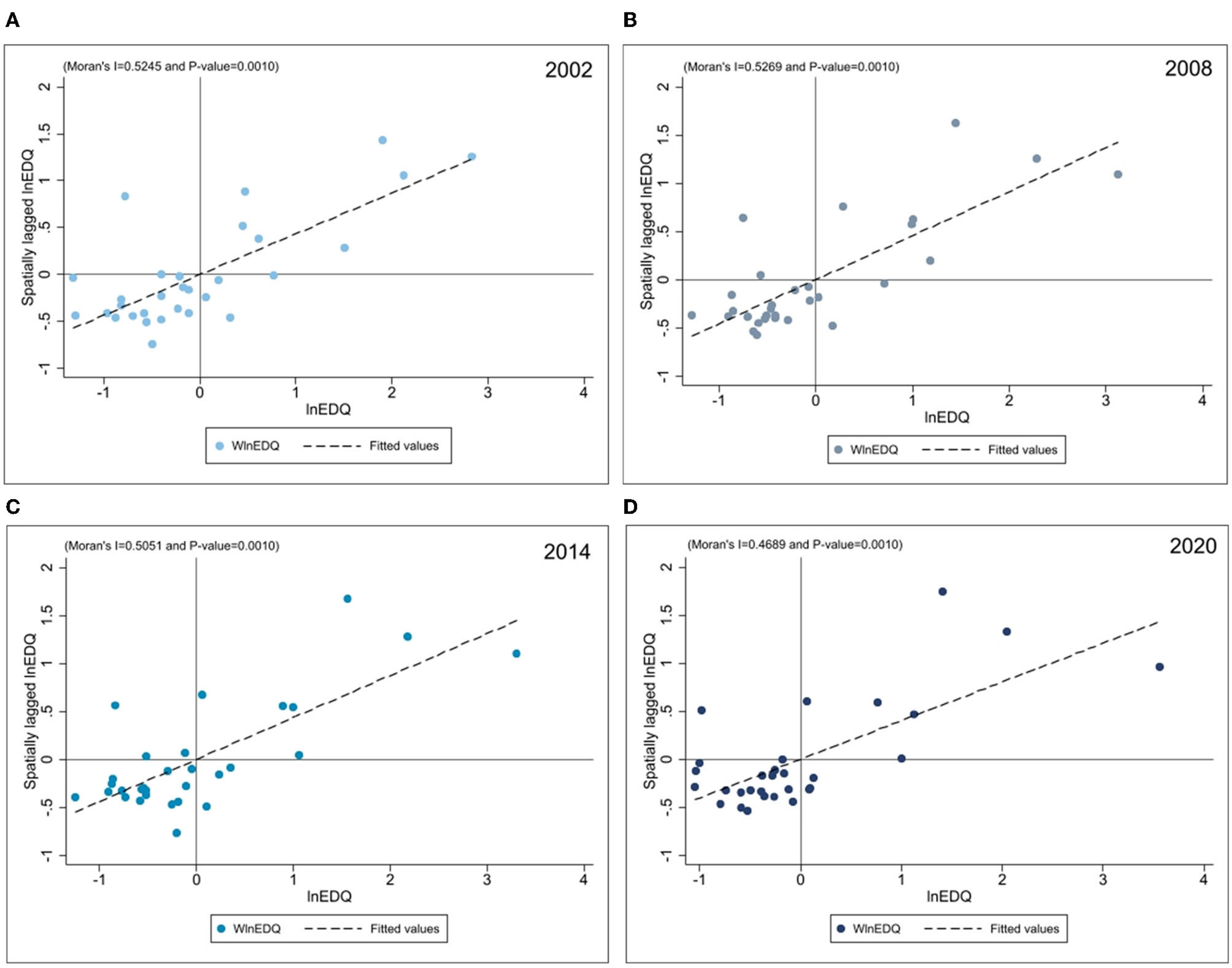

FIGURE 2
(A–D) Local Moran's index scatters plot.

TABLE 4 Spatial model correlation test results.

Test	Type	Statistics	Results
LM test	LM test (error)	130.611***	SDM model
	Robust LM test (error)	14.924***	
	LM test (lag)	185.069***	
	Robust LM test (lag)	69.382***	
Hausman test	Difference in coeffs not systematic	251.77***	Fixed effects
Wald test	SAR simplifies to SDM	92.02***	Refuse to simplify
	SEM simplifies SDM	48.14***	
LR test	SAR nested within SDM	85.44***	Refuse to simplify
	SEM nested within SDM	50.42***	

***, **, *represent the 1, 5, and 10% levels of significance, respectively.

TABLE 5 Estimation results.

Variables	Model 1	Model 2	Model 3
lnFER	−0.0081**		0.0327*
	(−2.05)		(1.96)
lnIER		0.144***	0.0809**
		(4.07)	(2.06)
lnFIER			0.0208**
			(2.34)
lnTS	0.0710***	0.0336*	0.0397**
	(4.35)	(1.94)	(2.27)
lnTR	0.0189**	0.0371***	0.0383***
	(2.20)	(3.87)	(3.93)
lnFERTS	−0.0160**		−0.0285***
	(−2.17)		(−3.59)
lnFERTR	0.0126***		0.0136**
	(3.03)		(2.37)
lnIERTS		0.0474**	0.0572***
		(2.21)	(2.59)
lnIERTR		−0.0278**	−0.0677***
		(−1.98)	(−4.97)
lnVgdp	0.195***	0.0533***	0.105***
	(8.45)	(5.08)	(8.12)
lnVmark	0.183***	0.113***	0.142***
	(6.27)	(6.39)	(7.86)
lnVfin2	0.138***	0.0583**	0.0904***
	(5.43)	(2.32)	(3.66)
lnVrd	0.0507***	0.0573***	0.0587***
	(3.85)	(4.25)	(4.37)
ρ	0.584***	0.527***	0.481***
	(17.21)	(13.51)	(11.78)
sigma2_e	0.00221***	0.00235***	0.00221***
	(16.63)	(16.64)	(16.67)
R^2	0.933	0.887	0.903
N	570	570	570

lnFIER represents lnFER×lnIER, lnFERTS represents lnFER×lnTS, lnFERTR represents lnFER×lnTR, lnIERTS represents lnIER×lnTS, lnIERTR represents lnIER×lnTR. ***, **, *represent the 1, 5, and 10% levels of significance, respectively. *t* statistics in parentheses.

externalities between regions should not be ignored when studying the regional EDQ.

Models 1 and 2's regression findings demonstrate that FER's coefficient is significantly negative (−0.0081), which reveals that FER inhibits EDQ. The reason may be that FER policies are easily affected by factors such as government implementation efficiency. The implementation of regulations is not targeted, and the same standards are adopted for the pollution control of different enterprises, which negatively affects the level of EDQ. Currently, "follow the cost effect" dominates, which is consistent with Sinn's findings. The IER's coefficient is significantly positive (0.144), showing that the IER enhances the EDQ, which would align with Michael et al.'s results. The effect of IFE's resource allocation distortion is frequently not evident because of its non-mandatory nature. It will effectively encourage enterprises' innovative compensation effects to achieve a win-win situation of environmental protection and efficiency improvement. The results above demonstrate how different ER forms have distinct effects on EDQ. Hypothesis 1 is verified.

The coefficients of the TS (0.071 in model 1, 0.0336 in model 2) and TR (0.0189 in model 1, 0.0371 in model 2) are both significantly positive, indicating that industry upgrading would promote EDQ. This may be because rational adjustments have promoted the matching of production factor input and output structures, and improved the efficiency of resource allocation, thereby promoting EDQ. The advanced adjustment causes both organizational productivity and service in sector proportion to keep rising. This reduces energy consumption and, as a result, advanced manufacturing pollution, promoting the EDQ even further. That confirms Hypothesis 2.

The interaction term between FER and TR is significantly positive at the 1% level (0.0126). The interaction term between IER and TS is significantly positive at the 5% level (0.0474). The above conclusions indicate that TR has a significant promoting effect on the relationship between FER and EDQ, and TS has a major promoting effect on the relationship between IER and EDQ. ER can promote EDQ by promoting industrial upgrading. The benign interaction between ER and industrial upgrading will help enterprises optimize resource allocation to the greatest extent and promote the continuous improvement of the coordination level among various industries. However, this kind of benign interaction can encourage enterprises to carry out technological transformation and innovation, enhance their pollution treatment capabilities, and thereby support EDQ. Hypothesis 3 is verified.

Model 3 adds the interaction terms of FER and IER in accordance with Models 1 and 2. The regression analysis found that the interaction term's coefficient appeared positively significant. The FER's coefficient changed from to 0.0081 in model 1 to 0.0327 in model 3. The impact of FER on EDQ switched from inhibiting to promoting. FER and IER have a substitution relationship. When FER is weak or ineffective, IER can fully utilize the public and environmental protective groups' oversight strengths to promote

EDQ further. IER can well supervise the implementation of FER, and FER can promote the formation of IER. The mechanisms of dual ER complement and encourage each other. Hypothesis 4 is verified.

From the perspective of control variables, the coefficients of economic development level, marketization level, financial development level, and technological innovation level are strongly positive. The enhancement of people's awareness of environmental protection, the improvement of marketization level, the progress of financial development level, and the increase of enterprise R&D investment are all conducive to EDQ moving toward a goal of superb quality.

4.4. Space effect decomposition discussion

The coefficients of the spatial Durbin model cannot accurately describe the marginal impact of explanatory variables, and only the decomposed direct effects, indirect effects, and total effects can truly reflect the "local-adjacent" effect (66). The direct implications represent the impact of locally relevant factors on the region's EDQ. The indirect effect is the spillover effect. It reflects the influence of neighboring provinces on the economic development level of the province. It also reflects that neighboring provinces have an impact on their own economic development level and further affect the province's economic development level through a circular feedback system. The total effect is the sum of the direct and indirect effects. The specific calculation process is as follows:

The general form of the spatial Durbin model:

$$Y = \alpha l_n + \rho WY + \beta X + \gamma WX + \varepsilon \quad (5)$$

It can be simplified into the following structure *via* conversion:

$$(I_n - \rho W)Y = \alpha l_n + \beta X + \gamma WX + \varepsilon \quad (6)$$

Let $L(W) = (I_n\text{-}\rho W)^{-1}$ and $S_m(W) = L(W)\,(I_n\beta_m + \gamma_m W)$, then the formula (6) can be written as:

$$Y = \sum_{m=1}^{k} S_m(W)X_m + L(W)\alpha l_n + L(W)\varepsilon \quad (7)$$

The matrix below is formed through transformation:

$$\begin{bmatrix} Y_1 \\ Y_2 \\ \vdots \\ Y_n \end{bmatrix} = \sum_{m=1}^{k} \begin{bmatrix} S_m(W)_{11} & S_m(W)_{12} & \cdots & S_m(W)_{1n} \\ S_m(W)_{21} & S_m(W)_{22} & \cdots & S_m(W)_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ S_m(W)_{n1} & S_m(W)_{n2} & \cdots & S_m(W)_{nn} \end{bmatrix} \begin{bmatrix} X_{1m} \\ X_{2m} \\ \vdots \\ X_{nm} \end{bmatrix} + L(W)\alpha l_n + L(W)\varepsilon \quad (8)$$

The first matrix on the right side of the equal sign is the partial differential matrix, and the elements on its diagonal reflect the direct effects, direct $= dY_i/\,dX_{im} = S_m(W)_{ii}$. Off-diagonal elements reflect spatial spillover, indirect $= dY_i/\,DX_{jm} = S_m(W)_{ij}$. This part analyzes the decomposition of spatial effects under the same framework that incorporates dual ER and industrial upgrading. Table 6 displays the outcomes.

The direct effect of FER is significantly positive (0.0319), indicating that FER has stricter and more direct control means for environmental governance. It can directly promote the local EDQ. The IER's direct (0.0832) and indirect (0.0655) effects are both statistically positive at 5%, proving that it works with neighbors as partners to advance EDQ. The control of pollutants by IER can effectively reduce the spread of contaminants, thus enabling the province's and neighboring provinces' EDQ. The cross product of FER and IER has a significant positive direct (0.0225) and indirect (0.0182) effect, indicating that the dual ER can coordinately promote EDQ and has a positive spatial spillover effect. Hypothesis 4 is further verified.

The direct effects of TS (0.0416) and TR (0.0343) are both significantly positive, indicating that industrial upgrading can promote the high-quality development of the province's economy. Hypothesis 2 is verified. From the perspective of indirect effects, TS (0.0331) between adjacent areas forms an economic development model with neighbors as partners. The reason is that the local TS can encourage the innovative progress's "spillover effect," which helps to advance nearby regions' technology and encourages an improvement

TABLE 6 Spatial effects decomposition results.

Variables	Direct effect	Indirect effect	Total effect
lnFER	0.0319*	−0.0218	0.0101
	(1.77)	(−1.17)	(0.29)
lnIER	0.0832**	0.0655**	0.149**
	(2.05)	(2.09)	(2.09)
lnFIER	0.0225**	0.0182**	0.0407**
	(2.36)	(2.20)	(2.32)
lnTS	0.0416**	0.0331**	0.0747**
	(2.34)	(2.33)	(2.38)
lnTR	0.0343***	−0.0630**	−0.0287
	(3.57)	(−2.07)	(−0.85)
lnFERTS	−0.0295***	−0.0238***	−0.0533***
	(−3.54)	(−3.03)	(−3.39)
lnFERTR	0.0139**	0.0112**	0.0250**
	(2.24)	(2.12)	(2.22)
lnIERTS	0.0597***	0.0484**	0.108**
	(2.58)	(2.29)	(2.49)
lnIERTR	−0.0703***	−0.0567***	−0.127***
	(−4.92)	(−3.92)	(−4.65)
lnVgdp	0.111***	0.0890***	0.200***
	(8.88)	(7.24)	(9.93)
lnVmark	0.150***	0.120***	0.270***
	(8.21)	(5.76)	(7.84)
lnVfin2	0.0972***	0.0776***	0.175***
	(3.62)	(3.56)	(3.73)
lnVrd	0.0608***	0.0490***	0.110***
	(4.42)	(3.75)	(4.28)

lnFIER represents lnFER×lnIER, lnFERTS represents lnFER×lnTS, lnFERTR represents lnFER×lnTR, lnIERTS represents lnIER×lnTS, lnIERTR represents lnIER×lnTR. ***, **, * represent the 1, 5, and 10% levels of significance, respectively. *t* statistics in parentheses.

in the EDQ as a whole. The TR (−0.0630) has formed a beggar-thy-neighbor economic development model. Local governments have improved the TR under the influence of various policies, which has aggravated the spatial selection effect of polluting businesses. The manifestation is that enterprises with lower productivity migrate to neighboring cities because they cannot adapt to stricter legal policies, thus reducing the EDQ level of neighboring towns.

The cross product of FER and TR has significant direct and indirect effect coefficients of 0.0139 and 0.0112, respectively, both of which are positive at the 5% level. It shows that TR and FER between adjacent provinces have a development partnership model with neighbors. FER can promote EDQ through TR. The interaction variables between IER and TS have significantly positive direct (0.0597) and indirect (0.0484) influence estimates. It shows that the TS and IER between adjacent provinces have an economic development model with neighbors as partners. It also shows that IER can promote EDQ through the TS. This further validates Hypothesis 3.

Considering all control variables, economic development, marketization, financial development, and technological innovation have significant positive direct, indirect, and total effects on regional EDQ. The local EDQ will encourage the economic development of adjacent provinces through spillover effects due to the enhancement of the economic development level, the marketization level, the financial development level, and the technological innovation level. Overall, the spatial Durbin model's impact decomposition findings indicate the reliability of the aforementioned empirical findings.

4.5. Spatial heterogeneity analysis

The exact effects of ER and industrial upgrading on economic development vary depending on the historical, geographical, and social characteristics of different locations in China. Therefore, a discussion of spatial heterogeneity is required. This study divides the research samples into three groups according to geographical location: east, middle, and west. Table 7 shows the empirical results.

ER and industrial modernization in the three major regions have diverse effects on EDQ from a spatial standpoint. Table 7 shows that FER has both positive direct and indirect effects on the EDQ of the eastern and central areas. The direct effect of ER on the western region is negative, and the indirect effect is not significant. The eastern region's established economy, vibrant market, and comparatively thorough policy framework are the primary causes of this outcome. As manufacturing costs rise due to stricter ER, most businesses can devote more funds to technology advancements that support EDQ in their local and neighboring areas. The center region is less developed than the eastern region, and ER has less impact on fostering the EDQ of the local and surrounding areas. The western region has the lowest degree of development. Local governments prioritize economic development but frequently disregard environmental protection. Implementing ER raises production costs for businesses and impedes regional economic growth.

Both direct and indirect effects of IER on EDQ in the eastern region are significantly positive, which is consistent with the main empirical evidence of this study. IER's direct and indirect effects on EDQ are insignificant in the central and western regions. This conclusion reflects the strong environmental awareness of the public in the eastern region. The population is still largely passive and pays less attention to environmental protection in the central and western regions. FER serves as the basic foundation for improving EDQ. This is related to China's ineffective environmental education and government-led environmental protection system. Industrial structure upgrading has both large positive direct and indirect effects on the eastern region but with no visibly direct effects on the middle and western regions. This condition can be connected to the eastern region's stronger industrial structure. While the indirect impact on the economic growth of the center region is negligible, it has a significantly positive impact on the western region. This demonstrates that improving industrial structure has a considerable favorable spillover effect on the western region. Industrial structure rationalization has a significantly positive direct impact on the EDQ of the eastern, central, and western areas.

TABLE 7 Spatial effect decomposition by region.

Variables	Spatial effect	Eastern region	Central region	Western region
lnFER	Direct effect	0.0904***	0.0231**	−0.0115*
		(7.25)	(2.36)	(−1.70)
	Indirect effect	0.177***	0.0605**	0.00117
		(4.82)	(2.14)	(0.70)
	Total effect	0.267***	0.0835**	−0.0104*
		(5.97)	(2.22)	(−1.67)
lnNER	Direct effect	0.201***	0.105	−0.124
		(5.62)	(1.50)	(−1.64)
	Indirect effect	0.0840***	0.260	0.0109
		(3.60)	(1.50)	(0.60)
	Total effect	0.285***	0.365	−0.113
		(5.62)	(1.51)	(−1.55)
lnTS	Direct effect	0.471***	−0.0531	−0.00913
		(11.53)	(−1.29)	(−0.38)
	Indirect effect	0.201***	−0.0624	0.179**
		(3.36)	(−0.36)	(2.39)
	Total effect	0.671***	−0.116	0.170**
		(7.34)	(−0.56)	(2.14)
lnTR	Direct effect	0.131***	0.123***	0.0455***
		(5.81)	(3.88)	(3.23)
	Indirect effect	0.0546***	0.314*	0.110***
		(3.82)	(1.85)	(3.20)
	Total effect	0.185***	0.437**	0.155***
		(5.95)	(2.21)	(3.87)

***, **, *represent the 1, 5, and 10% levels of significance, respectively. *t* statistics in parentheses.

TABLE 8 Robustness test.

Variables	Model 1		Model 2		Model 3	
	Direct	Indirect	Direct	Indirect	Direct	Indirect
lnFER	−0.0117**	−0.0137**			0.0284	−0.0257
	(−2.55)	(−2.52)			(1.54)	(−1.31)
lnIER			0.145***	0.153***	0.0745*	−0.116
			(4.01)	(4.35)	(1.68)	(−1.05)
lnFIER					0.0197**	0.0165*
					(2.01)	(1.86)
lnTS	0.0666***	0.0784***	0.0483***	0.0517**	0.0587***	0.0498***
	(4.02)	(4.05)	(2.72)	(2.57)	(2.98)	(2.61)
lnTR	0.0248***	0.0293**	0.0365***	0.0392***	0.0288***	0.0242***
	(2.61)	(2.52)	(3.73)	(3.28)	(2.96)	(2.64)
lnFERTS	−0.0121	0.101***			−0.0308***	−0.0262***
	(−1.41)	(3.00)			(−3.65)	(−2.91)
lnFERTR	0.00895*	−0.0233			0.0144**	0.0122**
	(1.91)	(−1.27)			(2.30)	(2.11)
lnIERTS			0.0440*	0.0474*	0.0399*	0.0335
			(1.92)	(1.82)	(1.70)	(1.61)
lnIERTR			−0.0604***	−0.0651***	−0.0646***	−0.0545***
			(−4.47)	(−3.59)	(−4.45)	(−3.58)
lnVgdp	0.104***	0.122***	0.0560***	0.0594***	0.123***	0.103***
	(7.80)	(7.66)	(5.38)	(5.70)	(8.21)	(5.35)
lnVmark	0.122***	0.145***	0.236***	−0.145***	0.141***	0.119***
	(6.32)	(5.37)	(8.07)	(−2.73)	(7.65)	(5.06)
lnVfin2	0.130***	0.153***	0.0944***	0.101***	0.120***	0.127*
	(4.85)	(4.66)	(3.74)	(3.55)	(4.06)	(1.79)
lnVrd	0.0303**	−0.000211	0.0564***	0.0604***	0.0429***	0.0360***
	(2.04)	(−0.00)	(3.95)	(3.55)	(3.07)	(2.88)

***, **, *represent the 1, 5, and 10% levels of significance, respectively. *t* statistics in parentheses.

The direct promotion effect is also greatest in the eastern region, followed by the middle region, and least in the western region. This is related to the degree of structural and industrial development in each region. The indirect effects of industrial structure rationalization are all positive, indicating that industrial structure rationalization has a positive spillover effect on the level of EDQ across the country. Rationalizing the industrial structure between adjacent cities forms an economic development model with neighbors as partners.

5. Robustness and endogeneity test

5.1. Robustness test

The above empirical results have well verified the theoretical hypothesis of this study. This study employed a geographical distance weight matrix to retest the aforementioned empirical findings and further confirm that the relationship between dual ER, industry transformation and upgrading, and EDQ is solid. The model construction and estimating procedures follow precedents. The results are shown in Table 8. The regression results show that the sign and significance of the explanatory variables in model 1, model 2, and model 3 are consistent with the original model. It shows that the impact of dual ER and industrial transformation and upgrading on EDQ is robust.

5.2. Endogeneity test

The increase in the level of EDQ may also have an impact on local ER policies. To avoid the resulting error caused by endogeneity in the regression, the GMM system is used to re-estimate the original equation. System GMM is a commonly used method for endogenous testing. A consistent estimate can be generated by including the lagged items of endogenous explanatory variables as instrumental variables in the regression equation. The estimated results are shown in Table 9. The regression findings show that all of the *p*-values for the AR (1) test are below 0.01, whereas all of the *p*-values for

TABLE 9 Endogeneity test.

Variables	Model 1	Model 2	Model 3
L.lnEDQ	0.569***	0.640***	0.573***
	(18.16)	(23.66)	(18.28)
lnFER	−0.018***		0.009
	(−5.59)		(0.58)
lnIER		0.004	−0.033
		(0.38)	(−1.63)
lnFIER			0.016**
			(2.06)
lnTS	0.040***	0.043***	0.034**
	(3.12)	(3.27)	(2.68)
lnTR	0.012*	0.020**	0.011*
	(1.80)	(2.57)	(1.74)
lnFERTS	−0.000		0.001
	(−0.07)		(0.17)
lnFERTR	0.004		−0.002
	(1.02)		(−0.36)
lnIERTS		0.005	0.005
		(0.21)	(0.19)
lnIERTR		−0.012	−0.013
		(−1.36)	(−1.39)
lnVgdp	0.122***	0.092***	0.121***
	(12.63)	(10.94)	(11.96)
lnVmark	0.082***	0.047**	0.093***
	(4.15)	(2.71)	(4.56)
lnVfin2	0.120***	0.113***	0.128***
	(6.91)	(5.95)	(7.05)
lnVrd	0.039***	0.027***	0.038***
	(5.01)	(4.07)	(5.08)
Constant	−0.827***	−0.706***	−0.904***
	(−11.15)	(−7.98)	(−9.60)
AR(1)	0.000	0.000	0.000
AR(2)	0.171	0.169	0.189
Hansen	0.745	0.718	0.796

***, **, *represent the 1, 5, and 10% levels of significance, respectively. *t* statistics in parentheses.

the AR (2) test are over 0.01. The residual term exhibits first-order autocorrelation, whereas second-order autocorrelation is absent. The regression results passed the serial correlation test. All of the *p*-values for the Hansen test were higher than 0.1, demonstrating the validity and rationale of the instrumental variables. ER has an inhibitory effect on EDQ, and NER has a promoting effect. The synergy between the two can significantly improve EDQ. The upgrading of the industrial structure can promote the regional EDQ, which is the same as the result of panel regression.

6. Conclusions and policy implications

This study built a spatial Durbin model to investigate the effects of dual ER and industry upgrading on EDQ based on theoretical analysis. The following are the primary conclusions: (1) The EDQ has visible spatial heterogeneity, and regions show strong local spatial agglomeration characteristics. (2) The impact of ER on EDQ is heterogeneous. FER has a restraining effect, while IER has a promoting effect. Dual ER interacts to promote EDQ. (3) The TS has a direct role in promoting EDQ and forms an economic development model of neighbors as partners; the TR has a direct role in promoting EDQ and forms an economic development model of beggar-thy-neighbor. (4) The TR is the main channel for FER to promote EDQ, and the TS is the main channel for IER to promote EDQ. (5) The impact of ER on EDQ is spatially heterogeneous and plays a greater role in developed regions.

This study provides the following policy recommendations based on the aforementioned findings.

First, the government should implement differentiated action for diverse ER and fully account for the variety of ER when formulating regulatory policies. Policymakers should find a balance between the combination of FER and IER and give full play to the policy effect of ER to promote EDQ. Second, local governments should not blindly introduce enterprises due to industrial transfer caused by ER. Still, they should establish appropriate industrial support development mechanisms to maximize the synchronization and complementarity among constructions in various locations and the judicious distribution of resources. Additionally, it is crucial to strengthen cooperation between regions, prevent the formation of the pollution shelter effect, and encourage the coordinated development of the industrial structure. Third, the government should formulate corresponding ER policies according to the status quo of different industrial structures. FER should be the primary focus when the industrial system is dominated by sectors with high energy requirements and emissions. The government should now create stringent regulatory measures, plan and guide enterprises toward clean production, and encourage regional industrial structure upgrades. IER should be the main focus in areas dominated by knowledge- and technology-intensive industries. The government should gradually adjust the environmental protection policy, stimulate the innovative compensation effect of ER, implement the regional coordinated development strategy, speed up the establishment of a new growth pattern, and effectively push regional coordinated development.

Future work will resolve a few of this study's limitations. Scholars have defined the selection of indicators from different perspectives. The metrics chosen within that work were derived from existing research. The innovation and comprehensiveness of indicators need to be further improved. This study mainly analyzes the implementation effect of environmental policies and the direction of industrial transformation and upgrading at the provincial level. It is necessary to further study the prefecture-level city level and deeply analyze the implementation path of regionally coordinated development.

Data availability statement

The datasets presented in this study can be found in online repositories. The names of the repository/repositories and accession number(s) can be found below: China Statistical Yearbook (http://www.stats.gov.cn/tjsj/ndsj/, accessed on 6 June 2022), China Environmental Yearbook (http://www.stats.gov.cn/ztjc/ztsj/hjtjzl/, accessed on 6 June 2022), and the EPS database (http://www.epsnet.com.cn/, accessed on 6 June 2022).

Author contributions

YL: conceptualization, software, resources, and data curation. WL: validation and supervision. YL and WL: methodology, formal analysis, writing—original draft preparation, and writing—review and editing. All authors have read and agreed to the published version of the manuscript.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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Coupling coordination analysis of urbanization and the ecological environment based on urban functional zones

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Urbanization is an inevitable process in human social progress; additionally, the ecological environment is the carrier and foundation of human social development. Considering central Shanghai, China, as an example, this study quantitatively analyzed the coupling coordination relationship between urbanization and the ecological environment based on urban functional zones; remote sensing images, Open Street Map roads, and point of interest data were analyzed for the urban functional zones *via* the remote sensing-based ecological index (RSEI), comprehensive nighttime light index (CNLI), and coupling coordination degree (D). The results revealed that urban functional zones in central Shanghai were mainly mixed functional zones and comprehensive functional zones, which formed a spatial structure that gradually radiated outward from the urban core. Additionally, CNLI values were high; the proportion of CNLI between 0.6 and 1 was 94.37%. Moreover, the RSEI showed spatial differentiation; it was low in the center and gradually increased outward. Additionally, D was at the primary coordination level. The coupling coordination type in the core area corresponded to an ecological environment lag, which gradually transitioned to a state of systematic balanced development from the core area outward, but showed sluggish urbanization in some areas. This quantitative analysis of the coupling coordination between urbanization and the ecological environment based on urban functional zones provides effective scientific references for optimization of spatial planning.

KEYWORDS

urbanization, sustainable development, coupling coordination degree, RSEI, central Shanghai

1. Introduction

China has been open to the world since reforms more than 40 years ago. During this period, the urbanization rate has increased from 17.92% in 1978 to 63.89% in 2020 (1). Urbanization is the driving force of socio-economic development and promotes population transformation, industrial restructuring, industrial development, scientific and technological progress, cultural exchange, and more. However, with the advancement of urbanization, highly concentrated populations and the rapid expansion of construction land have led to changes in species richness, climate, vegetation phenology, air quality, water quality, human settlements, and the marine environment (2–15). Ecological and environmental problems have gradually come to the fore and seriously affect the sustainable development of the region. Nevertheless, these issues have gradually become the basic conditions that restrict urban sustainable development. Therefore, analyzing the coupling coordination between urbanization and the ecological environment has become a critical issue in the field of sustainable urban development.

In 2015, the United Nations adopted the 2030 Global Sustainable Development Goals (SDGs), which aim to make cities and human settlements inclusive, safe, resilient, and sustainable (16). In 2021, China's 14th Five-Year Plan explicitly called for a new, improved urbanization strategy that enhances the quality of urbanization development. This new urbanization strategy includes accelerating the citizenship of transferred agricultural populations, improving the spatial layout of urbanization, and comprehensively upgrading the quality of cities (17, 18). Sustainable cities and human settlements focus on sustainable development, and new urbanization prioritizes ecological livability and harmonious development. Therefore, their goals are highly compatible. The relationship between urbanization and the ecological environment is an important element of both sustainable cities and human settlements and new urbanization.

Research on the coupling coordination between urbanization and the ecological environment has mostly focused on geography, urban planning, ecology, environmental science, and economics. Related theories include the environmental Kuznets curve, planetary boundaries theory, tele-coupling theory, sustainable livelihood framework, STIRPAT model, meta-coupling framework, and coupling coordination degree model (19–24). Studies have examined the national, regional, urban agglomeration, provincial, and city scales (19, 25–28). Research methods have included system analyses, mathematical models, and GIS spatial analyses. These studies have mainly focused on the coupling coordination relationships between urbanization and ecological environmental quality, ecological risk, ecological security, ecosystem service value, ecosystem health, geo-ecological environment, and energy efficiency (29–40). Exploring the coupling and coordination relationships between urbanization and the ecological environment can aid in understanding the spatial differentiation and development status of these two factors, which is important for the effective use of geographical location advantages, reasonable urban development planning, and sustainable regional development.

Although previous studies have analyzed the coupling coordination relationship between urbanization and the ecological environment at various levels and scales, certain limitations remain. Most previous studies constructed indicator systems based on socio-economic statistical data, which results in tedious and time-consuming evaluation processes (19). Moreover, the caliber of socio-economic statistics leads to poor spatial resolution of the research results; thus, they cannot reflect coupling coordination relationships at the pixel level (41, 42). Additionally, previous studies have mainly focused on national, regional, urban agglomeration, provincial, and city scales but have failed to express spatial locations and interrelationships of the various functional elements within cities in detail, so that suggestions for optimizing the urban spatial pattern could not be provided (25–27, 41, 42). Furthermore, urbanization in previous studies mainly refers to the urbanization of geographic space, whereas, other studies show that population urbanization provides the largest contribution to urbanization (43). Moreover, few studies have explored the impacts of population urbanization on the ecological environment.

Owing to recent developments, satellite remote sensing has become an effective assessment method for regional urbanization and the ecological environment by remedying defects, such as poor timeliness and low spatial resolution, in socio-economic statistics. Moreover, each city is a complex whole composed of various types of urban functional zones, and the proportion and spatial differentiation characteristic of each functional zone notably affect their operation efficiency, which in turn affects the socio-economic development of the city (44). As the core city of the Yangtze River Delta urban agglomeration, Shanghai has been the most affected by urban diseases and ecological and environmental problems due to its high population density, rapid expansion, severe pollution, and high-risk resource and environmental security threats (45). Therefore, considering central Shanghai as the study area, this study combined population urbanization and geographic space urbanization and quantitatively analyzed the coupling coordination relationship between urbanization and the ecological environment at the pixel level based on urban functional zones.

Overall, this study aimed to accurately identify urban functional zones based on Open Street Map (OSM) road data, point of interest (POI) data, and kernel density estimation methods. Additionally, we examined the spatial patterns of various parameters. The comprehensive nighttime light index (CNLI) was calculated based on nighttime lighting data to reflect the urbanization level throughout geographic space. The remote sensing-based ecological index (RSEI) was calculated based on the normalized difference vegetation index (NDVI), land surface temperature (LST), wetness (WET), and normalized difference bare soil index (NDBSI) to reflect the quality of the regional ecological environment. Furthermore, we aimed to analyze the coupling coordination relationship between urbanization and the ecological environment based on urban functional zones *via* the coupling coordination degree model.

2. Materials and methods

2.1. Study area

The municipality of Shanghai is the international economic, financial, and trade center of China (Figure 1). Shanghai is located on the west coast of the Pacific Ocean, between 105°17′E-110°11′E and 28°10′N-32°13′N. Central Shanghai includes the Huangpu, Xuhui, Changning, Jing'an, Putuo, Hongkou, and Yangpu Districts and the Pudong New Area (within the outer ring only), which is a highly urbanized area with a compact urban spatial form, high population density, economic vitality, and convenient transportation. Therefore, central Shanghai is a typical and representative area for studying the coupling coordination relationship between urbanization and the ecological environment based on urban functional zones.

2.2. Data processing

Considering the research goals and data accessibility, the data utilized in this study included OSM road data, POI data, remote sensing image data (Landsat 8 OLI TIRS, NPP-VIIRS, and Worldpop), and administrative division data. The details are shown in Table 1.

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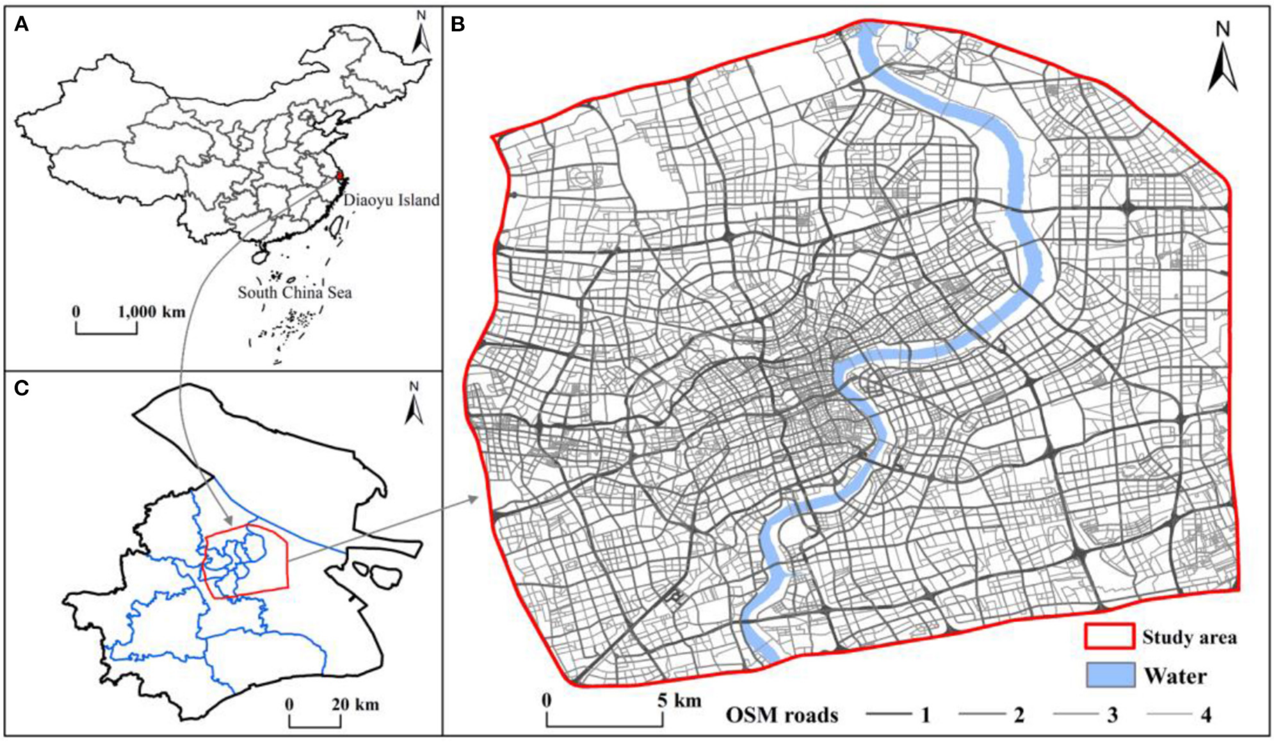


FIGURE 1
Location of the study area **(A)** China, **(B)** Shanghai, and **(C)** central Shanghai.

TABLE 1 Data sources and descriptions.

Data types	Data descriptions	Time	Data sources
OSM	Roads	2020	OpenStreetMap
POI	Point	2020	AMAP Data Open Platform
Landsat 8 OLI TIRS	30 m	2020.07-2020.08	United States Geological Survey
Population	100 m	2020	https://www.worldpop.org
NPP-VIIRS	500 m	2020	https://www.ngdc.noaa.gov
Administrative division	Boundaries	2022	http://xzqh.mca.gov.cn/map

2.3. Methods

2.3.1. Identification of urban functional zones

2.3.1.1. Dividing research units based on OSM road data

OSM data were used to divide the city into different research units. The specific process was as follows: First, based on OSM road classification data, motorway, trunk, primary, secondary, tertiary, residential, and unclassified roads were selected and classified as OSM roads I, II, III, and IV. Road network data was obtained *via* processing the extendline, trimline, and topological check. Subsequently, 40-, 20-, 10-, and 5-m buffers were generated according to the respective road classes, and the buffers were removed from the study area (46, 47). Finally, research units with small areas were discarded to generate the independent research units.

2.3.1.2. Kernel density estimation of POI data

The POI data obtained by AMAP Map has issues such as cross duplication; therefore, it is necessary to eliminate duplicate data based on their attributes. Using the Urban Land Classification and Planning and Construction Land Standard (GB_50137-2011) as the standard, and considering the actual situation in central Shanghai, the POI data were divided into six major categories, namely residential, industrial, commercial, public, science and education, and green square. The division criteria are detailed in Table 2 (48).

Kernel density estimation (KDE) is an empirical probability density function used to estimate smoothing; its development is based on the first law of geography, which reflects the regularity of spatial location information and distance decay. KDE is widely used in urban public service evaluation, traffic section risk assessment, economic clustering, and other related studies (49–51). It is calculated as follows:

$$f(s) = \sum_{i=1}^{n} \frac{1}{h^2} \varphi\left(\frac{s - c_i}{h}\right) \tag{1}$$

TABLE 2 POI data classification.

Primary classification	Secondary classification	Quantity	Proportion (%)
Commercial	Shopping services, catering services, accommodation services, leisure, entertainment, and finance	94857	28.78
Green Square	Tourist attractions and park squares	2021	0.61
Industrial	Corporations, industrial and mining plant, and industrial park	94146	25.56
Public	Government agencies, healthcare services, and public facilities	91809	27.86
Residential	Residential area and commercial residential area	21600	6.55
Science and education	Institutions of higher learning, vocational colleges, middle schools, primary schools, scientific, and educational places	25162	7.63

where $f(s)$ is the KDE function located at position s, h is the attenuation value (bandwidth), c_i is the position of the i^{th} POI, n is the number of POI locations whose path distance from position s is not higher than h, and φ is the predetermined kernel function. The kernel function has minimal effect on the KDE results, whereas the bandwidth has a notable effect. The larger the bandwidth, the smoother the kernel density surface, masking hot spots in the study area and obscuring their features. When the bandwidth is too small, the kernel density surface becomes uneven, which can reveal fine local features but cannot ensure continuity and correlation in large-scale data, leading to fragmented result patches (52).

2.3.1.3. Identification of urban functional zones

Based on the KDE of the POI data and research units divided by the OSM road data, the frequency density (F_i) of each type of POI within each research unit was calculated. Among them, the weights of residential, industrial, commercial, public, science and education, and green square were 30, 40, 15, 50, 60, and 90, respectively (53). The formula for calculating F_i is as follows:

$$F_i = (W_i * d_i) / \sum_{j=1}^{s} \left(W_i * d_i\right) * 100\% \quad (2)$$

where F_i, W_i, and d_i are the frequency density, weight, and kernel density of the i^{th} type of POI within the research unit, respectively. When the F_i of a POI type was $\geq 50\%$, the unit was considered as a single type of functional zones; when the F_i of two types of POIs in the research unit were both between 20 and 50%, the research unit was considered as a mixed functional zone of two types. Other units were classified as comprehensive functional zones.

2.3.2. Calculation of CNLI

The CNLI can reflect the intensity of human activity and the level of urbanization in a region. In this study, the CNLI was constructed based on the average relative light intensity (I) and the ratio of the light area to the study area (S) to characterize the level of urbanization (54, 55) as follows:

$$\mathrm{CNLI} = \mathrm{I} * \mathrm{S} \quad (3)$$

$$I = \frac{\sum_{i=P}^{DN_M} (DN_i * n_i)}{N_L * DN_M} \quad (4)$$

$$S = \frac{Area_N}{Area} \quad (5)$$

Where, DN_i indicates the grayscale value of the i^{th} image element in the study area, n_i is the total number of the grayscale image elements in the region, P is the threshold value for error removal, DN_M is the maximum possible grayscale value, N_L and $Area_N$ are the total number and area of image elements in the region that satisfy the condition $P \leq DN \leq DN_M$, and $Area$ is the area of the entire region.

2.3.3. Calculation of RSEI

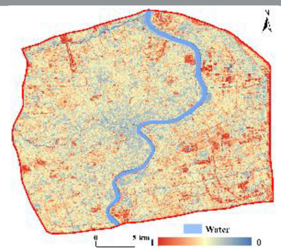
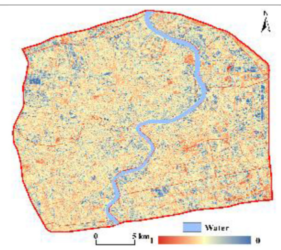
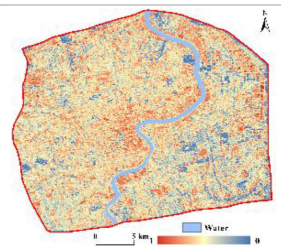
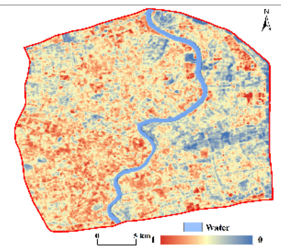
The RSEI is an index for rapid and objective evaluation of the quality of the regional ecological environment using remote sensing data, which is between 0 and 1. The closer the RSEI is to 1, the better the quality of the ecological environment; the closer the RSEI is to 0, the worse the quality of the ecological environment (56–58). The RSEI was determined by first calculating each component index (NDVI, WET, NDBSI, and LST) separately and standardizing them according to Table 3. Subsequently, the first component of principal component analysis (PC1) and related statistical results were obtained by combining the characteristics of the four indexes; these were normalized to obtain the RSEI.

In this table, ρ_{Red}, ρ_{Green}, ρ_{Blue}, ρ_{Nir}, ρ_{Swir1}, and ρ_{Swir2} correspond to each band of the Landsat 8 OLI TIRS; T_s is the land surface temperature; T_a is the atmospheric temperature, which is generally constant and was taken as 293.16 in this study; T_i is the brightness temperature of thermal infrared band; a and b are constants and are−67.355 and 0.459, respectively; ε is the surface specific emissivity; and τ is the atmospheric transmittance.

2.3.4. Coupling coordination degree (D)

The D can characterize the interaction of two or more systems and their coordination degree. It is mainly used to analyze coordination levels and has widely been used in the study of the coupling coordination relationships among urbanization, social economy, the ecological environment, and industrial structure (59–65). Urbanization includes both geospatial urbanization and population urbanization. Geospatial urbanization provides support and assurance for urbanization, and population urbanization is the essence of urbanization. In this study, the CNLI and population represented geospatial and population urbanization, respectively. To explore the coupling coordination relationship between urbanization and

TABLE 3 Calculation of indicators.

Index	Formula		Result
NDVI	$NDVI = (\rho_{Nir} - \rho_{Red})/(\rho_{Nir} + \rho_{Red})$	(6)	
WET	$WET = 0.1511 * \rho_{Blue} + 0.1973 * \rho_{Green} + 0.3283 * \rho_{Red} + 0.3407 * \rho_{Nir} - 0.7117 * \rho_{Swir1} - 0.4559 * \rho_{Swir2}$	(7)	
NDBSI	$IBI = \{\frac{2\rho_{Swir1}}{(\rho_{Swir1}+\rho_{Nir})} - [\frac{\rho_{Nir}}{(\rho_{Nir}+\rho_{Red})} + \frac{\rho_{Green}}{(\rho_{Green}+\rho_{Swir1})}]\} / \{\frac{2\rho_{Swir1}}{(\rho_{Swir1}+\rho_{Nir})} + [\frac{\rho_{Nir}}{(\rho_{Nir}+\rho_{Red})} + \frac{\rho_{Green}}{(\rho_{Green}+\rho_{Swir1})}]\}$ $SI = \frac{(\rho_{Swir1}+\rho_{Red})-(\rho_{Nir}+\rho_{Blue})}{(\rho_{Swir1}+\rho_{Red})+(\rho_{Nir}+\rho_{Blue})}$ $NDBSI = (IBI + SI)/2$	(8) (9) (10)	
LST	$T_s = [a * (1 - C - D) + (b * (1 - C - D) + C + D) * T_i - D * T_a]/C$ $C = \varepsilon * \tau$ $D = (1 - \tau) * [1 + (1 - \varepsilon) * \tau]$	(11) (12) (13)	

the ecological environment, we integrated the CNLI and population at equal proportions (i.e., 0.5 each) into the urbanization system and built the urbanization index. The formula for the D is as follows:

$$C = \{\frac{U_1 * U_2}{\left[\frac{(U_1+U_2)}{2}\right]^2}\}^{\frac{1}{2}} \quad (6)$$

$$T = \alpha * U_1 + \beta * U_2 \quad (7)$$

$$D = \sqrt{C * T} \quad (8)$$

where C is the coupling degree; U_1 and U_2 are the index values of urbanization and the ecological environment, respectively; T is their comprehensive evaluation value; and α, β are coefficients. We considered that urbanization and the ecological environment were equally important; therefore, $\alpha = \beta = 0.5$. The D is the coupling coordination degree; the larger the D, the better the coupling coordination degree and the more coordinated the development level between urbanization and the ecological environment.

3. Results

3.1. Urban functional zones

Based on the OSM road network data, central Shanghai was divided into 6,219 research units and 20 types of urban functional zones, including six single-type, 13 two-type mixed, and one comprehensive functional zone types (Figure 2). The spatial distribution of the single-type functional zones is shown in Figure 2A. Public functional zones were the most numerous among these, at 1,666 units, which accounted for 26.79% of the total units. Figure 2B shows the two-type mixed functional zones, the most numerous of which were industrial-public functional zones, with 1,546 instances, which comprised 24.86%. The comprehensive functional zones totaled 944, accounting for 15.18% (Figure 2C). Overall (Figure 2D), mixed functional zones and comprehensive functional zones were predominant in central Shanghai, accounting for 54.91% of the total units. These zones gradually decreased from the center of the city to the perimeter, forming a spatial structure that gradually radiates outward from the core of the city; this indicates that the distribution of urban functional zones was reasonable, which helps improve the efficiency of urban operation and enhance urban vitality. The single-type functional zones were scattered throughout the core of the city but gradually clustered outward; this was especially true of the industrial functional zones, which were mainly concentrated in the Gaoqiao and Shanghai New Cao Yang industrial parks.

3.2. Spatial patterns of the parameters

3.2.1. Comprehensive nighttime light index

The CNLI can reflect the urbanization level of a region, which we utilized to reveal the urbanization levels in central Shanghai from the perspective of urban functional zones. Utilizing ArcGIS, the CNLI was divided into five classes: I (0–0.6), II (0.6–0.7), III (0.7–0.8), IV (0.8–0.9), V (0.9–1.0). The results are shown Figure 3A. The CNLI was high in the core of the city (with an average value of 0.92) and gradually decreased toward the periphery; simultaneously, it had good continuity, which indirectly reflects the close connection between social and economic activities and population flow within these areas. The percentages of the II, III, IV, and V classifications were 7.51, 13.42, 26.20, and 47.24%, respectively.

3.2.2. Sensing-based ecological index

The RSEI ranged from 0 to 1 and, overall, was low in the center of the city and gradually increased toward the periphery. The RSEI was also divided into five classes using the equal interval method in ArcGIS as follows: poor (0–0.2), fair (0.2–0.4), moderate (0.4–0.6), good (0.6–0.8), and excellent (0.8–1). Figure 3B shows that the RSEI in central Shanghai was primarily between 0.4 and 0.6; thus, the ecological environment was in moderate condition. The RSEI in the core of the city was mostly between 0.2 and 0.4; therefore, the ecological environment was fair in the city core. The ecological environment quality in the periphery of the central city was notably better than that in the core area, especially in some areas in southeastern central Shanghai, where the ecological environment was in excellent condition. Additionally, the area and proportion of the five classes were separately calculated. The area in the moderate class was 225.05 km^2, comprising 51.39% of the area; the percentages of the areas of the remaining classes in descending order were as follows: fair (33.86%) > good (11.15%) > poor (3.16%) > excellent (0.44%).

3.3. Spatial pattern of coupling coordination degree (D)

The D was between 0 and 1 (Figure 4A) and was classified into five classes using the equal interval method of ArcGIS (Figure 4B) as follows: serious imbalance (0–0.2), moderate imbalance (0.2–0.4), primary coordination (0.4–0.6), moderate coordination (0.6–0.8), and high coordination (0.8–1), which accounted for 2.46, 23.32, 54.73, 18.69, and 0.80% of research units, respectively. The mean D value in central Shanghai was 0.48, which indicates a primary coordination level; this is closely related to the high urbanization level and high population density in the region. In terms of the spatial heterogeneity of the D, the core of Shanghai was generally in a state of primary coordination. The D gradually increased from the core area outward and gradually transitioned to the moderate coordination level. In the eastern areas of central Shanghai, moderate imbalance and primary coordination were predominant, indicating that the D between urbanization and the ecological environment was relatively low in this region. Nevertheless, some areas showed a high degree of coordination, such as Gongqing National Forest Park and Tongji University, which are mostly science and education, green square, or public functional zones. Although the five types of the D showed dispersed spatial differentiation, there were also clustering phenomena in some areas, such as in a newly developed industrial park, which was within the moderate imbalance level.

We integrated the CNLI and population with 0.5 to create a unified urbanization index (U). As shown in Table 4, these values were combined with the RSEI (E) to classify the specific types of coupling coordination into three major categories: ecological environment lag, sluggish urbanization, and systematic balanced development. The results show that within central Shanghai, the main category was systematic balanced development; the percentages of areas with ecological environment lag, sluggish urbanization, and systematic balanced development were 10.53, 37.28, and 52.20%, respectively.

Combined with the classification of coupling coordination shown previously, the specific types of coupling coordination were further classified into 15 categories. As shown in Table 4, the proportion of areas with primary coordination-systematic balanced development was the highest, reaching 29.32%; this was followed by primary coordination-sluggish urbanization at 20.67%. Only two types had a percentage between 10 and 20%, namely moderate imbalance-systematic balanced development and moderate coordination-systematic balanced development; all other specific types of coupling coordination were below 10%. Figure 4C shows the spatial characteristics of the specific types of coupling coordination; the predominant type of coupling coordination in the core of central Shanghai was ecological environment lag. However, this gradually transitioned to a state of systematic balanced development from the core area outward but showed sluggish urbanization in some areas of Pudong New Area, Baoshan District, and Changning District. In general, this was consistent with the actual urbanization and ecological situation of central Shanghai.

4. Discussion

4.1. Why utilize the perspective of urban functional zones?

Accurate identification of urban functional zones plays a significant role in spatial planning and sustainable development decisions at various scales (66). The coupling coordination between urbanization and the ecological environment is an important element of urban sustainable development (67). This study examined this relationship through the perspective of urban functional zones because existing studies have mostly constructed indicator systems based on socio-economic statistics, which have poor precision. Moreover, the research scales of previous studies have mostly been based on countries, regions, urban agglomerations, provinces, and cities; thus, they cannot directly reflect spatial differences in

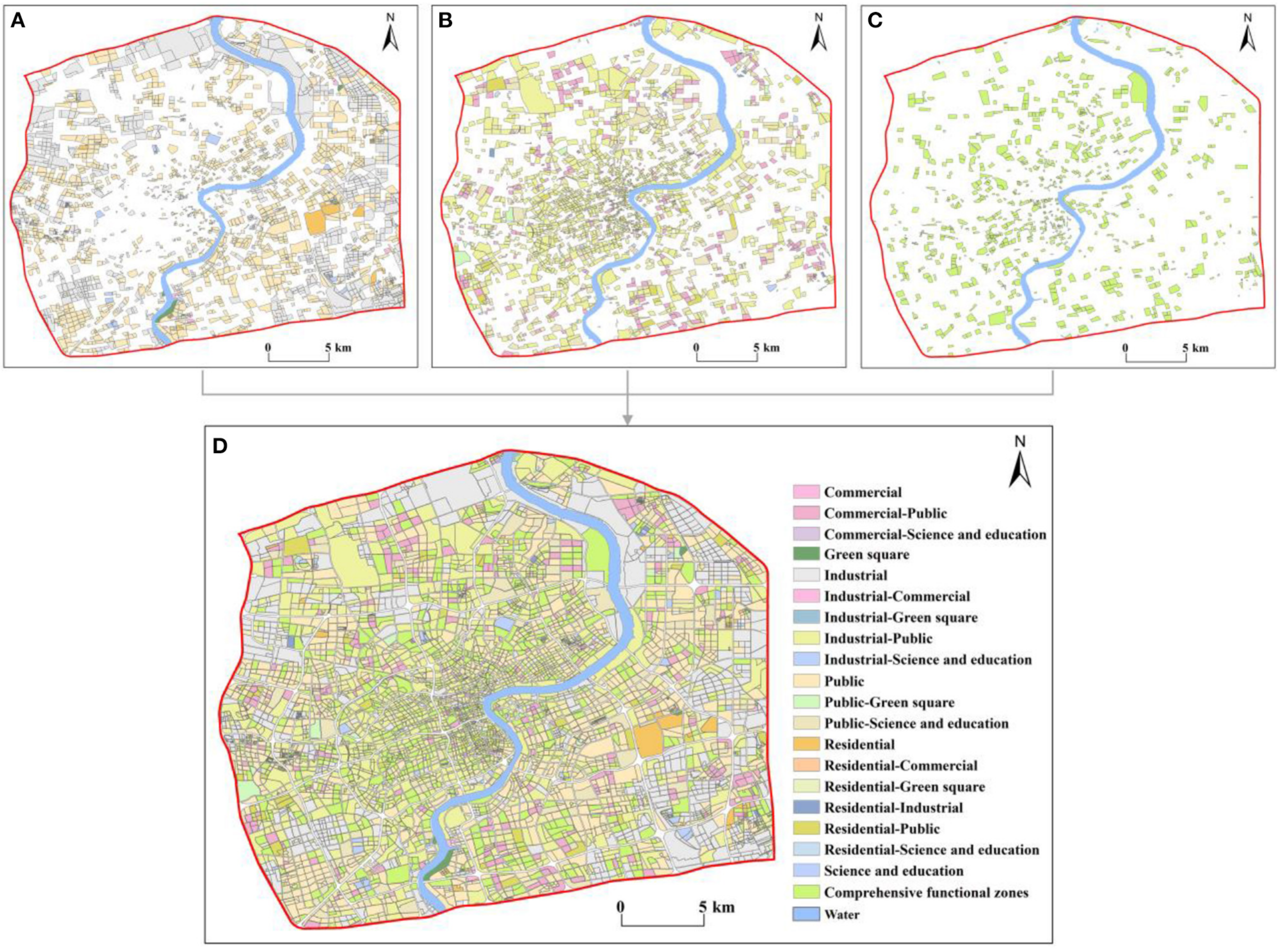


FIGURE 2
Classification of urban functional zones in central Shanghai **(A)** single-type functional zones, **(B)** two-type mixed functional zones, **(C)** comprehensive functional zones, and **(D)** all functional zones within central Shanghai.

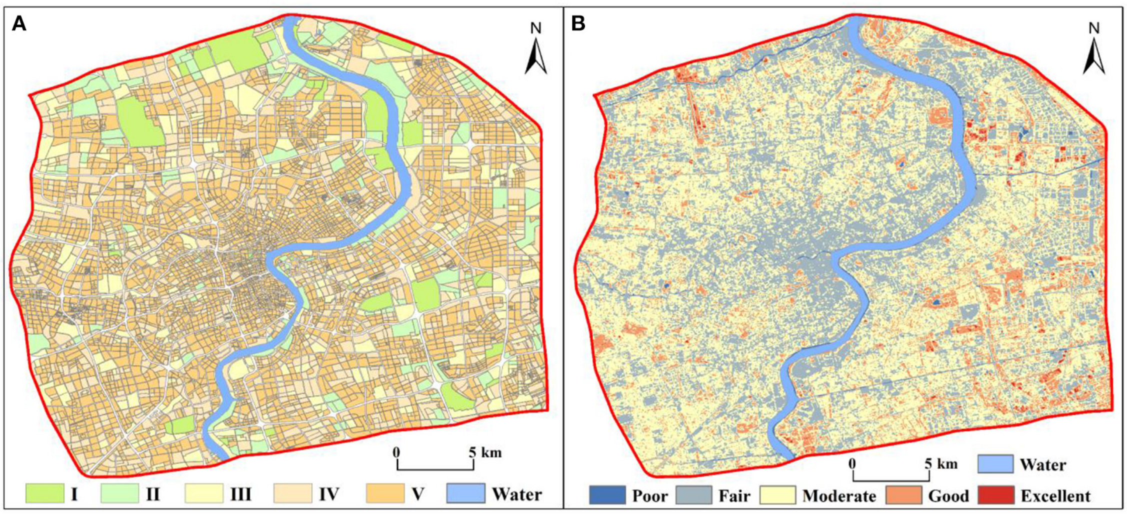


FIGURE 3
Spatial patterns of the CNLI **(A)** and RSEI **(B)** in central Shanghai.

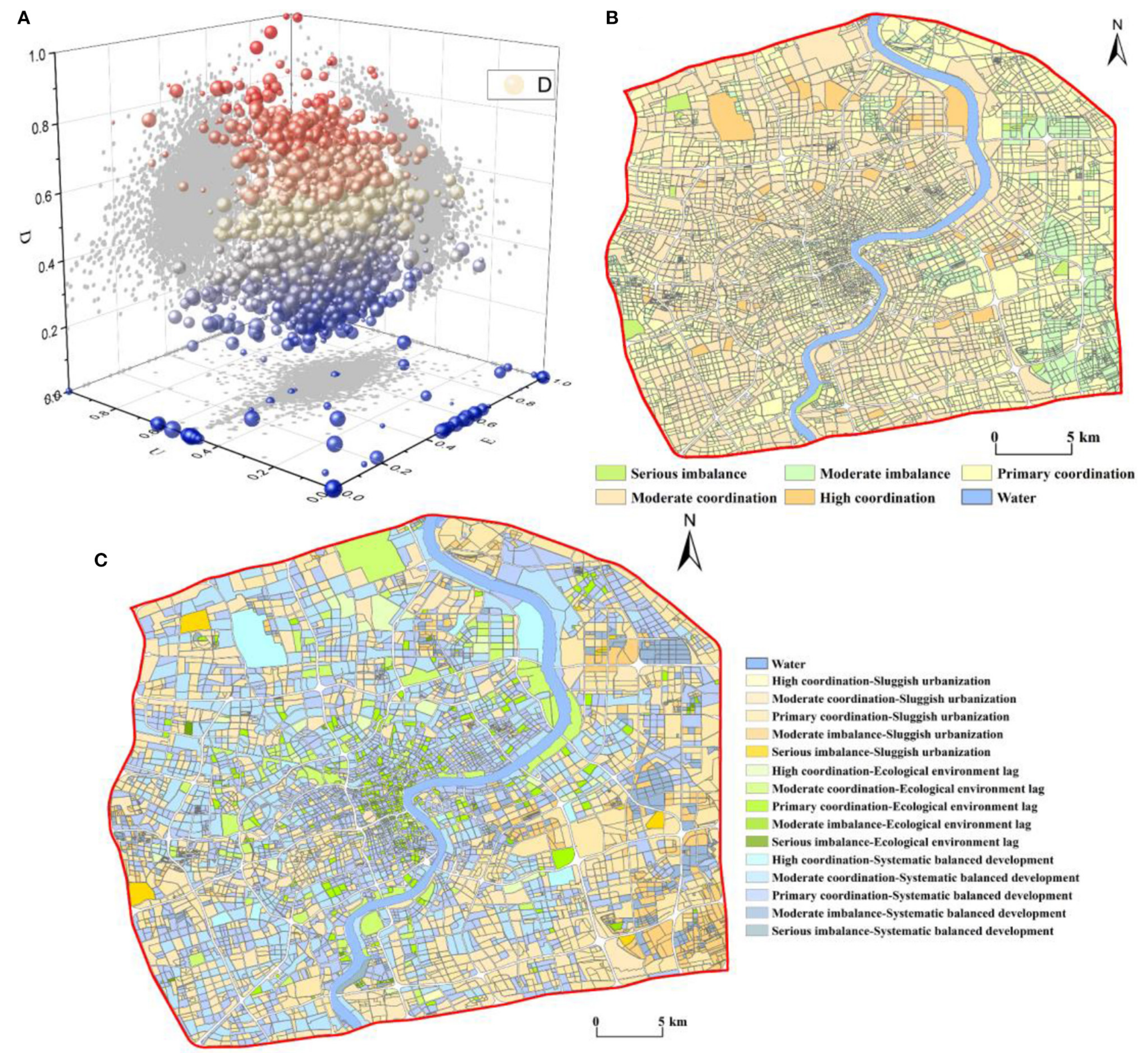


FIGURE 4
Spatial pattern of the D in central Shanghai **(A)** 3D scatter plot of D, **(B)** classes of D, and **(C)** coupling coordination classifications.

the coupling coordination relationship between urbanization and the ecological environment within cities (19, 25–27). Additionally, urban roads are the basis for urban development and lead to further development; moreover, they have far-reaching influences on socio-economic development. Hence, the parcels formed by urban road connections are the basic units of urban planning and give rise to urban socio-economic functions. The OSM road data have high positioning accuracy and good topological relationships and are widely used in network and service-zone analysis (68), thereby enabling accurate identification of urban functional zones. Overall, multi-source data are more reasonable for quantitatively exploring the coupling coordination relationship between urbanization and the ecological environment within cities based on urban functional zones.

In summary, we divided the study area into research units based on OSM road data and identified urban functional zones based on POI data. Subsequently, the CNLI and RSEI were calculated based on remote sensing image data to quantitatively analyze the coupling coordination relationship between urbanization and the ecological environment within each urban functional zone. This method overcomes the limitations of previous studies, considers the urban spatial structure composed of urban roads, and expresses the coupling coordination at a fine scale. Moreover, exploring the coupling coordination relationship between urbanization and the ecological environment within a city provides effective scientific references for formulating urban development strategies and optimizing spatial planning; it can also effectively promote socio-economic development and construction of an ecological civilization.

TABLE 4 Classification categories for the coupling coordination of urbanization and the ecological environment.

Composite category	Coordination level	Subcategory	Systematic exponential comparison	Subcategory	Percent (%)
Coordinated development	$0.8 < D \leq 1$	High coordination	E-U > 0.1	Sluggish urbanization	0.10
			$\lvert E\text{-}U \rvert \leq 0.1$	Systematic balanced development	0.21
			E-U < −0.1	Ecological environment lag	0.50
Transformation development	$0.6 < D \leq 0.8$	Moderate coordination	E-U > 0.1	Sluggish urbanization	6.31
			$\lvert E\text{-}U \rvert \leq 0.1$	Systematic balanced development	10.32
			E-U < −0.1	Ecological environment lag	2.07
	$0.4 < D \leq 0.6$	Primary coordination	E-U > 0.1	Sluggish urbanization	20.67
			$\lvert E\text{-}U \rvert \leq 0.1$	Systematic balanced development	29.32
			E-U < −0.1	Ecological environment lag	4.75
Uncoordinated development	$0.2 < D \leq 0.4$	Moderate imbalance	E-U > 0.1	Sluggish urbanization	9.03
			$\lvert E\text{-}U \rvert \leq 0.1$	Systematic balanced development	11.60
			E-U < −0.1	Ecological environment lag	2.68
	$0 < D \leq 0.2$	Serious imbalance	E-U > 0.1	Sluggish urbanization	1.17
			$\lvert E\text{-}U \rvert \leq 0.1$	Systematic balanced development	0.75
			E-U < −0.1	Ecological environment lag	0.53

4.2. Differences among various types of urban functional zones

The refined urban functional zones (Figure 2) were categorized into commercial, industrial, residential, public, green square, and science and education functional zone types. As shown in Figure 5A, public-dominated functional zones were predominant in central Shanghai, accounting for 64.91% of the total units, followed by industrial-dominated functional zones at 29.18% of the total. Figure 5B shows differences in the CNLI among functional zones. The CNLI was high throughout; notably, the average CNLI value in public and industrial-dominated functional zones was above 0.90. The mean RSEI value was ∼0.50; the RSEI was higher in residential- and public-dominated functional zones (Figure 5C). Figure 5D shows differences in the D among various types of functional zones. The D of green square-dominated functional zones was the lowest, whereas the D was the highest in public-dominated functional zones. The D in the remainder of functional zones decreased from residential- to industrial-, science and education-, and commercial-dominated functional zones.

The percentages of ecological environment lag, sluggish urbanization, and systematic balanced development in the different types of urban functional zones were calculated to reveal spatial patterns in the D. The results are shown in Figure 6; note that functional zone types with low numbers were removed from the calculation. The commercial, green square, industrial-science and education, residential, residential-public, science and education, and comprehensive functional zones primarily showed sluggish urbanization. In contrast, ecological environment lag was predominant in commercial-public, industrial-commercial, and public-green square zones. Additionally, industrial, industrial-public, public, and public-science and education zones mainly showed systematic balanced development. Although comprehensive functional zones predominantly showed sluggish urbanization, 42.06% of these zones showed systematic balanced development, indicating that their urbanization was nevertheless coordinated with the development of the ecological environment.

4.3. Recommendations for urban planning

The United Nations Sustainable Development Goals (SDGs) propose that cities and human settlements should be inclusive, safe, resilient, and sustainable. Similarly, new urbanization is an urbanization process that harmonizes the population, economy, resources, and environment and emphasizes improving the capacity for sustainable urban development (69). The coupling coordination between the development of urbanization and the ecological environment is the core issue for both SDGs and new urbanization. Central Shanghai is the political and economic center of the city and has a high level of urbanization and a highly aggregated population. As urbanization continues to advance in Shanghai, the pressure on the ecological environment will continuously increase. Therefore, promoting high-quality development *via* new urbanization and construction of an ecological civilization is a long-term test for central Shanghai.

Research reveals that the impact of urbanization on coupling coordination is 7.2 times higher than that of the ecological environment; therefore, to improve the coupling coordination

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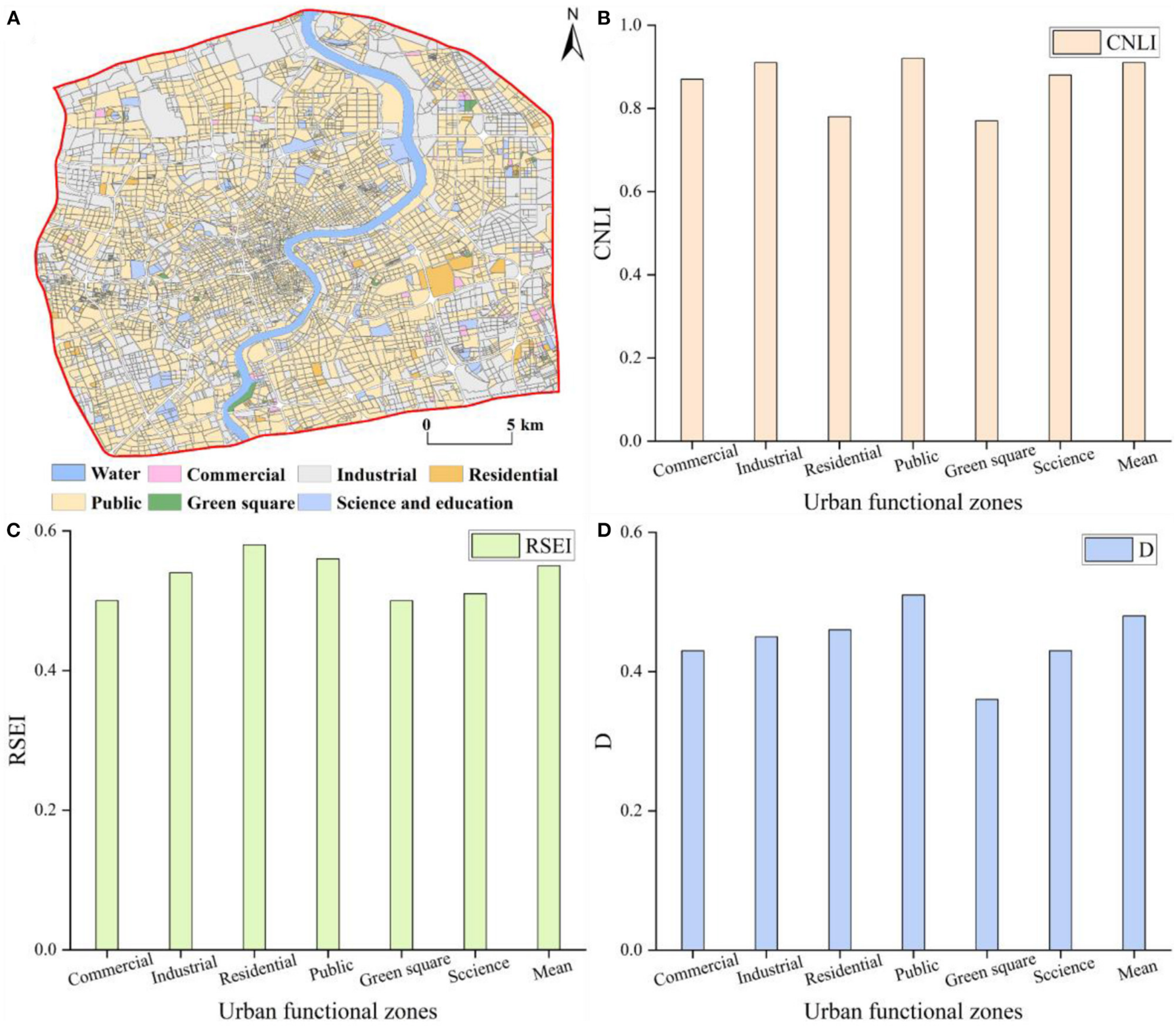

FIGURE 5
Differences in indices in various urban functional zones **(A)** functional zones by dominant type, **(B)** CNLI, **(C)** RSEI, and **(D)** D.

relationship between urbanization and the ecological environment, increasing the quality of urbanization is important (42). Territorial spatial planning provides a spatial blueprint for urban sustainable development and integrates the functions and characteristics of spatial planning; thus, it is an important tool to improve the quality of urbanization (70). In the context of the COVID-19 epidemic, new urbanization and the construction of sustainable cities and human settlements should be set as the goal; territorial spatial planning considered as the method; urban functional zones used as the scale; the rational allocation and renewal of the urban infrastructure and public service facilities optimized; the coupling coordination relationship between urbanization, population, and the ecological environment improved; urban ecological resilience enhanced; and sustainable development promoted.

In this study, the coupling coordination relationship in the core area of central Shanghai primarily manifested as ecological environment lag, indicating that its ecological spatial pattern should be further optimized; simultaneously, public awareness of ecological environmental protection should be further strengthened to enhance the environmental carrying capacity and improve regional ecological and environmental benefits. The coupling coordination relationship between urbanization and the ecological environment in some areas at the periphery of central Shanghai showed sluggish urbanization. The urbanization process in these areas should be appropriately strengthened and its quality actively improved. Additionally, the population flow should be reasonably guided, such that the population level can be gradually raised to alleviate the pressure on the ecological environment caused by high population density and traffic congestion in the core urban area. While accelerating urbanization, we should also consider protecting the ecological environment by implementing precise monitoring and management policies and maintaining the steady progress of ecological civilization construction. Moreover, enterprises should increase their investment in green development, thereby improving the overall environmental

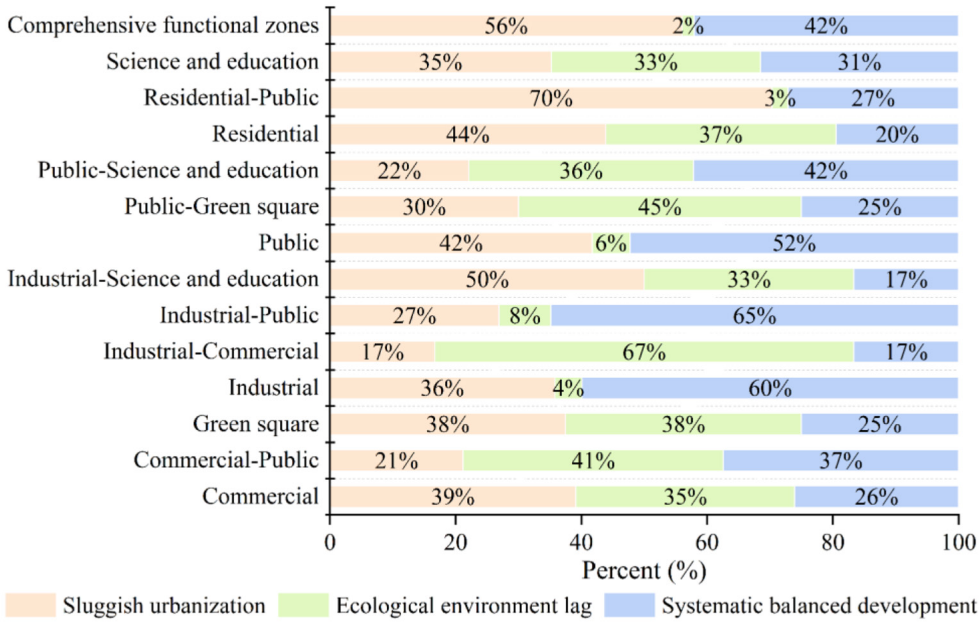

FIGURE 6
Percentage of coupling coordination classifications in each urban functional zone.

quality of the city and realizing sustainable development in the region.

4.4. Limitations

The exploration of the coupling coordination relationship between urbanization and the ecological environment based on urban functional zones has certain limitations. OSM road data have high positioning accuracy and good topological relationships; however, in their application to urban functional zone delineation, the grades used have an influence on the final delineation results. In future study, we will combine OSM data with high-resolution remote sensing image data to improve the precision of the delineation, as well as its consistency with the spatial structure and development pattern of the city (71). Moreover, we only analyzed the coupling coordination relationship between urbanization and the ecological environment in central Shanghai, which is small in scale. In the future, this relationship can be analyzed for urban agglomerations and other larger areas. The impact of population urbanization on the ecological environment can also be further refined to provide solid theoretical support for the implementation of national strategies, such as ecological environmental protection and high-quality development (72).

5. Conclusions

We examined central Shanghai, China, *via* GIS spatial analysis and KDE using multi-source data, such as remote sensing images, OSM roads, and POIs, and analyzed the spatial differentiation of the coupling coordination relationship between urbanization and the ecological environment based on urban functional zones. The main conclusions of this study are as follows: Central Shanghai had a high urbanization level and a moderate ecological environment quality. Additionally, the D mainly indicated a primary coordination level, showing a gradual increase to a moderate coordination level from the core area outward. The specific coupling coordination types mainly showed a systematic balanced development; ecological environment lag, sluggish urbanization, and systematic balanced development were found in 10.53, 37.28, and 52.20% of study units, respectively. At the same time, different types of urban functional zones had different coupling coordination relationships. industrial, industrial-public, public, and public-science and education zones mainly showed systematic balanced development.

This study examined the relationship between urbanization and the ecological environment from the perspective of urban functional zones, which is conducive to understanding the spatial differentiation and development status of urbanization and the ecological environment within cities. This perspective not only ensures a complete and accurate urban spatial structure and plot size, but also avoids overly fragmented divisions, providing a new perspective for related research. Moreover, with reference to the limitations of previous research, exploring the coupling coordination relationship between urbanization and the ecological environment based on the perspective of urban functional zones also provides a breakthrough idea for future generations to perform similar research. Additionally, this study emphasizes the importance of population urbanization in the urbanization process, which is important for optimizing the spatial distribution of populations and urban planning. In subsequent research, we will integrate multi-source data, such as high-resolution remote sensing image data, to enhance the recognition accuracy for urban functional zones and compare the coupling coordination relationship between urbanization and the ecological environment at multiple scales to provide theoretical support for hierarchical and classified territorial spatial planning.

Data availability statement

The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding author.

Author contributions

WL: all aspects of this study. XL: investigation, analysis, validation, writing – original draft, and writing – review and editing. YL: writing – review and editing. TX: identification of urban functional zones and writing – review and editing. All authors contributed to the article and approved the submitted version.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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Impact of environmental comfort on urban vitality in small and medium-sized cities: A case study of Wuxi County in Chongqing, China

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China's urbanization has exceeded 64% and a large number of small and medium-sized cities are the key development areas in the new stage. In urban planning, it is very important to reveal the influence of environmental comfort on urban vitality to improve the life quality of residents in these towns. Thus, the study investigated the impact of environmental comfort on urban vitality using ordinary least squares regression in Wuxi County. Environmental comfort was assessed through a comprehensive analysis of a built-up area and urban vitality was represented by vitality intensity. In addition, the influence pathways were identified and model validation was verified. The conclusions are as follows: (1) Environmental comfort and urban vitality are distributed spatially similarly, and both gradually decline from the center to the periphery. It is high in the east and low in the west, high in the south and low in the north. (2) Population density, POI mixing degree, building density, and road network density have significant positive effects on urban vitality. Population density has the greatest impact on urban vitality. Building height, building age, and river buffer have significant negative effects on urban vitality. (3) The impact of comprehensive environmental comfort on urban vitality is positive, and in terms of time, the order of impact is afternoon > morning > evening. Finally, a method for assessing the impact of environmental comfort on urban vitality was constructed, and the promoting effect of environmental comfort improvements on the vitality was verified. These findings will fill the gap between urban physical space and social needs in planning practices and provide reference to improve vitality for urban planning in small and medium-sized cities.

KEYWORDS

environmental comfort, urban vitality, built-up areas, small and medium-sized cities, Wuxi County

1. Introduction

According to the United Nations, the urbanization rate of the developed countries will reach 86% in 2050, and that of China will reach 71.2% in 2050 (1–3). China's urbanization rate increased rapidly from 13.26% in 1953 to 64.72% in 2021 (4, 5), and the current rate is increasing at an annual rate of about 1% (6). There are about 20 thousand small and medium-sized towns, accounting for a significant portion of the population now. China is vigorously promoting the new urbanization plan and rural revitalization strategy. In the new urbanization strategy, the central government has set the tone to enhance the roles of small and medium-sized cities and small towns through industrial development, public services, employment absorption, and population agglomeration, which has opened up new opportunities and broad space for the development of small and medium-sized cities in China (7). Urban planning in the new stage should focus on the development of urban and rural spaces, improvements in urban quality, and the construction of an ecological civilization (8). The municipal land space planning guidelines clearly specify that the comfort and artistry of land space should be improved, that the quality and value of land space should be improved, and that improvements in urban quality and vitality should be included in urban renewal goals (9). China will invest much effort in the development of small and medium-sized cities in the future (10, 11). As the connections between villages and large cities, small and medium-sized cities and small towns can not only alleviate the pressure on the large cities but also promote the development of villages and the steady progress of new urbanization and rural revitalization strategies. However, relevant research on small and medium-sized cities is far more sparse than is research on large cities due to location disadvantages, poor geographical environments, and slow economic development in small and medium-sized cities. In the future, the advancement of new urbanization will gradually boost the development and construction of small and medium-sized cities, enhance environmental comfort, and promote the attractiveness of small and medium-sized cities. Therefore, the study of small and medium-sized cities is of great significance to rural revitalization as well as territorial spatial planning.

Early studies on environmental comfort mainly emphasized the comfort of natural climatic environments on a macro scale (12, 13). Then research gradually focused on more specific climate factors including sound, light, and heat (14–22). Most current studies have focused on the comprehensive evaluation of the natural, the built, and the social environment (23, 24). Clark examined the effect of environmental comfort on urban population growth along four dimensions: natural environmental comfort (climate, overall natural attractiveness, etc.), built environment comfort (large institutions, small firms, etc.), socioeconomic composition and diversity (residents' income, education, etc.), and residents' values and attitudes (friendly, hostile, etc.), and found that counties with high environmental comfort had higher growth rates (23). The relevant studies involved the environmental comfort of mesoscale spaces, such as residential (25) and commercial areas (26), and the environmental comfort of microscale interior spaces of buildings, such as office and residential buildings (27). This study will also evaluate environmental comfort in terms of the three aspects mentioned above, and these comfort features may enhance the attractiveness of a specific place.

From the general perspective of urban sociology, urban vitality is composed of economic vitality, social vitality, and cultural vitality, and urban vitality is only a spatial representation of economic, social, and cultural activities. In contrast, from an architecture and urban planning perspective, urban vitality is more people-driven. Jacobs (28) and Lewis Mundford et al. (29) pointed out that the urban spatial environment has a significant impact on human behavioral activities and that a dense population is a key element contributing to the vitality of public spaces (30). Urban vitality can be created through design (31). Urban vitality is directly and closely related to users, places, and activities (32) and is simultaneously affected by multiple environmental factors (33, 34). Many studies use pedestrian flow and attendance rates to represent urban vitality (35). Current studies on the impact of environmental comfort on urban vitality mainly focus on the impact of thermal comfort on urban vitality (36–39), and some studies also consider auditory and visual quality. The effects of various environmental factors must be simultaneously studied to ensure the overall environmental comfort of built-up areas.

Previous studies pay more attention to big cities, however, there are a large number of small and medium-sized ones that should be focused. Meanwhile, the built environment is complex, and the influencing factors of urban vitality exist diversification. As urban vitalities mainly consist of human beings and the influencing factors involve all aspects of the environment, it is particularly important to combine qualitative and quantitative research methods. With the further promotion of new urbanization and rural revitalization, it is imperative to investigate the environmental comfort and urban vitality of small and medium-sized cities. There is urgency to investigate the environmental comfort and urban vitality of small and medium-sized cities.

This study collected environmental factors and data of urban vitality of a built-up area in Wuxi County and used regression analysis to conduct their correlation. The objectives were formulated: (1) investigate the temporal and spatial distribution of environmental comfort and urban vitality; (2) conduct the impact of the environmental comfort on urban vitality; and (3) identified and verified the main influencing factors in residential and commercial areas. This study is not only a beneficial attempt to combine qualitative and quantitative data but can also effectively make up for the shortcomings of existing research on environmental comfort.

2. Data and methods

2.1. Study area

Wuxi is located in northeast of Chongqing with mountains surrounding in the west, is in a relatively closed state due to transportation and communication challenges. The influence of external factors recognized in existing studies on large cities can be excluded. The urban area of Wuxi is mostly composed of mountainous areas connected by the Baiyang River, forming a structure with three clusters in the city (Figure 1). Laocheng, Mazhenba, and Fenghuang, respectively represent small cities that are in the saturated development, accelerated and initial development period. In 2019, the built-up area of the city was 7.38 km^2 with 115,600 resident persons. To facilitate the quantitative analysis and the establishment of a database, the study area was divided into 703 grid cells with a size of 200 m×200 m.

2.2. Data acquisition and processing

2.2.1. Environment comfort

2.2.1.1. Subjective environmental comfort factors

The indicators were constructed based on subjective and objective data. Subjective data were obtained through field surveys and questionnaire surveys to estimate natural, built and social environment by respondents. The Likert scale was used in this study to divide satisfaction into five levels (40), namely very

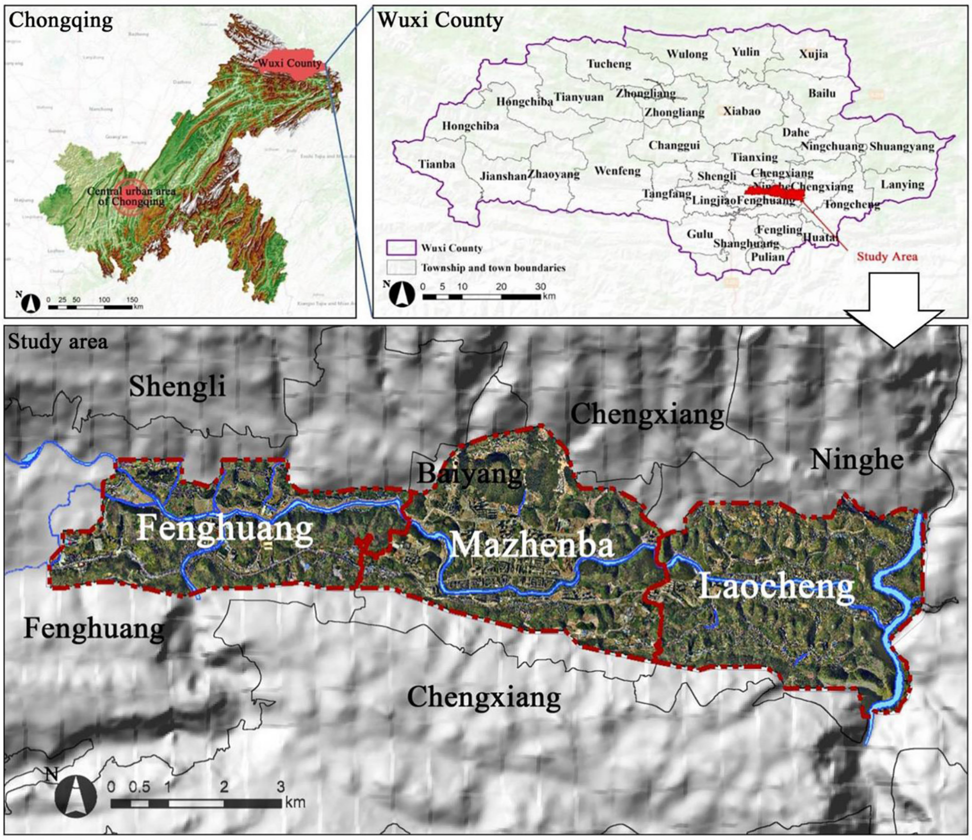


FIGURE 1
Location of the study area.

TABLE 1 Subjective environmental comfort factors.

Environment attributes	Environmental factors	Score
Natural environment	Temperature and humidity	
	Natural ventilation	
	Air quality	Very satisfied (five points)
Built environment	Auditory environment	Relatively satisfied (four points)
	Visual environment	Neutral (three points)
	Green environment	Relatively dissatisfied (two points)
	Event venues	Very dissatisfied (one point)
	Transportation convenience	
Social environment	Safety	
	Overall evaluation	

satisfied (five points), relatively satisfied (four points), neutral (three points), relatively dissatisfied (two points), and very dissatisfied (one point) (Table 1). A total of 372 questionnaires were distributed, and 357 (96%) recovered questionnaires were valid.

2.2.1.2. Objective environmental comfort factors

Thirteen environmental comfort factors were selected for objective environmental comfort in three categories (natural, built, and social environment) (Table 2). Data from: Wuxi County administrative boundary and water system layers from the National Center for Basic Geographic Information System; basic data from the processed third national land survey of Wuxi County; road network system integrated with the 2019 urban control plan of Wuxi County; satellite remote sensing image maps of Wuxi County; topographic survey current building vector data of Wuxi County in 2019 (containing the number of floors, shape, and other attributes of each building); Wuxi County 2019 Statistical Yearbook; relevant partial door data of Wuxi County. The calculation methods are as follows.

a) Slope (SL). Using the ArcGIS 10.5 spatial analysis tool to analyze the elevation information of the research area, according to the suitability evaluation of urban construction land, the slope is divided into 5 grades, namely $\leq 10°$, 10–15°, 15–20°, 20–25°, $\geq 25°$, respectively represent "suitable construction area," "more suitable construction area," "basically suitable construction area," "unsuitable construction area" and "non-construction area."
b) River buffer zone (RBZ). The area covered by 100, 200, 300, 400 m and more than 400 m, based on the river's shoreline and

TABLE 2 Objective environmental comfort factors.

Environmental factors	Factors	Description	Positive (P) or negative (N) effects	Weight coefficient
Natural environment	River buffer zone (RBZ)	The further away from the river, the greater the value.	N	2.91%
	Slope (SL)	The higher the SL, the larger the value	N	0.82%
Built environment	Sky visibility (SV)	The higher the SV, the higher the value	P	0.36%
	Green coverage rate (GCR)	The higher the GCR, the higher the value	P	2.37%
	Road network density (RND)	The greater the RND, the greater the value	P	3.82%
	Comprehensive accessibility (CA)	The higher the CA, the higher the value	P	0.60%
	Building density (BD)	The greater the BD, the greater the value	N	0.52%
	Building height (BH)	The higher the BH, the larger the value	N	0.99%
	Building age (BA)	The newer the building, the higher the value	P	12.01%
	Density of public service facilities (PSF)	The greater the PSF, the greater the value	P	35.56%
	POI mixing degree (PMD)	The higher the PMD, the larger the value	P	14.52%
Social environment	Population density (PD)	The greater the PD, the greater the value	P	14.75%
	Per capita living area (PLA)	The larger the area, the larger the value	P	10.77%

extending outward, indicates the areas of high, higher, average, lower and low using the river's landscape resources respectively.

c) Sky visibility (SV). Firstly, the three-dimensional urban space environment of the research area is established. Then use the skyline and skyline map tools in the ArcGIS platform to calculate the sky visibility of a point in the three-dimensional space.

d) Green coverage rate (GCR). The green coverage rate was obtained by comparing the canopy density information in the second survey data of the Forestry Bureau, the park green space information of the Wuxi County Third National Land Survey, the park green space information of the current land use, and satellite images.

e) Road network density (RND). The road network selected in this study includes four categories: urban arterial roads, urban secondary arterial roads, urban branch roads, and urban pedestrian paths. Use the current road analysis map and satellite image map integrated in the 2019 regulatory detailed planning of Wuxi County to improve the current road network map. Calculate the ratio of the total road length to the area in each grid as the road network density value.

f) Comprehensive accessibility (CA). The average weighted travel time from the origin to all facilities. The walking mode is the main way, with each residential point as the starting point and the public service facility point as the destination point, and the walking time cost is set to 5km/h. Starting from starting point i, the average weighted travel time to all facilities j is Eq. 1, where T_i is the accessibility of starting point i, p_{ij} is the travel probability from starting point i to facility j (Equation 2); t_{ij} is the starting travel time from starting point i to facility point j; m_j is the area of facility j; a represents the attenuation coefficient, and $a = 2.0$ is selected in this paper; d_{ij} is the distance from starting point i to facility j. The lower the calculated value, the higher the accessibility, and the higher the value, the lower the accessibility.

$$T_i = \sum_{\substack{j=1 \\ j\neq i}}^{n} (p_{ij}t_{ij}) \tag{1}$$

$$p_{ij} = \frac{m_j/d_{ij}^a}{\sum_j m_j/d_{ij}^a} \tag{2}$$

g) Building density (BD). In ArcGIS 10.5, the proportion of the building is calculated through the outer frame of the building, the mass points of the building are extracted, and the building density is calculated using the spatial kernel density analysis tool.

h) Building height (BH). Building height = number of building floors * 3, extract the mass points of the building in ArcGIS 10.5, and use the kernel density analysis tool in the spatial analysis to obtain the building height.

i) Building age (BA). The age of buildings is divided into five categories: before 1980, 1980–1990, 1990–2000, 2000–2010, 2010–2020, respectively assigned 1, 2, 3, 4, 5 points in ArcGIS 10.0.

j) Density of public service facilities (PSF). Using the ArcGIS 10.0 spatial network analysis tool, the service scope of public service facilities with different service levels is established, and the density of public service facilities is obtained.

k) POI mixing degree (PMD). By writing python code, the POI data of Gaode map and Baidu map POI data in the research area were crawled, a total of 8,668 items. The data was collected in December 2020. Through data screening and cleaning, the data outside the scope of the study area, as well as data with repeated coordinate points and repeated information were eliminated. Finally, a total of 7,548 pieces of data were obtained. All data have undergone coordinate correction, space correction and projection (CGCS2000). POI data is divided into 10 categories: government, transportation, business, enterprise, education, green space, residential, medical, sports, and others. Use the method of information entropy to calculate the POI mixing degree of each cell grid (Equation 3). It is used to represent the mixed degree of land use. The higher the calculated value, the better the mixed function of the plot.

$$H(X) = -\sum_{i=1}^{N} Pi \log Pi \tag{3}$$

where $H(X)$ is the entropy of random variable X; Pi is the probability of X taking Xi. N is the number of types of POI types, and Pi is the relative density of the i-th type of POI in the unit grid divided by the sum of the relative densities of various POIs in the unit grid.

l) Population density (PD). According to the data of Wuxi County Statistics Bureau, the population data of each street and each residential group in the study area are obtained. Extract a total of 536 current residential land plots in 2020 (including information such as plot area, plot ratio, building density, etc.), and calculate the average population density of the research area through the land area and plot ratio (Equation 4)

$$RAPD = TP \times \frac{PPR \times PA}{CARL} \times \frac{1}{PA} \tag{4}$$

where $RAPD$ is the residential area population density, TP is the township population, PPR is the plot ratio of the parcel, PA is the plot area, $CARL$ is the total construction area of residential land

m) Per capita living area (PLA). First, all the buildings covered by the residential plot are calculated as residential buildings, and the residential buildings are extracted. Second, using the building as a particle, use Equation 5 to calculate the per capita living area. The resulting PLA was divided into five categories: >55 m^2, 47–55 m^2, 39–47 m^2, 31–39 m^2, and <30 m^2. Respectively, the per capita living area is high, relatively high, normal, relatively low and low.

$$PLA = \frac{\sum_{i=1}^{n} BA_i \times BS_i}{PURP} \tag{5}$$

where BA_i is the building area, BS_i is the Building Stories, $PURP$ is the total number of residents in the unit.

The weight coefficient of each environmental indicator was calculated using the entropy method. First, the data were non-dimensionalized using range standardization to standardize the values of indicators with different measurement units and different properties. Assuming that k indicators ($X_1, X_2, \ldots, X_k$, where $X_i = \{x_1, x_2 \ldots x_n\}$) are given, the formula is as follows which Equation 6 is applicable to indicators with positive impacts, and Equation 7 is applicable to indicators with negative impacts:

$$X_{ij}^{'} = \frac{X_{ij} - min[X_j]}{max[X_j] - min[X_j]} * 100 \tag{6}$$

$$X_{ij}^{'} = \frac{\max[X_j] - X_{ij}}{max[X_j] - min[X_j]} * 100 \tag{7}$$

where $i = 1..., n$ (n is the number of grid); $j = 1..., m$ (m is the number of indicators); X_{ij} represents the value of the jth indicator of the ith grid cell; $\max[X_j]$ is the maximum value of the indicator series;$[X_j]$ is the minimum value of the indicator series; and $X_{ij}^{'}$ is the standardized value of the jth indicator of the ith grid.

Second, the entropy method was used to determine the weights of environmental factors (41). The information entropy of each set of data was calculated using the definition of information entropy from information theory (Equation 8):

$$E_j = -ln(n)^{-1} \sum_{i=1}^{n} [P_{ij} \, lnP_{ij}] \tag{8}$$

where $P_{ij} = X' / \sum_{i=1}^{n} X_{ij}'$ (if $P_{ij} = 0$, then $E_j = 0$); and n is the number of grid cells in the study.

The information entropy of each indicator could be calculated by Equation 9. Then, the weight of each indicator was calculated and the values are shown in Table 2:

$$P_{ij} = \frac{1 - E_j}{k - \sum_{j=1}^{k} E_j} \tag{9}$$

2.2.2. Urban vitality data

The Tencent Easygo heat map records real-time geographic information left by users when they visit WeChat, QQ, and Tencent Maps, which are updated every 15 min. The number of users in each location can better reflect the population distribution characteristics in a specific area and time period and intuitively express urban vitality in an area. Real-time heat map data from 06:00 to 24:00 were crawled from the Tencent Easygo heat map (https://heat.qq.com/document.php). Python language were used to collect the real-time data through interface of Tencent Map. The data of August 14, 2020 (weekdays) and August 15, 2020 (weekends) were, respectively crawled with 1 h interval. A total of 38 groups of data (including time, longitude, dimension and population characteristics) were collected. All data are summarized to represent the comprehensive urban vitality of the study area. Using the spatial analysis tool, it is presented spatially and we can obtain the spatial distribution data of urban vitality in the study area. In terms of temporal distribution, the values of each time point are summarized form the data of the city's variation value to form urban vitality of each period (morning, afternoon, evening). Finally, we obtained the data with a size of 25 ×25 m, and all data are spatially corrected and projected (CGCS2000). And the values were averaged to a size of 200 ×200 m using ArcGIS10.5.

2.3. Methods

2.3.1. Assessing environmental comfort

The subjective environmental indicators were evaluated using the average value. A multi-indicator comprehensive evaluation method (42) was used to evaluate objective environmental comfort in the following steps: (1) data standardization, (2) determination of the weights of environmental factors using the entropy method (41), and (3) calculation of environmental comfort using the multi-indicator comprehensive evaluation method. This research proposes a general algorithm: S = A*Qz+B*Qk (Qz: subjective; Qk: objective). Different cities may have different values of A and B due to various sizes, locations, and stages of economic development. Based on previous studies (43–45) and the actual situation, the values of A and B in this study were determined to be 0.3 and 0.7, respectively.

The above method was used to calculate the environmental comfort of a single grid, and then, ArcGIS 10.5 was used for the spatial visualization analysis. The natural breaks method was used to divide environmental comfort into five levels, namely high, relatively high, moderate, relatively low, and low.

2.3.2. Analysis of urban vitality

The kernel density of the heat map data was calculated on the ArcGIS platform. After excluding values of 0 (areas with no vitality), the calculated heat map data were divided into five levels from high to low using the natural breaks method (46) including high-vitality, relatively high-vitality, moderate-vitality, relatively low-vitality, and low-vitality areas.

2.3.3. Ordinary least squares (OLS) regression analysis

OLS regression analysis is a statistical analysis method used to determine the quantitative relationship between two or more variables. Environmental comfort involves many factors, the OLS method is a representative option for the regression analysis of environmental comfort. The bivariate calculation method for determining local indicators of spatial association (LISA), i.e., Moran's I statistic, was used to analyze the spatial relationship between environmental comfort and comprehensive urban vitality. Through SPSS 2021, a regression model was established based on qualitative and quantitative data, and the regression coefficients and fitted values were used to explain the impact of environmental comfort on urban vitality.

2.3.4. Urban vitality enhancement in residential and commercial areas

Residential areas are the places most closely associated with people's lives, and commercial areas are highly common public spaces used by residents. Residential and commercial areas both account for a high proportion of urban land. Therefore, residential and commercial areas were selected to validate the underlying impact of environmental comfort on urban vitality.

The typical residential area on the north bank of the Baiyang River in Laocheng was constructed a long time ago. Therefore, the current facilities are relatively out of date, the spatial connectivity is poor, and the green space is scarce. The Yiboyuan community in Mazhenba is a modern residential area that is dominated by high-rise buildings, but the community is relatively closed and has poor connectivity to the outside world. The third and fourth communities of Shuangfeng Village are two concentrated residential areas in Fenghuang. All the case areas are close to rivers, and the surrounding construction land types are simple, which reduces additional impacts caused by the surrounding land.

Yuning Street and Nanzheng Street are the commercial centers in northern Laocheng. The commercial center mainly has modern commerce with the mostly commercial complexes buildings on the east side of Xiaoyao Square in Mazhenba. The study areas were all close to the river, and the surrounding land was mainly residential land. The main factors affecting the urban vitality of residential and commercial areas obtained by using correlation analysis and OLS regression, respectively, are first optimized for the current situation to verify their contribution to urban vitality. For convenience, the case areas were divided into 20 × 20 m grid cells.

3. Results and analysis

3.1. Characteristics of environmental comfort

In spatial distribution, the green coverage rate, building height, per capita living space, and road network density exhibited similar multicenter patterns (Figure 2A). The high values of public service facilities density, POI mixing degree, and population density were mainly existed in Laocheng and Mazhenba, with a single-center pattern (Figure 2B). However, the spatial distributions of rivers, slopes, and sky visibility were similar (Figure 2C). Green coverage rates were clustered toward multiple points, and those for roads, squares, and commercial land were lower than the surrounding environment. Public service facilities, which are most closely related to the daily life of residents, were mainly concentrated in the places where people gather, with a heterogeneous spatial distribution, and their density slowly decreased outwards with Mazhenba as the center. based on the spatial distribution and directions of the rivers, the river buffer zones relatively concentrated in Fenghuang and Laocheng.

The comprehensive environmental comfort is shown in Figure 2D. The spatial distribution pattern of environmental comfort was similar to public service facilities, road network density, comprehensive accessibility, and population density patterns. The overall comfort gradually decreased from east to west, and it was comparable in Laocheng and Mazhenba and lowest in Fenghuang.

Public service facilities and population density had great impacts on environmental comfort. High environmental comfort mainly concentrated in Mazhenba and Laocheng, which had the highest population densities, POI mixing degrees, and a large-scale public service facility. These features indicated that the comfort in Laocheng and Mazhenba was highest. Relatively high comfort concentrated in the central parts of the three clusters, including residential areas, public activity spaces, urban arterial roads, and spaces along the banks of the Daning River, Baiyang River, and Xiaoxi River. These areas basically cover the land for public service facilities (such as administrative offices, commercial services, healthcare, and education et al.) and show spatial correspondence with population density and public service facilities. Relatively low comfort mainly distributed at the southern end of the Daning River, Wangjiapo, and Shuangfeng Village, which are located relatively close to rivers. But the areas have greatly undulated terrain, large slopes, low population densities, a small number of residential areas, large land area, sparse population, few supporting facilities, and a lack of residential land and other facilities.

3.2. Characteristics of urban vitality

3.2.1. Temporal characteristics

Weekdays and weekends were divided into three time periods: morning (07:00–12:00), afternoon (13:00–18:00), and evening (19:00–24:00). It indicated that urban vitality was the highest in the

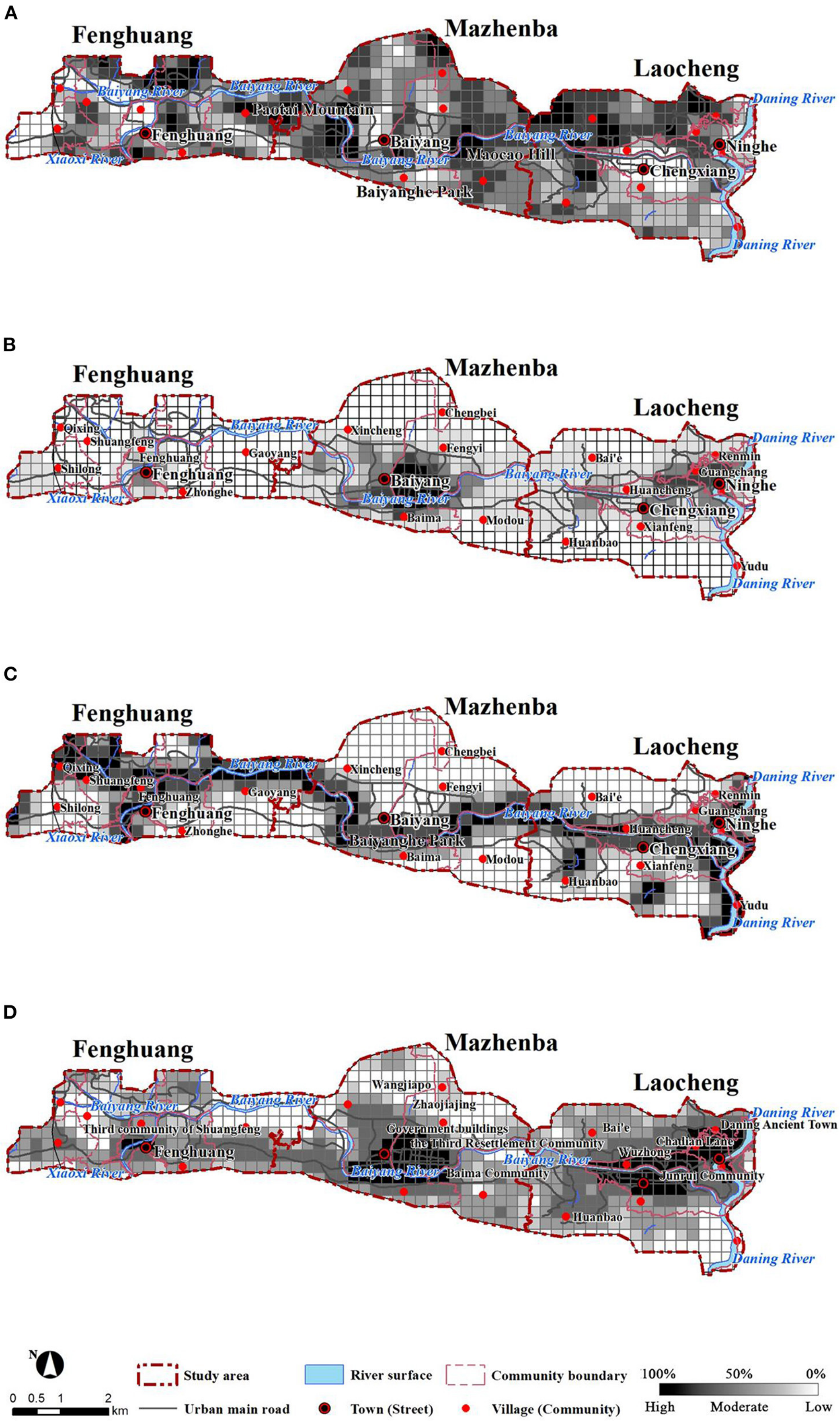


FIGURE 2
Distribution of environmental factors: green coverage rate **(A)**, density of public service facilities **(B)**, river buffer zones **(C)**, and comprehensive environmental comfort **(D)**.

afternoon (Figure 3). The morning total accounted for 31% of the day, and that for the afternoon and the evening were, respectively 36 and 33%.

From the morning to the afternoon, the population exhibited an inflow. In the morning, urban vitality changed rapidly. Activities changed from static activities to dynamic activities. The population

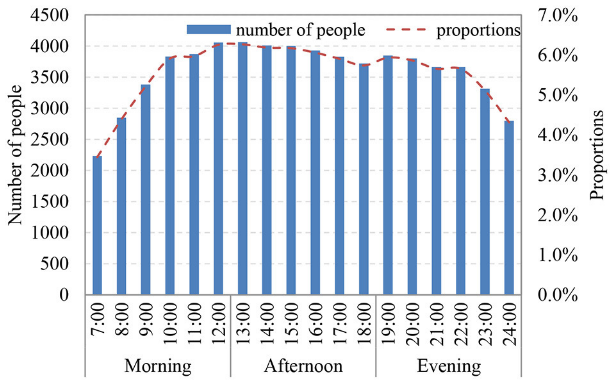


FIGURE 3
Changes in proportions of urban vitality from morning to evening.

mobility was large. The residents transitioned from rest to work or to leisure and entertainment. The type and scope of activities also changed significantly, and the number of people participating in urban activities increased. Among the surveyed population, 43% of the people worked and lived in various clusters, and 10% worked outside the urban area, indicating that from morning to afternoon, there was more crowd flow between the three clusters and a small population outflow at the same time.

Urban vitality declined from the afternoon to the evening, manifesting as a population outflow pattern. However, urban vitality in the evening (36%) was still higher than that in the morning (31%). The number of people who participated in activities in the evening was the highest, indicating that the facilities provided people with employment and various services. In the evening, the population flow was small, and the residents entered the rest state relatively late. The mismatch between workplaces and residence can be the part reason and the limited function of urban land use. For example, Mazhenba can provide many employment opportunities and rest and entertainment services, and Fenghuang can provide low-cost residential services.

3.2.2. Spatial characteristics

The scope of vitality was the largest in the morning and the lowest in the evening (Figure 4). Vitality intensity was the highest in the afternoon and the lowest in the morning. In the morning, the high-vitality areas concentrated in Laocheng and Mazhenba, and the distributions of high vitality performed multiple points in the afternoon, Low-vitality areas concentrated in Fenghuang and the transition areas between the three clusters. In the afternoon, the scope of high-vitality areas gradually increased. There was high vitality in the people's square in the north of Laocheng, relatively high vitality in Fenghuang. The scope of low-vitality areas decreased, and the vitality between Mazhenba and Fenghuang increased. The distribution of vitality in the evening was similar to that in the morning, From the morning to the evening, areas with no vitality increased in Fenghuang, and the urban vitality decreased significantly in southern Mazhenba.

Population density, buildings, and various public service facilities (such as residential land such as the Yiboyuan) mainly distributed in the central parts of the three clusters. The urban functional areas were relatively consistent with urban vitality. The urban centers with abundant industries and complete public service facilities can satisfy most current needs, provide job opportunities on weekdays, and attract the surrounding residents for shopping, dining, leisure and entertainment on weekends. The activities of most residents concentrated in the urban centers. Therefore, urban vitality is high in urban centers. Fenghuang, an area with low vitality, has limited commercial and recreational facilities, with a large scope of vitality but a low overall vitality.

Due to the shortage of construction land, the burden on the urban centers was relatively large, but improvements in environmental comfort could be achieved by upgrading and improving existing spaces. The southern and northern marginal areas have relatively poor terrains, challenges with regard to development and construction, a low population density, and relatively low urban vitality. In Fenghuang, all types of facilities and supporting infrastructure are in the early stages of development and cannot provide more job opportunities on weekdays or leisure and entertainment facilities on weekends. Although Fengcheng has a large scope of vitality, its vitality is low due to the small spaces with high population agglomeration.

3.3. Relationship between environmental comfort and urban vitality spatial distribution

The bivariate calculation method for determining local indicators of spatial association (LISA), i.e., Moran's I statistic, was used. The analysis results were divided into five types: high-comfort and high-vitality (HH), high-comfort and low-vitality (HL), low-comfort and high-vitality (LH), low-comfort and low-vitality (LL), and non-significant (NS). The matching degree in the afternoon was better than that in the evening or morning (Table 3).

Spatially, the HH region contained Mazhenba and Laocheng as the center (Figure 5). From the center to out, there were HH, LH, NS, HL, and LL areas. Both Laocheng and Mazhenba exhibited obvious agglomeration, with a large proportion of HH and a smaller proportion of HL and LH zones, and a better spatial match between environmental comfort and urban vitality. In Fenghuang, NS and LL areas were dominant, and HL and LH areas accounted for a relatively large proportion. Overall, the spatial match between environmental comfort and urban vitality was high. HH and LL zones accounted for a higher proportion and were distributed in the central urban area and the urban fringe with better natural environment, respectively. The urban vitality in the central city is high and the environmental comfort is at a better level. HL and LL zones are less spatially distributed.

3.4. Impact of environmental comfort on urban vitality

3.4.1. Correlation analysis

The correlations between the 13 factors and urban vitality were assessed be calculating Pearson correlation coefficients. Environmental factors and comfort were significantly correlated with urban vitality. Building density and building age were relatively highly correlated with population density, and comprehensive environmental comfort, population density, POI mixing degree, and

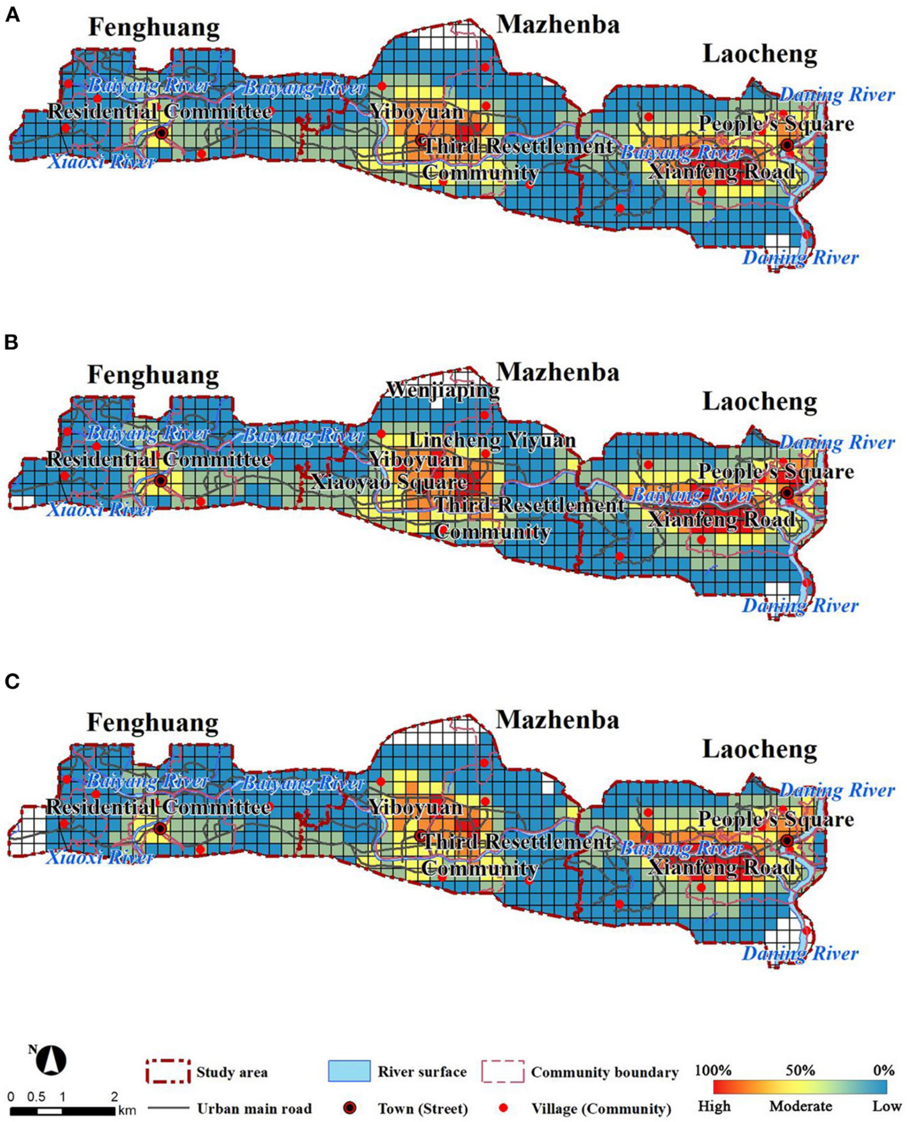


FIGURE 4
Distributions of urban vitality: morning **(A)**, afternoon **(B)**, and evening **(C)**.

TABLE 3 Proportions of different matching types of environmental comfort and urban vitality.

Types	Morning	Afternoon	Evening
NS	46.09%	46.09%	46.09%
HL	2.28%	1.99%	2.13%
LH	1.42%	0.85%	1.00%
LL	33.71%	34.28%	34.57%
HH	16.50%	16.79%	16.22%

building density were relatively highly correlated with urban vitality. The correlations between slope, river buffer zones, sky visibility, and per capita living area were low (Figure 6).

3.4.2. Multivariate regression analysis

Based on the correlation results, stepwise OLS regression analysis was performed on the 13 factors. The results showed that the variance inflation factor (VIF) values of the 13 factors all <7.5, indicating that all factors can be included in the calculation. The 13 environmental factors were used as independent variables, and urban vitality in the morning, urban vitality in the afternoon, and urban vitality in the evening were used as dependent variables for the OLS regression analysis. Table 4 shows the OLS regression analysis results when different conditions are controlled. The R^2 value for the model for urban vitality in the afternoon was 0.888, indicating that the 13 environmental factors explain 88.8% of the variance in urban vitality in the afternoon. Additionally, the degree of fit was better for the evening than for the morning and evening, indicating that the effect of overall factors on urban vitality was more significant.

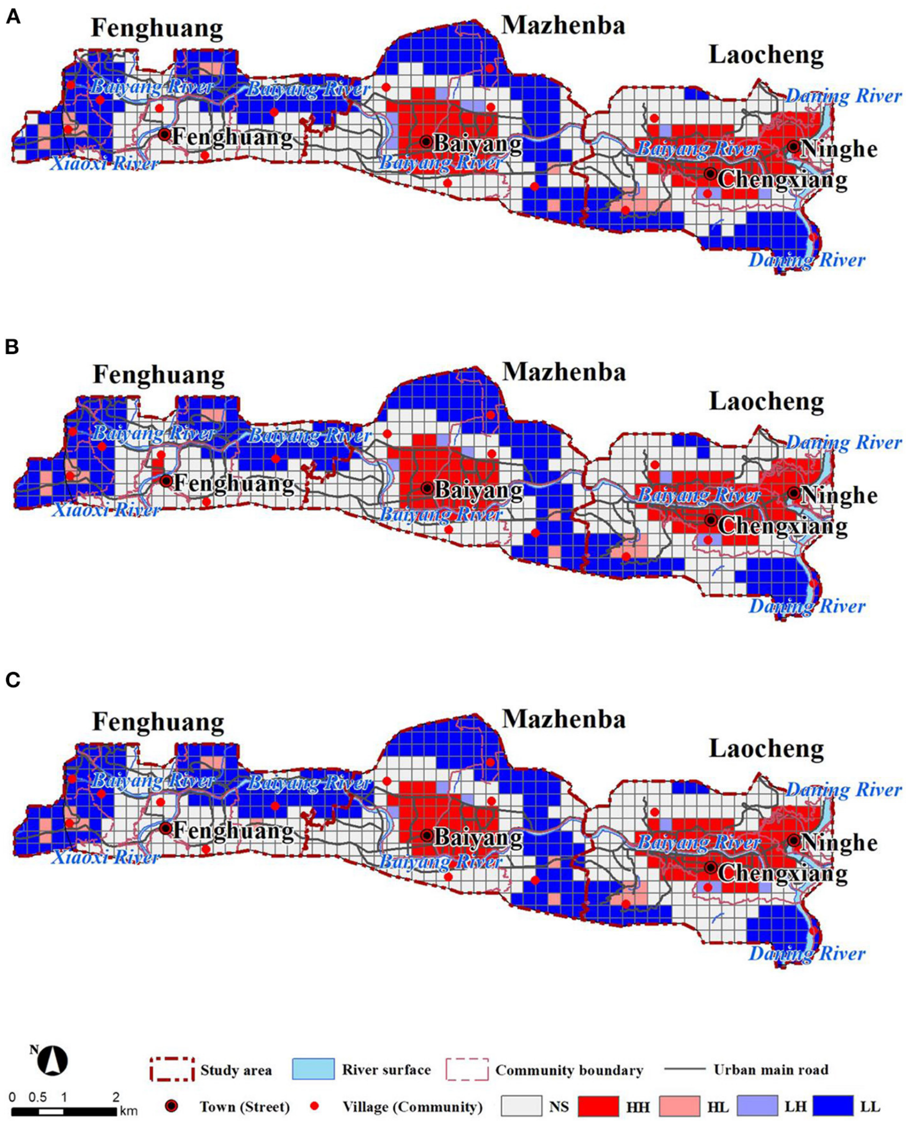
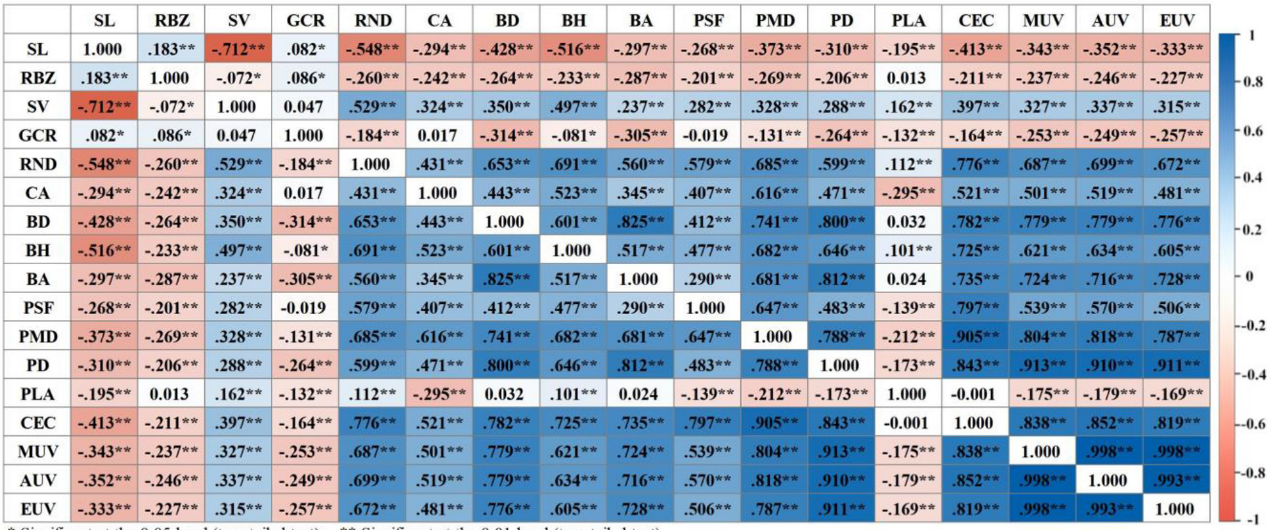


FIGURE 5
Spatial matching of environmental comfort and urban vitality: morning **(A)**, afternoon **(B)**, and evening **(C)**.

The impact of environmental factors on urban vitality in the three time periods was consistent. Population density, POI mixing degree, building density, and road network density had significant positive impacts on urban vitality, and the increase in these four factors promoted urban vitality. The regression coefficients for population density were 0.793, 0.762, and 0.823 for the morning, afternoon, and evening, respectively. The impact of population density on urban vitality was greater in the evening than in the morning or afternoon, and population density had a greater impact on urban vitality than did other factors (that is, population density had the greatest impact on urban vitality). Road network density had the second highest impact on urban vitality, and the regression coefficients in the morning, afternoon, and evening were 0.227, 0.220, and 0.233, respectively, indicating that the impact was the largest in the evening. The impact of POI mixing degree on urban vitality was the greatest in the afternoon, and the impact of building density was the greatest in the morning. Areas with a high road network density, POI mixing rate, building density, and population density had high urban vitality. High values of these factors and urban vitality mainly concentrated in central areas with many squares and roads and high sky visibility, for example, public service facilities on the banks of the Baiyang River and the Shuiyuan Mall in the central areas. Building height, building age, and river buffer zones had significant negative impacts on urban vitality, indicating that taller buildings, newer buildings, and buildings farther away from rivers reduced urban vitality. New and high buildings and areas far away from rivers (such as the southern and northern urban areas and newly built residential areas) were had low-vitality. Effect of the other factors on urban vitality were not evident, indicating that urban vitality may not depend on these factors.

3.4.3. Impact of environmental comfort

Table 5 provides the results of the OLS regression analysis of the impact of comprehensive environmental comfort on urban vitality. For the environmental factors, the goodness-of-fit for the afternoon



	SL	RBZ	SV	GCR	RND	CA	BD	BH	BA	PSF	PMD	PD	PLA	CEC	MUV	AUV	EUV
SL	1.000	.183**	-.712**	.082*	-.548**	-.294**	-.428**	-.516**	-.297**	-.268**	-.373**	-.310**	-.195**	-.413**	-.343**	-.352**	-.333**
RBZ	.183**	1.000	-.072*	.086*	-.260**	-.242**	-.264**	-.233**	-.287**	-.201**	-.269**	-.206**	0.013	-.211**	-.237**	-.246**	-.227**
SV	-.712**	-.072*	1.000	0.047	.529**	.324**	.350**	.497**	.237**	.282**	.328**	.288**	.162**	.397**	.327**	.337**	.315**
GCR	.082*	.086*	0.047	1.000	-.184**	0.017	-.314**	-.081*	-.305**	-0.019	-.131**	-.264**	-.132**	-.164**	-.253**	-.249**	-.257**
RND	-.548**	-.260**	.529**	-.184**	1.000	.431**	.653**	.691**	.560**	.579**	.685**	.599**	.112**	.776**	.687**	.699**	.672**
CA	-.294**	-.242**	.324**	0.017	.431**	1.000	.443**	.523**	.345**	.407**	.616**	.471**	-.295**	.521**	.501**	.519**	.481**
BD	-.428**	-.264**	.350**	-.314**	.653**	.443**	1.000	.601**	.825**	.412**	.741**	.800**	0.032	.782**	.779**	.779**	.776**
BH	-.516**	-.233**	.497**	-.081*	.691**	.523**	.601**	1.000	.517**	.477**	.682**	.646**	.101**	.725**	.621**	.634**	.605**
BA	-.297**	-.287**	.237**	-.305**	.560**	.345**	.825**	.517**	1.000	.290**	.681**	.812**	0.024	.735**	.724**	.716**	.728**
PSF	-.268**	-.201**	.282**	-0.019	.579**	.407**	.412**	.477**	.290**	1.000	.647**	.483**	-.139**	.797**	.539**	.570**	.506**
PMD	-.373**	-.269**	.328**	-.131**	.685**	.616**	.741**	.682**	.681**	.647**	1.000	.788**	-.212**	.905**	.804**	.818**	.787**
PD	-.310**	-.206**	.288**	-.264**	.599**	.471**	.800**	.646**	.812**	.483**	.788**	1.000	-.173**	.843**	.913**	.910**	.911**
PLA	-.195**	0.013	.162**	-.132**	.112**	-.295**	0.032	.101**	0.024	-.139**	-.212**	-.173**	1.000	-0.001	-.175**	-.179**	-.169**
CEC	-.413**	-.211**	.397**	-.164**	.776**	.521**	.782**	.725**	.735**	.797**	.905**	.843**	-0.001	1.000	.838**	.852**	.819**
MUV	-.343**	-.237**	.327**	-.253**	.687**	.501**	.779**	.621**	.724**	.539**	.804**	.913**	-.175**	.838**	1.000	.998**	.998**
AUV	-.352**	-.246**	.337**	-.249**	.699**	.519**	.779**	.634**	.716**	.570**	.818**	.910**	-.179**	.852**	.998**	1.000	.993**
EUV	-.333**	-.227**	.315**	-.257**	.672**	.481**	.776**	.605**	.728**	.506**	.787**	.911**	-.169**	.819**	.998**	.993**	1.000

* Significant at the 0.05 level (two-tailed test); ** Significant at the 0.01 level (two-tailed test).

Note: SL=Slope; RBZ=River buffer zone; SV=Sky visibility; GCR=Green coverage rate; RND=Road network density; CA=Comprehensive accessibility; BD=Building density; BH: Building height; BA=Building age; PSF=Density of public service facilities; PMD=POI mixing degree; PD=Population density; PLA=Per capita living area; CEC=Comprehensive environmental comfort; MUV=Morning urban vitality; AUV=Afternoon urban vitality; EUV=Evening urban vitality.

FIGURE 6
Pearson correlation between objective environmental comfort factors and urban vitality. *Significant at the 0.05 level (two-tailed test); **Significant at the 0.01 level (two-tailed test). SL, Slope; RBF, River buffer zone; SV, Sky visibility; GCR, Green coverage rate; RND, Road network density; CA, Comprehensive accessibility; BD, Building density; BH, Building height; PSF, Density of public service facilities; PMD, POI mixing degree; PLA, Per capita living area; CEC, Comprehensive environmental comfort; MUV, Morning urban vitality; AUV, Afternoon urban vitality; EUV, Evening urban vitality.

TABLE 4 The OLS regression model between urban vitality and 13 environmental factors.

	Urban vitality		
	Morning	Afternoon	Evening
Slope	0.025	0.024	0.026
River buffer zone	−0.029*	−0.032*	−0.025
Sky visibility	0.015	0.017	0.012
Green coverage rate	−0.020	−0.024	−0.015
Road network density	0.227**	0.220**	0.233**
Comprehensive accessibility	0.019	0.029	0.009
Building density	0.096**	0.094**	0.097**
Building height	−0.113**	−0.102**	−0.124**
Building age	−0.172**	−0.176**	−0.166*
Density of public service facilities	−0.010	0.025	−0.046
POI mixing degree	0.132**	0.140**	0.123**
Population density	0.793**	0.792**	0.823**
Per capita living area	−0.018	−0.020	−0.017
R^2	0.881	0.888	0.871
Adjusted R^2	0.879	0.886	0.868
F	394.235	422.273	357.595

*Significant at the 0.05 level (two-tailed test). **Significant at the 0.01 level (two-tailed test).

was better than that for the morning or evening. The R^2 values for the model in the morning, afternoon, and evening were 0.701, 0.726, and 0.671, respectively, and the corresponding regression coefficients of the model were 0.838, 0.852, and 0.819, indicating that comprehensive environmental comfort had a significant positive impact on urban vitality.

In terms of the impact of time, the impact of environmental comfort on urban vitality followed the descending order of afternoon> morning> evening. Environmental comfort had a fixed value, and the urban vitality intensity followed the descending order of afternoon> evening> morning, indicating that in the morning and evening, urban vitality was also affected by environmental factors in addition to comprehensive environmental comfort.

3.5. Residential and commercial area adjustment and optimization

3.5.1. Residential area

The current situation of the three residential areas was analyzed and optimized in terms of land use type, road network density and public service facilities (Figure 7).

The densely built residential areas of Laocheng have few public spaces, resulting in a unsystematic road network and poor use of existing public spaces. Improving environmental comfort requires not only coordination with the surrounding area, but also attention to the circulation of the system within the system. The public space in Laocheng should be utilized to increase the area of green space and reduce the building density appropriately. Therefore, the specific measure is to integrate the unused public space into small squares within the district. Besides, some old buildings were demolished and integrated to form pedestrian paths, which increased

TABLE 5 Results of the OLS regression analysis of the impact of comprehensive environmental comfort on urban vitality.

Urban vitality	Comprehensive environmental comfort	R^2	Adjusted R^2	F
Morning	0.838**	0.702	0.701	1648.605763
Afternoon	0.852**	0.726	0.726	1864.033411
Evening	0.819**	0.670	0.670	1428.776543

*Significant at the 0.05 level (two-tailed test). **Significant at the 0.01 level (two-tailed test).

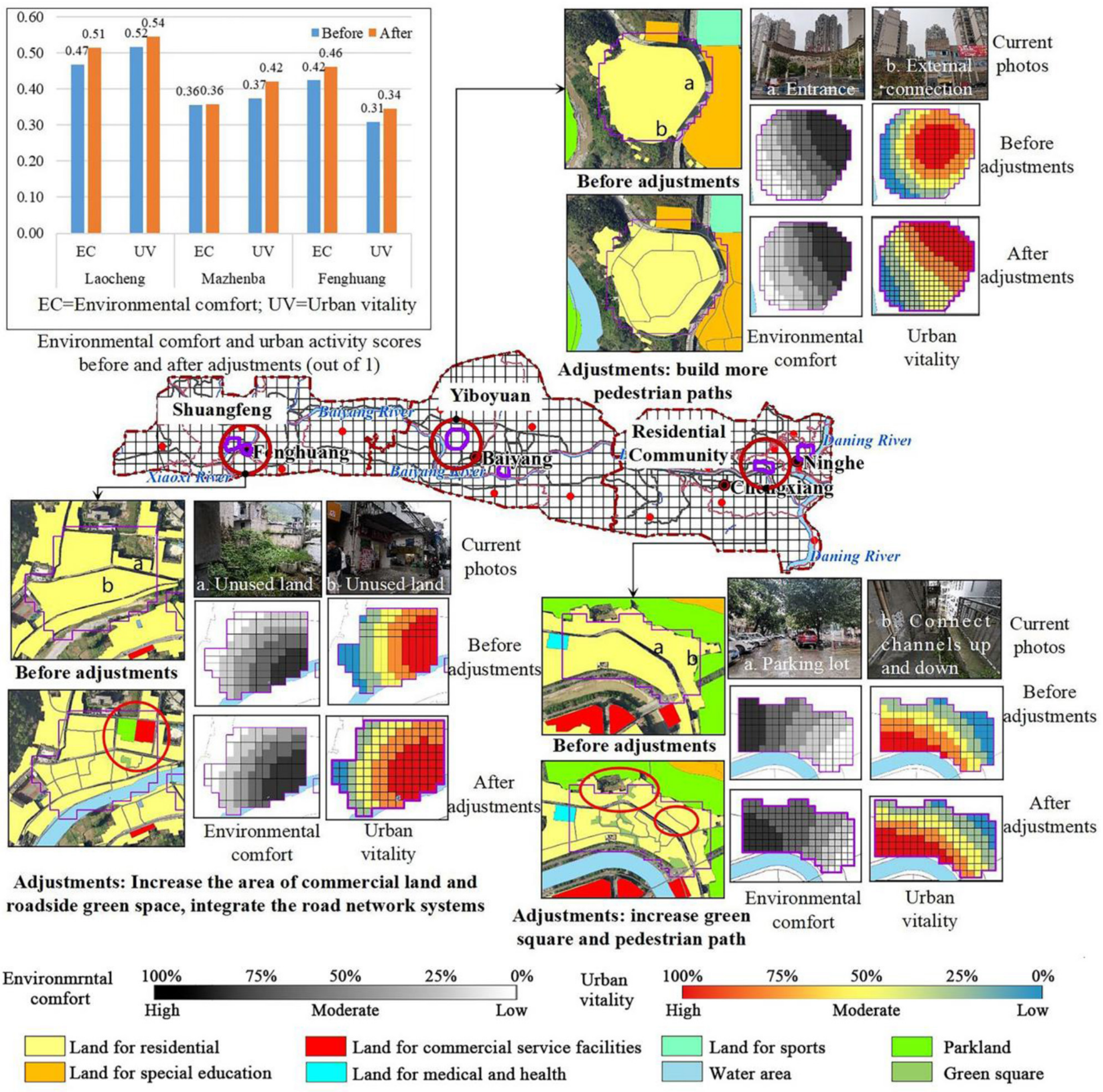


FIGURE 7
Vitality before and after adjustments of environmental factors in residential areas.

the internal connectivity of residential areas. The adjustments slightly reduced the building density and improved the green coverage. The local road network density and accessibility improved to certain extents. In addition, the average overall environmental comfort increased by 9.70%, and the urban vitality increased by 5.49%.

The new residential area in Mazhenba has relatively low green coverage, low building density, and is a high-rise building. There are more public spaces in the residential area, and the surrounding environment is relatively well equipped. However, due to the closed nature of the district, it is not closely connected with the surrounding areas. A complete pedestrian system should be established to increase the connection with the surrounding areas. Thus, major adjustments mainly occurred with roads. In order to improve the accessibility of residential areas, more pedestrian roads accessible to the outside were built. After adjustments, the local accessibility and road network density improved, the average environmental comfort increased by 0.71% with the average urban vitality increasing by 12.56%.

The residential area of Fenghuang is similar to Laocheng in terms of architecture. The difference is that the surrounding facilities are lacking, and the population is not concentrated due to topographical factors and the different development centers within the clusters, and there are multiple centers in the city. The coverage of public service facilities should be increased, and the internal transportation system should be improved, public green areas should be increased, and the accessibility of residential areas should be improved. In northern Fenghuang, the proportion of commercial land and street green space increased, and the road network systems inside the residential areas were integrated. After adjustments, the average environmental comfort increased by 9.12%, and the average urban vitality increased by 11.77%.

3.5.2. Commercial area

The current site conditions of the three commercial areas were analyzed and optimized in terms of site type, road network density, and public service facilities, respectively (Figure 8).

The commercial area of Laocheng is one of the high-vitality areas, and although it has a certain scale, it will be interspersed with residential land uses. Take advantage of the mix of current sites to improve the public service facilities support and road network system. Improve accessibility, enhance the flow of people with the surrounding sites, and promote the generation of urban vitality. The commercial areas of Laocheng were combined with unused land in the north. It is supplement to the existing public service facilities and increases the area of green space and commercial land. It promotes the connectivity between the land parcels, and pedestrian paths. After adjustments, the local road network density, accessibility, and also increases density of public service facilities. In addition, the average environmental comfort increased by 28.33% with average vitality increasing by 39.48%.

The center of Mazhenba's business district is modern, with a certain advantage in terms of building age, building density and public services, with a high level of POI mix and integrated accessibility already achieved. The main adjustment was to build more pedestrian paths in Mazhenba. It was recommended that the parking lot for the current administrative office should be adjusted to that on green space or underground. The increase in ground public space will attract more people, thus improving vitality. After the adjustment, the green coverage rate and accessibility both increased, the average environmental comfort increased by 0.15%, and the average urban vitality increased by 47.60%.

The commercial centers in Fenghuang are relatively concentrated, and most of the commercial functions are already embedded in the residential land. Increasing the density of public service facilities and road network in the commercial areas and appropriately renewing the buildings will help improve environmental comfort and urban vitality. Due to the lack of green space, the unused land in the residential areas was adjusted to green space, which increased the green coverage rate and the density of public service facilities. Finally, the average comfort increased by 10.50% along with 6.10% increasing of vitality.

4. Discussion

4.1. Residential area vitality enhancement strategy

Before adjustment, the environmental comfort in residential areas followed the descending order of Laocheng> Fenghuang> Mazhenba, and the urban vitality followed the descending order of Laocheng> Mazhenba> Fenghuang. Fenghuang had higher environmental comfort but lower urban vitality than Mazhenba. The result indicated that environmental comfort had a positive role in promoting urban vitality. However, in residential areas, the higher the environmental comfort was, the lower the urban vitality. A place with better environmental conditions and basic service facilities is more attractive, but in small and medium-sized cities, few people can afford housing in an excellent environment (which means higher housing prices and basic costs) due to the poor economic conditions. In contrast, the consumption level of places with low environmental comfort can easily matches people's expectation. Therefore, these places attract more people, thereby enhancing urban vitality. In the residential areas of small and medium-sized cities, although environmental comfort has a positive role in promoting urban vitality, higher comfort does not necessarily mean higher vitality.

For residential areas at different stages of development, they should be targeted to improve environmental comfort and urban vitality. Laocheng's residential areas are development saturated neighborhoods, usually with high building density and old age, few public spaces and poor road network systems. Therefore, improving environmental comfort requires not only coordination with the surrounding area, but also attention to the circulation of the system within the system. Reasonable use of the current public space, increase the green space, moderate reduction of a certain amount of building density. The residential areas in the accelerated development period have been built for a short period of time and are not integrated enough with the surrounding environment, and the greening coverage of the newly built neighborhoods is relatively low. However, there are more public spaces in the residential areas and the surrounding environment facilities are relatively perfect. It is necessary to establish a perfect pedestrian system, increase the green coverage, echo the surrounding environment, create excellent environmental comfort, attract crowds, and thus improve urban vitality. The residential areas in the starting period are relatively lacking in various kinds of supporting facilities, polycentric and not concentrated in population in the surrounding area. It is recommended to integrate the surrounding resources, increase the coverage of public service facilities, increase public green areas, improve the internal transportation of residential areas and increase accessibility.

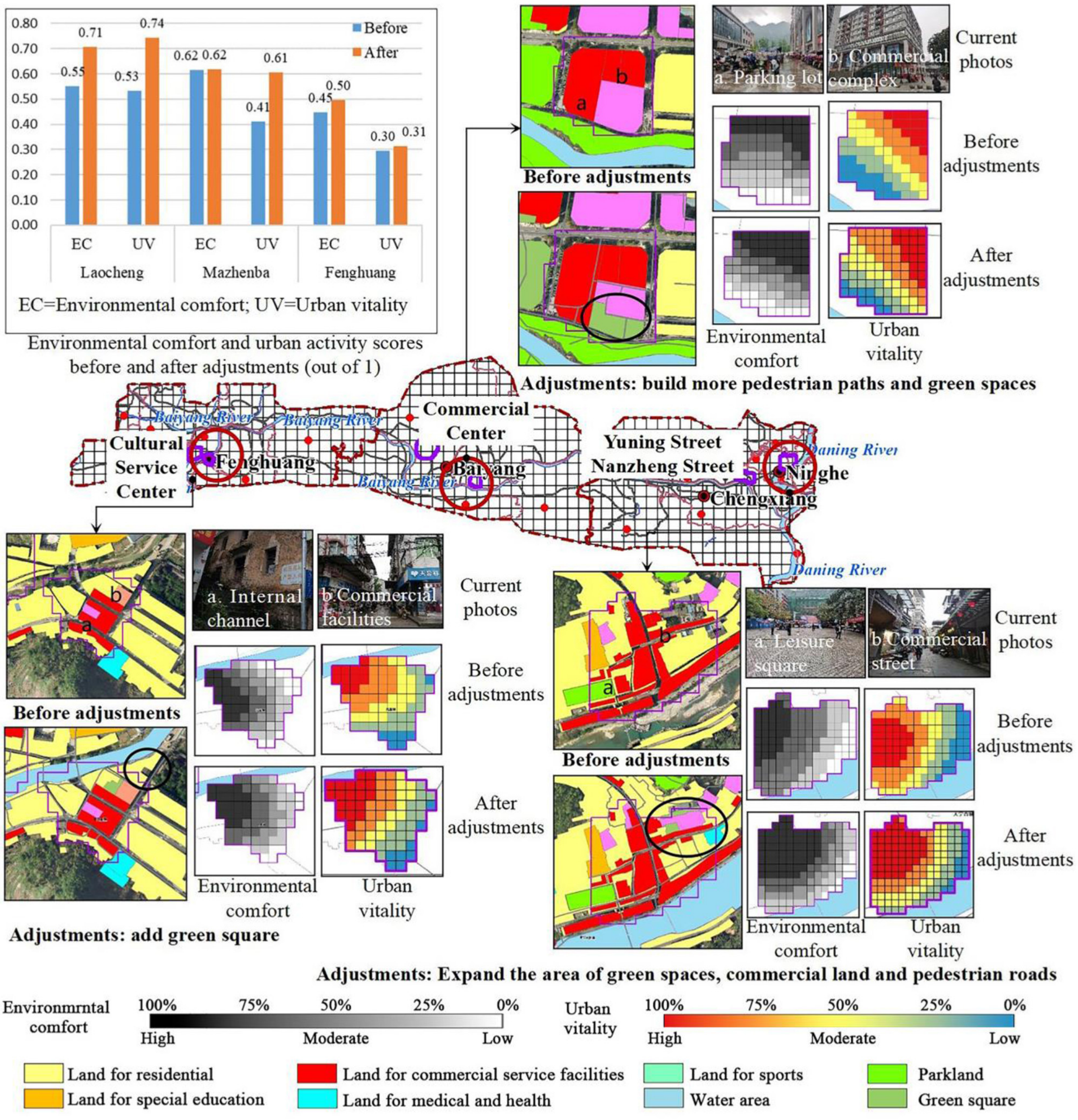


FIGURE 8
Vitality before and after adjustments of environmental factors in commercial areas.

4.2. Commercial area vitality enhancement strategy

Before adjustments, the environmental comfort followed the descending order of Mazhenba> Laocheng> Fenghuang, and the urban vitality followed the descending order of Laocheng> Mazhenba> Fenghuang (Figure 8). Mazhenba had higher comfort but lower vitality than Laocheng. The phenomenon indicating that environmental comfort had a positive promoting effect on vitality. In the commercial areas, higher comfort did not necessarily mean higher urban vitality. A place with better environmental conditions and basic service facilities is more attractive, however, newly established commercial centers with superior environmental quality may be less attractive due to their high consumption levels. In contrast, the commercial streets in Laocheng with lower environmental comfort attract more people because their consumption levels meet people's expectations, and naturally, they are more popular.

Commercial areas that have reached the saturation stage of development take advantage of the scale centrality of the existing commercial areas and the mixed scale with other sites. Improve public service facilities support and road network system. Improve accessibility and enhance the flow of people between the site and the surrounding sites. The commercial areas of small and medium-sized cities in the period of accelerated development have the characteristics of commercial centers of modern cities, and the buildings are mostly in the form of complexes. However, the poor comfort of the environment of the chemical outdoor space can lead to a contrast between the indoor and outdoor crowd stopping. It is suggested to strengthen the creation of outdoor public space, extend people's stay in outdoor public space as long as possible, and enhance the urban vitality of outdoor space. Also improve the transportation system within the commercial area to improve accessibility and attract crowds. The commercial area in the initial stage of development has more mixed commercial and residential sites with scattered business forms, making it difficult to form a large-scale and centralized commercial area. Taking into account the situation of the surrounding sites and the advantageous position of the commercial area, more merchants are attracted to move in, the density of public service facilities and road network in the commercial area is increased, and building renewal and the creation of outdoor public space are appropriately carried out.

4.3. Analysis of the influence pathways

Take Laocheng as an example. Urban vitality was simultaneously affected by multiple factors (Figure 9), and comprehensive environmental comfort had a significant positive impact on urban vitality.

Among the natural environmental factors, the interiors of the three clusters have a flat terrain and small slopes, and all are suitable for construction. Slopes did not exhibit a regular spatial variation pattern, and their impact on urban vitality was not significant. However, river buffer zones had a significant negative impact on urban vitality. Construction areas concentrated along the Baiyang River, Daning River, and Xiaoxi River. Areas farther away from the river had lower urban vitality. However, the river buffer zones cover a large proportion of the north of Paotai Mountain and north of the Fenghuang community, but the urban vitality was low due to the lack of urban construction activities.

Among the built environment factors, road network density, POI mixing degree, and building density exhibited the same trends as urban vitality. A large proportion of urban area was occupied by roads, and the areas with high POI mixing rates were mainly in the vicinity of Fenghuang Industrial Park and the Fenghuang Community Residential Committee, showing a dual-center pattern. However, urban vitality gradually decreased outward from the Fenghuang Community Residential Committee. Therefore, the specific impact of POI mixing rate cannot be determined. Road network density and urban vitality gradually decreased from the center out. A closer distance to the center, a denser road network, a higher building density, and a higher degree of POI mixing. The buildings in the central area are relatively old and were built in high density, with no significant difference in building height. The vitality there was high. However, the surrounding residential buildings are taller than the buildings in the central area. Hence, high building age and height always negatively impact urban vitality. The green coverage rate, sky visibility, comprehensive accessibility, and public service facilities did not significantly affect urban vitality. The urban areas had relatively high green coverage, high sky visibility, and small spatial heterogeneity, making it difficult to determine the impact of these factors. Accessibility, like road network density, density of public service facilities, and POI mixing degree, may positively impact urban vitality.

In the social environment, population density had a significant positive impact on urban vitality. Areas with higher environmental comfort are more likely to attract people. The central areas had high population densities and high urban vitality. The areas farther away from the urban centers had lower population densities and lower urban vitality. However, the impact of per capita living area was not significant, and the surrounding residential areas were scattered, with no evident centrality. In addition, the per capita living area was high in urban residential areas, but urban vitality was lower than commercial areas.

4.4. Limitations

There are still some limitations in the study, which need further exploration. First of all, our research focuses on mountainous cities. The research results can be better applied in mountainous cities, but it may be different from the construction of plain cities that are not affected by factors such as terrain. For other mountainous cities, the selection of environmental elements should also be adjusted according to local conditions to obtain more accurate results and apply them to the improvement of local environmental comfort. In the survey of plain cities, we can consider adding big data and spatial-temporal quantitative analysis, and adding more subjective satisfaction surveys. Second, the urban vitality investigated is mainly represented by Tencent Easygo heat map, but there are different interpretations of urban vitality, which should be further optimized. Then, although there are many types involved in environmental comfort elements, all the factors affecting environmental comfort still cannot be included. The factors of environmental comfort need to be improved in further study. Last but not least, the method used in the study involves multiple software and data processing, so there may be some problems in inter-technical parameter settings, and optimization is needed in the future.

5. Conclusion

Multiple data sources were used to analyze the impact of environmental comfort on urban vitality as well as their spatial autocorrelation and spatial matching. It was found that:

(1) Environmental comfort is significantly positively correlated with urban vitality. The environmental comfort and urban vitality of the three groups all present a single-center pattern. Environmental comfort and urban vitality decrease from the city center to the periphery, and gradually decrease from east to west as a whole. It is high in the east and low in the west, high in the south and low in the north.

(2) Urban vitality is significantly influenced favorably by population density, POI mixing percentage, building density, and road network density. Population density has the greatest impact on urban vitality, followed by road network density. The influence of POI mixing degree on urban vitality is greatest in the afternoon, and the influence of building density is greatest in the morning. Building height, building age, and river buffer have significant negative effects

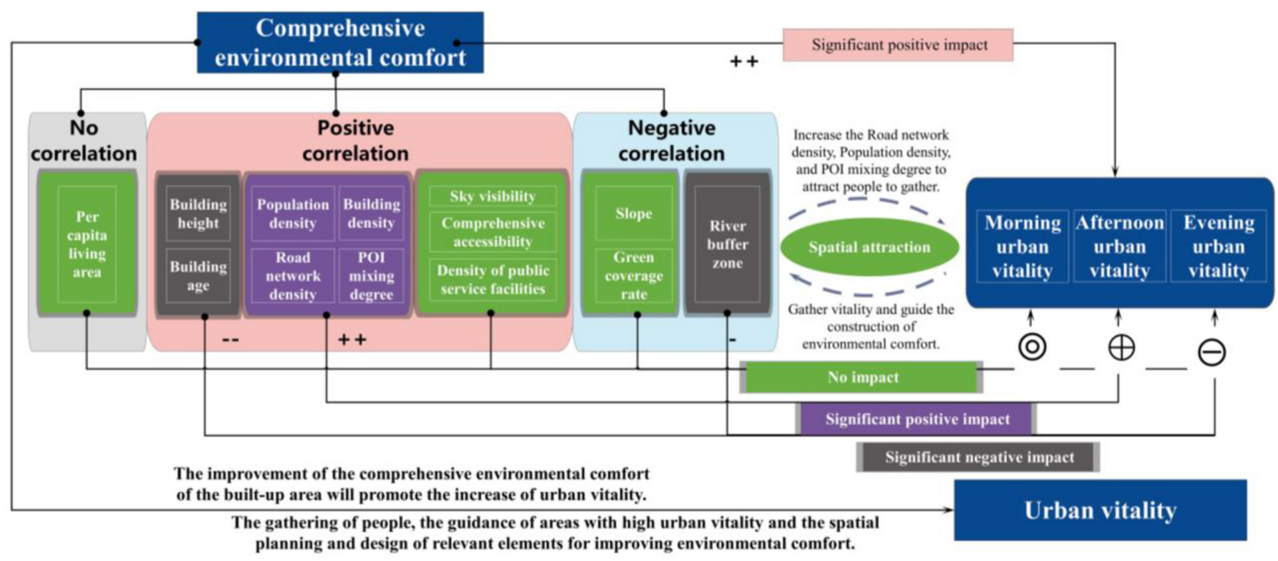


FIGURE 9
Analysis of the influence pathways in Laocheng.

on urban vitality, indicating that buildings that are taller, newer, and farther from the river reduce urban vitality.

(3) Comprehensive environmental comfort has a significant positive impact on urban vitality. In terms of time, the influence of comprehensive environmental comfort on urban vitality in descending order is afternoon > morning > evening.

By looking for the matching degree between environmental comfort and urban activities, this study discovered the main environmental factors that affect urban vitality and finally constructed an evaluation method for the impact of environmental comfort on urban vitality. Although population density and building density can promote urban vitality, excessive population density and building density can cause damage to people's physiology and psychology. In the development of the urban built environment, attention should be paid to the balance between the needs of developing cities in different periods and with different characteristics to meet the needs of improving urban vitality at different levels. When the development of small and medium-sized cities reaches saturation, they should pay attention to the evacuation of the central area and improve the comfort of the environment outward. When the development is accelerated, use the central area to drive the synchronous development of the surrounding areas. When the development is in its infancy, strengthen the construction of the central area.

In residential areas, we recommend that during the period of saturated development, the current public space be utilized judiciously, green spaces be increased, and building density be appropriately reduced. During the accelerated development period, establish a complete pedestrian system to improve the connection with the surrounding area. To develop residential areas in the initial stage, integrate surrounding resources, increase the coverage of public service facilities, increase public green spaces, improve internal traffic in residential areas, and improve accessibility. For the commercial districts, to increase population mobility and encourage the creation of urban vitality, public service facilities and the road network system should be improved once development has reached saturation. During the accelerated development period, indoor and outdoor spaces' attractiveness, the length of time people spends in public areas, the internal transportation system, accessibility, and the creation of a top-notch shopping environment should all be improved. Improve the transportation system while introducing commercial and public service facilities during the early stages of development.

Overall, our findings and evaluation methods can promote large improvements in vitality under minor adjustment. It is of great significance on urban spatial planning and promotion of new urbanization and rural revitalization. Meanwhile, it can provide reference for planning and design in small and medium-sized cities.

Data availability statement

The data analyzed in this study is subject to the following licenses/restrictions: The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation. Requests to access these datasets should be directed to hangf@cqu.edu.cn.

Author contributions

GL: conceptualization, formal analysis, investigation, data curation, and writing—original draft. JLe: formal analysis, resources, and writing—review and editing. HQ, JN, and JC: writing—reviewing and editing. JLu: resources and writing—review and editing. GH: conceptualization, methodology, funding acquisition, supervision, and writing—review and editing. All authors contributed to the article and approved the submitted version.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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Quantitative evaluation of urban resilience in underdeveloped regions: a study of six cities in Sichuan & Tibet, China

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Introduction: Urban resilience construction can aid in the management of urban crises and enhance the quality of the human living environment. Compared to metropolises in developed regions, cities in underdeveloped regions with unsatisfactory natural environments, insufficient economic and social development, and inadequate infrastructure construction are highly vulnerable to challenges posed by natural disasters, epidemics, and climate change. Comprehensive quantitative evaluations are needed to identify avenues for enhancing urban resilience.

Methods: This study employs the TOPSIS entropy weight method and coupled coordination model to evaluate the economic, social, environmental, and infrastructure resilience of six cities and states along the Sichuan-Tibet Railway in China from 2015 to 2020. Furthermore, correlation and gray correlation analysis are used to identify the primary factors influencing the urban resilience of underdeveloped regions.

Results: Firstly, during 2015-2020, the overall urban resilience of each city and state maintained an increasing trend, with different trends in the evolution of the four resilience indices and differences among cities, and the highest overall resilience is in Lhasa. Secondly, the coupling coordination between the overall resilience and each resilience aspect maintained an increasing trend and differed significantly from each other. Finally, the social and economic resilience of each city and state maintained an increasing trend and differed significantly from each other.

Discussion: Economic, social, environmental, and infrastructure factors each have their own characteristics in influencing urban resilience. Based on the results, we present a three-dimensional evaluation model for analyzing the evolutionary trajectories and resilience patterns of cities. This work intends to present new concepts for assessing and optimizing urban resilience in underdeveloped regions using quantitative methodologies, as well as providing references for urban resilience construction in these places.

KEYWORDS

resilient city, underdeveloped region, TOPSIS, coupled coordination model, built-up environment

1 Introduction

As complex systems, cities are exposed to long-term disturbances and shocks from the external environment, such as natural disasters (Zhou et el., 2022; Kondo and Lizarralde, 2021), economic crises (Ulfarsson et al., 2015; Tomao et al., 2021), climate change (Zimmerman and Faris, 2011) and the spread of infectious diseases (Cheng et al., 2022; Jin et al., 2023). City managers have incorporated the engineering concept of "resilience" into urban planning and construction to mitigate the negative effects of these shocks and assist cities in developing stably and sustainably (Murgatroyd and Hall, 2020; Wang L, 2022), as well as to improve the quality of the living environment and the standard of living for residents (Snep et al., 2020; Talubo et al., 2022). The concept of urban resilience is a comprehensive concept with multiple attributes (Dianat et al., 2022; Khatibi et al., 2022). Therefore, quantitatively assessing the overall resilience of cities from the perspectives of economy, society, culture, institutions, ecology, environment, and infrastructure (Lu et al., 2022a; Lin et al., 2022; Zhao et al., 2022), can aid in the construction and planning of urban resilience.

As the essence of increasing comprehensive urban resilience, it is necessary to promote coordination along economic and social development, ecological environment, urban governance, and infrastructure construction. Compared to metropolises in economically developed regions that regard communities as the basic unit of urban resilience (Graham et al., 2016; Bixler et al., 2021; Collier et al., 2013), cities in underdeveloped regions with lower levels of economic development, unfinished infrastructure construction, and weaker social governance are more susceptible to external shocks (Li et al., 2022; Song et al., 2022), while their population density is lower. These cities are frequently located in high-altitude and alpine regions, environmentally fragile locations, and regions with a high frequency of geological disasters (Arifin, 2022), and their urban systems are extremely susceptible to severe damage from natural disasters, climate change, and epidemics (Dobson, 2017; Wu et al., 2022). Consequently, it is of the utmost importance to conduct a complete quantitative evaluation of urban resilience in underdeveloped regions and to investigate ways to strengthen urban resilience with this support.

The Sichuan-Tibet Railway is a significant project for China to maintain national unity, enhance national cohesion, and promote economic development and social stability in Western Sichuan and Tibet's underdeveloped regions. The majority of the cities along its route are located in high-altitude and alpine regions, as well as minority gathering areas, which are constrained by the natural environment. The economic development and spatial evolution patterns of Chengdu, located at the eastern terminus of the railroad, differ significantly from those of other cities. The building and inauguration of the railroad and the influx of external resources have, on the one hand, contributed to the local economic and social development and, on the other hand, posed new difficulties to their urban resilience. Consequently, this study selects six typical cities and states along the Sichuan-Tibet Railway, namely Lhasa, Lhoka, Nyingchi, Qamdo, Garzê Tibetan Autonomous Prefecture, and Ya'an, combines the TOPSIS entropy weight method and coupled coordination model to quantitatively assess and compare the comprehensive urban resilience and coordination degree during 2015–2020 from economic resilience, social resilience, environmental resilience, and infrastructure resilience. Using Pearson correlation analysis and gray correlation analysis, this study analyzes the primary factors influencing urban resilience. It then employs a three-dimensional evaluation model to study and evaluate the development state and evolution pattern of urban resilience. The study provides a new comprehensive urban resilience evaluation system that can be used to explore the path of resilience evolution and to introduce resilience construction in underdeveloped regions of China and elsewhere.

The following sections comprise the remainder of this study: The "Literature Review" section reviews existing studies on urban resilience evaluation and analyzes the major methodological approaches to comprehensive urban resilience evaluation. The "Data" section describes the basic overview of the research subjects and the meaning and sources of the research indicators. The "Methodology" section introduces the framework for the comprehensive evaluation and analysis methods used in this study. The "Results" presents the outcomes of the comprehensive evaluation, coupled coordination analysis, and correlation analysis. The "Discussion" section discusses the results and the evolution of urban resilience. The "Conclusion" section summarizes the study's key findings, ramifications, and limitations.

2 Literature review

The concept of urban resilience derives from engineering and ecological resilience (Holling, 1973; Liao, 2012). Its definition is flexible and diverse (Meerow et al., 2016), generally referring to the defense, adaptation, and transformation capacity of urban composite systems in response to a variety of natural and man-made disaster disturbances (Pickett et al., 2004; Mou et al., 2021). The application of scientific and systematic evaluation criteria to quantify urban resilience can, on the one hand, enrich the theory of resilience and aid in the study of the development path of resilient cities (Ahern, 2011; Brown et al., 2012), and on the other hand, provide macro guidance for the practice of resilient city planning and construction.

Although the current research on urban resilience theories, principles, and characteristics has reached a relatively mature stage, the operational dimensions lack a scientific, consistent, and systematic evaluation methodology. Existing resilience evaluation studies predominantly begin from a single perspective, such as urban disaster preparedness and resilience under the influence of natural disasters (Capozzo et al., 2019; Liu et al., 2022) and climate evolution (Leichenko, 2011; Feldmeyer et al., 2019), as well as environmental resilience (Doherty et al., 2016; Bao et al., 2022), energy resilience (Sharifi and Yamagata, 2016), transportation resilience (Faturechi and Miller-Hooks, 2015; Tang et al., 2020), and infrastructure resilience (Alizadeh and Sharifi, 2020). Among them, Wang et al. (2023) assess the resilience of ecological networks in urban agglomerations from the perspective of robustness and redundancy balance. Tang proposed the Bayesian Network Model (BNM) to quantitatively evaluate the resilience of urban transportation systems by combining different factors in the design, construction, operation, management, and innovation phases. Another portion of the studies primarily takes communities as the evaluation objects and investigates community disaster preparedness and resilience (Jordan and Javernick-Will, 2013; Sharif, 2016). Cimellaro et al. (2016) proposed the PEOPLES assessment model based on seven dimensions of community resilience, including population and demographics, environmental and ecosystem, organized governmental services, physical infrastructures, lifestyle and community competence, economic development, and social-cultural capital. The model became one of the main frameworks for quantitatively measuring community resilience. As cities are complex systems, a single perspective evaluation system cannot assess all aspects of urban resilience, including economic, social, cultural, environmental, institutional, and infrastructure resilience. Therefore, a more systematic way of thinking and approach is required for city-based resilience evaluation.

Existing comprehensive urban resilience evaluation system construction concepts several types. Among them, some scholars take the basic constituent elements of cities as the main metric aspects of urban resilience, such as economic resilience, social resilience, organizational resilience, institutional resilience, ecological resilience, and infrastructure resilience, etc., and use them to establish an indicator system (Joerin et al., 2014; Song et al., 2018). Four subsystems, including economic, social, environmental, and infrastructure, are covered by a multidimensional and comprehensive urban resilience assessment model that is based on the system dynamics model (Datola et al., 2022). Numerous quantitative studies of cities or urban agglomerations in China also categorize urban resilience into these four categories (Lu et al., 2022b; Shen et al., 2022; Xia and Zhai, 2022), or replace environmental resilience with ecological resilience. Additionally, some studies have the assessment system take into account institutional (Zhao et al., 2022), demographic (Ye et al., 2022), and technical (Lu et al., 2022a) variables. For instance, Zhao established five levels of indicators combined with the barrier degree, including economic, social, institutional, environmental, and infrastructure. In general, these comprehensive resilience assessment techniques are comparable to conventional urban evaluation techniques, typically employed in current research.

Moreover, some scholars assess the resilience, redundancy, wisdom, rapidity, and other capacity characteristics of cities (Parsons and Morley, 2017), such as Heeks and Ospina (2019) establishing two types of indicator systems, including functional characteristics and enabling characteristics, and combining social equity elements to assess the urban resilience of developing countries. Such evaluation methods are more closely integrated with resilience theory. In addition, other Scholars start from the staging process of urban development, such as resistance (Bruneau et al., 2003), adaptation, and recovery. For instance, Bozza et al. (2017) presented a time-series-based independent, comprehensive quantitative evaluation methodology, which can simulate the probability of occurrence and damage state of urban disasters at different stages and uncover shortcomings in the resilience construction process, and permit targeted adjustments.

In conclusion, the establishment of a quantitative urban resilience evaluation system need to be based on the characteristic elements of urban resilience in the resilience theory, take into account different aspects of urban development to establish a systematic and comprehensive index system, and comprehend the dynamic nature of urban evolution and the differences between cities. This study, therefore, adopts an evaluation system based on the criteria of urban elements, including economic and social, ecological and environmental, and infrastructural elements. Most current resilience assessment studies concentrate on examining the features of integrated urban resilience's regional and temporal distribution, as well as the determining influence of each element on integrated urban resilience. This study examines these factors with the TOPSIS model and correlation analysis. In order to analyze the balance and coordination state among the urban resilience subsystems, this study also includes a coupled coordination analysis. Additionally, since the majority of underdeveloped regions are still in the early stages of resilience construction, this study builds a multidimensional model to illustrate the evolution trend of each city's comprehensive resilience. This model makes the presentation of the analysis results more comprehensible and convincing and offers recommendations for the ensuing resilience building of cities.

3 Data

3.1 Study object

Sichuan-Tibet Railway connects China's Sichuan Province and Tibet Autonomous Region, beginning in Chengdu (Sichuan) in the east and ending in Lhasa (Tibet) in the west, with an operating mileage of 1567.33 km, consisting of three parts. The Chengdu-Ya'an section is located in the Chengdu Plain, and opened for operation in 2018, with a total length of 140 km and a total of 11 stations. The Ya'an-Nyingchi segment traverses the Hengduan Mountains, whose topography, geology, climate, and other variables make building exceedingly challenging. The stretch from Lhasa to Nyingchi is situated in the midst of the Tibetan plateau and has a total length of 403 km. Construction began in June 2015 and was completed in June 2021. The Sichuan-Tibet Railway passes through Lhasa, Lhoka, Nyingchi, Qamdo, Garzê Tibetan Autonomous Prefecture, Ya'an, and Chengdu from west to east. Among them, Chengdu is one of the seven megacities in China with a high level of economic and social development and does not belong to the category of underdeveloped areas. Therefore, the other six cities and states are selected as the study objects in this study (Figure 1).

3.2 Study indicators

Based on pertinent domestic and international studies, this study classifies urban resilience into four aspects: economic resilience, social resilience, environmental resilience, and infrastructure resilience, and proposes an index system following these classifications. Among them, economic resilience reflects the level of economic and industrial development and the capacity to withstand economic risks, including indicators related to the national economy, industry, finance, banking, and urbanization levels. Social resilience reflects the living standard of residents and the level of urban social services, including indicators related to income, consumption, savings, and public service levels. Environmental resilience reflects the level of urban ecological services and environmental health, including indicators related to air quality, urban greening, and environmental hygiene. Infrastructure resilience reflects the efficiency of urban infrastructure development and resource use, including indicators related to transportation, water, and gas supply. The majority of the data used in this study come from the 2015–2020 China Urban Statistical Yearbook and the China Urban Construction Statistical Yearbook. The remaining data come from the statistical yearbooks of

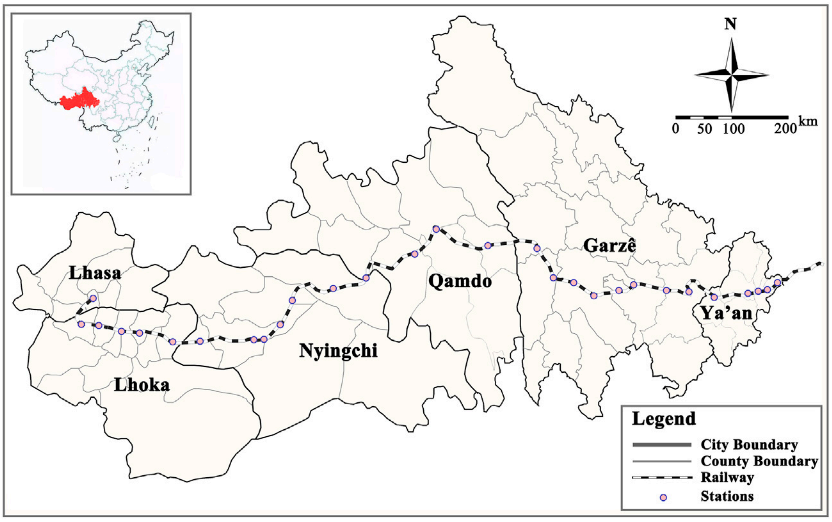

FIGURE 1
Sichuan-Tibet Railway and six cities (states) as study objects. GS (2022) 1873.

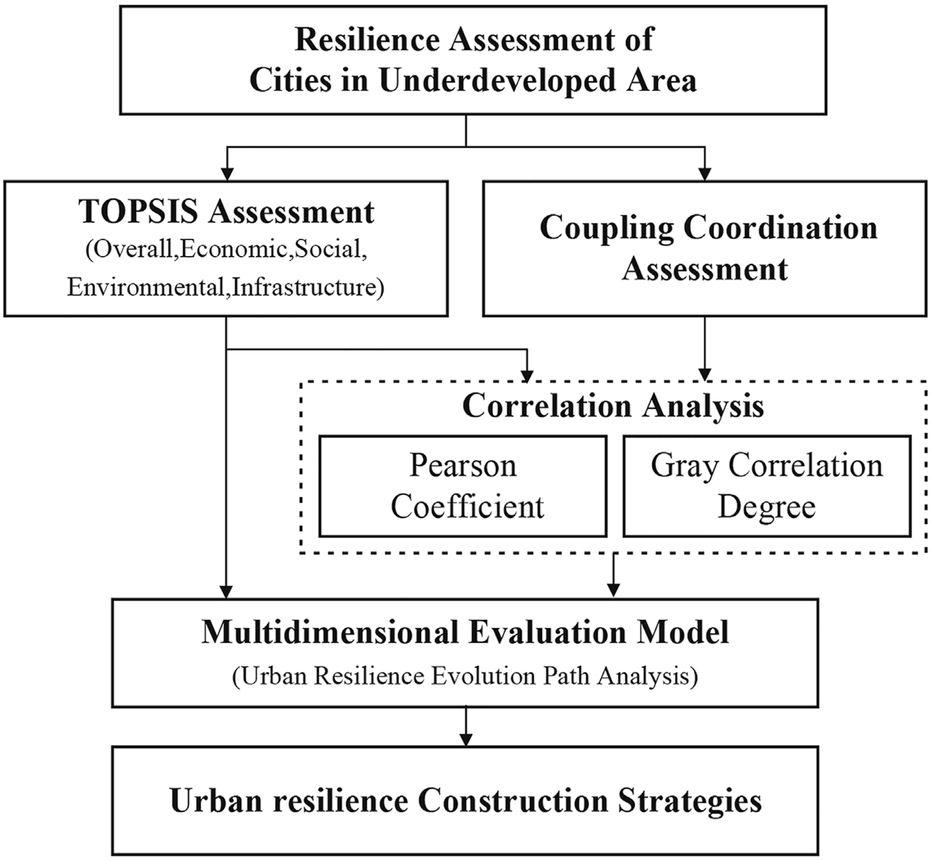

FIGURE 2
Framework for quantitative evaluation methodology.

TABLE 1 Evaluation indicators and weights.

Aspects	Indicators	Entropy	Utility value	Weight
Economic Resilience (0.2814)	GDP *per capita* (+)	0.919	0.081	0.0514
	GDP growth (+)	0.978	0.022	0.0142
	Share of tertiary industry (+)	0.965	0.035	0.0221
	Government revenue *per capita* (+)	0.942	0.058	0.0363
	Bank loan *per capita* (+)	0.929	0.071	0.0448
	Fixed asset investment *per capita* (+)	0.919	0.081	0.0509
	Share of tourism revenue (−)	0.974	0.026	0.0167
	Urbanization rate (+)	0.929	0.071	0.0451
Social Resilience (0.3114)	Bank balance *per capita* (+)	0.886	0.114	0.0719
	Disposable income *per capita* (+)	0.962	0.038	0.023
	Urban-rural income ratio (−)	0.983	0.017	0.0106
	Consumer price index (−)	0.975	0.025	0.0156
	Engel coefficient (−)	0.952	0.048	0.03
	Medical resources (+)	0.924	0.076	0.0483
	Compulsory education resources (+)	0.965	0.035	0.0222
	Mobiles *per capita* (+)	0.896	0.104	0.0658
	Pension insurance coverage (+)	0.964	0.036	0.024
Environmental Resilience (0.1841)	Park green space *per capita* (+)	0.925	0.075	0.0471
	Green coverage in the built-up area (+)	0.963	0.037	0.0232
	Average PM2.5 concentration (−)	0.977	0.023	0.0144
	Average air quality index (−)	0.963	0.037	0.0234
	Domestic waste disposal rate (+)	0.969	0.031	0.0197
	Sewage disposal rate (+)	0.988	0.012	0.0078
	Road cleaning rate (+)	0.923	0.077	0.0485
Infrastructure Resilience (0.2231)	Water supply penetration rate (+)	0.969	0.031	0.0197
	Gas supply penetration rate (+)	0.956	0.044	0.0276
	Road area *per capita* (+)	0.923	0.077	0.0484
	Road freight volume (+)	0.918	0.082	0.0517
	Density of water and drainage pipes (+)	0.971	0.029	0.0182
	Share of infrastructure land (+)	0.909	0.091	0.0575

Sichuan Province and Tibet Autonomous Region, cities and counties yearbooks, and the national economic statistical bulletins issued by city statistical bureaus. This study uses the interpolation approach to complete the few missing data (Figure 2).

Before undertaking an urban resilience evaluation, it is necessary to give weights to the selected indicators. Using information entropy, the Entropy Weight Method approach determines the coefficient of variation of indicators (Xu et al., 2018). The smaller the information entropy, the greater the coefficient of variation and the greater the weight of indicators. This strategy can avoid the apparent subjectivity of indicators and is more appropriate for the assignment of indicators for resilience evaluation. Table 1 displays the indicator weights derived from the entropy weighting method.

4 Methodology

This study presents a framework for quantitative evaluation that incorporates the TOPSIS approach, a linked coordination model, and correlation analysis. First, the overall urban resilience and economic, social, environmental, and infrastructure resilience are assessed by the TOPSIS method, while the degree of coordination of urban resilience is assessed by the coupled coordination model. On this basis, the degree of connection among the influencing factors of urban resilience is explored by correlation analysis, and the calculation results are combined with the resilience evaluation results to develop a multidimensional model to analyze urban resilience. Work is performed to aid urban resilience planning and construction.

4.1 Topsis

In this study, TOPSIS approach (Technique for Order Preference by Similarity to an Ideal Solution) is utilized as the major method for analyzing urban resilience in underdeveloped locations (Lai et al., 1994; Olson, 2004), which is essentially a relatively objective method for determining the relative proximity of each object to the optimal solution. Its computation technique consists of two stages, first calculating the normalized weighted matrix to determine the ideal and inferior options.

$$V_{ij} = X_{ij} \times W_i$$

$$V_i^+ = \left\{ maxV_{ij} \middle| i = 1, 2, \cdots, m; j = 1, 2, \cdots, n \right\}$$

$$V_i^- = \left\{ minV_{ij} \middle| i = 1, 2, \cdots, m; j = 1, 2, \cdots, n \right\}$$

where X is the normalization matrix and W is the weight of the indicators using the entropy value approach. V_{ij} is the value of the indicator j of the object i. V_i^+ and V_i^- are the maximum and minimum of the values.

After obtaining the optimal and inferior solutions, the Euclidean distance and the relative closeness between the evaluation object and the optimal and inferior solutions must be determined.

$$D_j^+ = \sqrt{\sum_{i=1}^{m} (V_{ij} - V_i^+)^2}$$

$$D_j^- = \sqrt{\sum_{i=1}^{m} (V_{ij} - V_i^-)^2}$$

$$T_j = \frac{D_j^-}{D_j^+ \times D_j^-}$$

where, D_j^+ is the distance between the evaluation object and the ideal solution, D_j^- is the distance between the evaluation object and the worst solution, T_j is the relative proximity to the optimal solution, and has a range of values between 0 and 1. The greater the relative proximity, the more resilient the city. When it is larger than 0.6, it implies that the level of urban resilience is high; when it is less than 0.3, it suggests that the level of urban resilience is low.

4.2 Coupled coordination degree

In addition to assessing the level of urban resilience, the degree of coordinated development of each resilience must also be evaluated. Therefore, we employ the coupled coordination degree model (CCDM) for our research (Wang X et al., 2022). The degree of coupling reflects the degree of dependency and mutual constraints among multiple systems. And the degree of coordination relates to the magnitude of benign coupling in the linked interaction relationship, which might indicate whether coordination is excellent or poor. The following model can be used to depict the coupling degree model of numerous system interactions.

TABLE 2 Standard of coupling coordination degree level.

D	Level	D	Level
$D < 1$	Severely uncoordinated	$5 \le D < 7$	Elementary coordinated
$1 \le D < 3$	Medium uncoordinated	$7 \le D < 9$	Medium coordinated
$3 \le D < 5$	Mildly uncoordinated	$D > 9$	Superiorly coordinated

$$C_n = \left\{ \frac{(u_1 \cdot u_2 \cdots \cdots u_n)}{\prod (u_1 + u_2)} \right\}^{1/n}$$

$$u_i = \sum_{i=1}^{m} w_{ij} u_{ij}, \sum_{j=1}^{m} w_{ij} = 1$$

where C_n is the coupling degree of the n-element system. Respectively, u_n is the contribution of the n-th subsystem to the total system order. In the ordered calculation, u_{ij} is the normalized value of the j-th indicator in the i-th subsystem. And using the entropy weight method, w_{ij} is the weight of the j-th indicator in the i-th subsystem. In some instances, the coupling index is difficult to accurately reflect the overall efficiency and synergy of the subsystem, and the extreme value calculation is dynamic and unbalanced. On this premise, the degree of coupling coordination can be computed using the following formula.

$$D = (C \cdot T)^{1/2}, T = au_1 + bu_2 + \cdots\cdots + iu_n$$

where C is the coupling degree and D is the coupling coordination degree, which is determined to lie between 0 and 10 and can be divided into six coordination levels (Table 2). T is a comprehensive evaluation index of the level of coupled and coordinated development. u_n designating the n-th system, a–i refer to the relative weights of each system.

4.3 Correlation analysis

This study uses the Pearson correlation coefficient to compare and analyze the correlation between four urban resilience influencing factors and urban resilience indicators, to examine and evaluate the degree of association between different factors and indicators and the level of urban resilience in underdeveloped areas, as well as to test the rationality of indicator selection. Following is the precise calculating formula.

$$\rho_{x,y} = \frac{\sum (X - \bar{X})(Y - \bar{Y})}{\sqrt{\sum (X - \bar{X})^2 + \sum (Y - \bar{Y})^2}}$$

where X and Y are the values of the two variables, respectively, and $\rho_{x,y}$ is correlation coefficients with values ranging from [−1, 1]. When the value is close to 1, the two variables exhibit a strong positive correlation, when it is close to −1, the two variables exhibit a strong negative correlation, and when the value is closer to 0, the correlation between the two variables is weaker.

Pearson correlation coefficient can effectively reflect the correlation degree between indicators (Yang et al., 2022), and gray correlation analysis

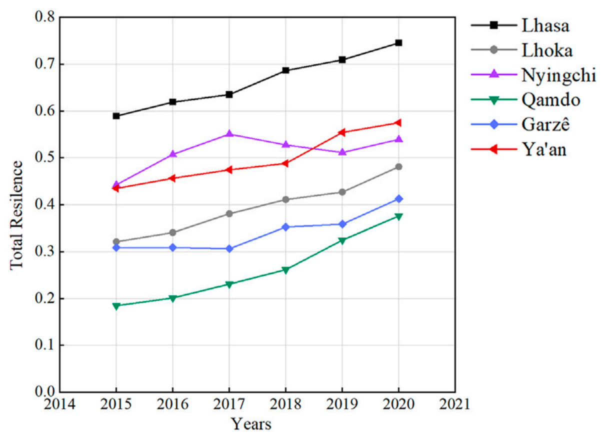

FIGURE 3
Trends in the evolution of the overall resilience level of study objects.

can be used to calculate the correlation degree between indicators and overall toughness level. Gray correlation analysis is a method for analyzing the correlation degree between factors of the system by comparing the similarity degree of data series geometric relationship and curve geometry (Liu and Yu, 2007). Following is the precise calculating formula.

$$\gamma_i(\mathbf{k}) = \frac{\min_i \min_k |x_0(k) - x_i(k)| + \mu \cdot \max_i \max_k |x_0(k) - x_i(k)|}{|x_0(k) - x_i(k)| + \mu \cdot \max_i \max_k |x_0(k) - x_i(k)|}$$

where γ_i is the grey correlation degree of factor i and takes values from 0–1. And μ is the resolution factor and takes values from 0–1. The smaller the resolution coefficient, the larger the disparity between the correlation coefficients and the better the capacity to differentiate, which is typically 0.5.

5 Results

5.1 Urban resilience evaluation

Using the TOPSIS entropy weighting approach, we calculate the overall resilience of the six cities and states along the Sichuan-Tibet Railway (Figure 3). During the period 2015–2020, the overall resilience of each city exhibits an upward trend. This indicates that the national policy support and the influx of external resources brought by the major project of the Sichuan-Tibet Railway have contributed to the development of towns and cities in underdeveloped areas along the route, regardless of whether or not the construction of the railroad begins. Lhasa has the highest overall resilience and has been at a high resilience development level since 2016. Nyingchi and Ya'an have the same overall resilience at the start of the study, but Nyingchi's resilience level is hindered after a high rate of increase, while Ya'an's resilience level steadily increases and gradually surpasses

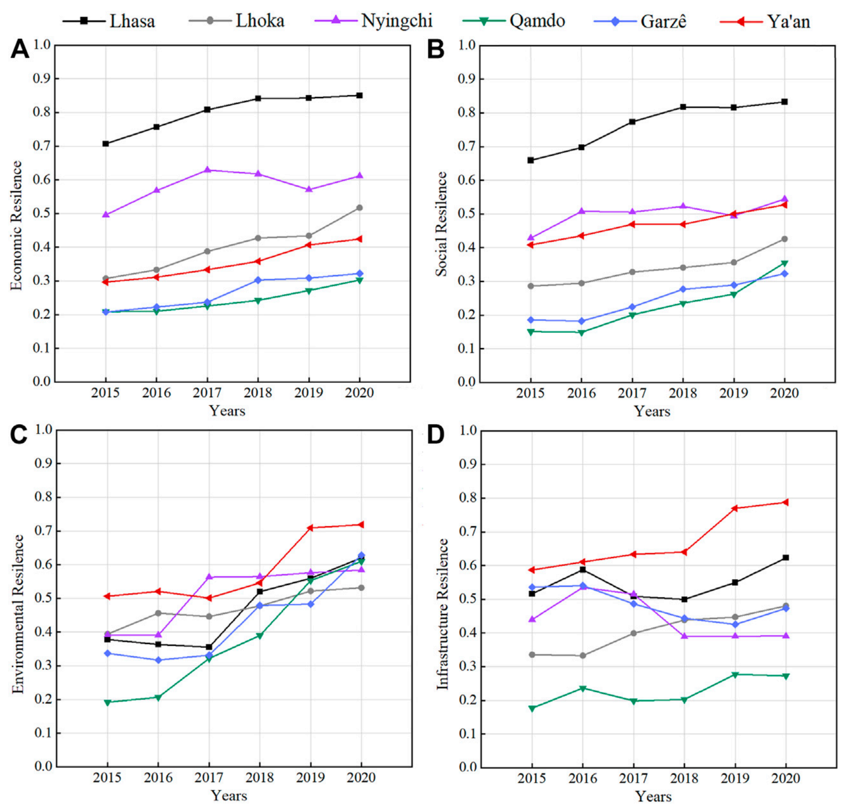

FIGURE 4
Trends in the evolution of various aspects of resilience levels. **(A)** Economic resilience. **(B)** Social resilience. **(C)** Environmental resilience. **(D)** Infrastructure resilience.

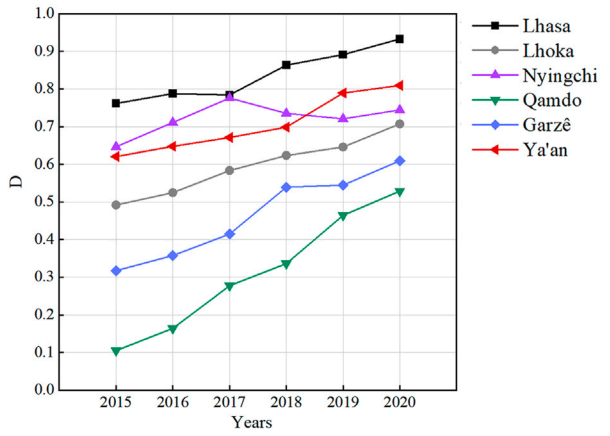

FIGURE 5
Trends in the evolution of resilience coupling coordination.

Nyingchi. Lhoka and Garzê have a similar process of urban resilience improvement, while Lhoka, which is in the railroad constriction zone, has a higher growth rate of resilience. Qamdo has the lowest level of resilience, but its overall resilience has increased throughout the study period, rising from low to medium resilience.

Figure 4 depicts the outcomes of the analysis of urban resilience levels in several economic, social, environmental, and infrastructure aspects across six cities and states. During the period 2015–2020, the economic and social resilience of each city has a consistently increasing trend, the environmental resilience demonstrates an inconsistent upward jump trend, and the infrastructure resilience fluctuates with clear city-to-city variances. Lhasa has the strongest economic and social resilience among all cities, and its environmental resilience has risen dramatically since 2017. Ya'an has greater environmental and infrastructure resilience than the other two aspects. Nyingchi shows a trend of stagnant development after a rapid increase in all resilience, and economic and infrastructure resilience has even declined. And Lhoka is at a medium level of development in all resilience, with a stable overall growth trend. Qamdo and Garzê, as cities without complete railroad projects, exhibit comparable tendencies in the evolution of various forms of resilience, with environmental resilience increasing more rapidly than infrastructure resilience, which remains essentially unchanged or declines somewhat.

5.2 Resilience coupling coordination

In the coupled coordination model computation, we assessed the total degree of coordination between the aspects of resilience and the degree of coordination between the two dimensions. In general (Figure 5), the overall coupling coordination degree of urban resilience for each city and state steadily increases and follows the same evolutionary pattern as the overall urban resilience. The coupling coordination degree of Lhasa is also the highest among the cities and provinces, essentially maintaining the intermediate and high-quality coordination status. Qamdo and Garzê are far behind the other cities, but their rate of improvement is faster, and they have gradually developed from a dysfunctional status to a preliminary coordination status. The evolutionary trends of Lhoka, Nyingchi, and Ya'an are similar. The coupling coordination degree in Nyingchi has gradually declined since 2017, which is consistent with the evolutionary characteristics of its urban resilience.

On this basis, we aggregate the economic, social, environmental, and infrastructure resilience and calculate their degree of linkage coordination (Figure 6). Comparatively, the evolution of the degree of coupling coordination between economic and social resilience is relatively similar, whereas the evolution of environmental and infrastructure resilience is more independent, indicating that the degree of connection between economic and social development may be closer than the other two aspects. Moreover, the evolution of the degree of coupling and coordination of each city's resilience also varies. For instance, the coupling coordination among economic, social, and infrastructure resilience in Lhasa is significantly higher than in other cities, maintaining a high-quality coordination status, whereas the coupling coordination with environmental resilience shows a phased increase. The coupling coordination among social, environmental, and infrastructure resilience in Ya'an is significantly higher, whereas the coordination degree of economic resilience is relatively low. In Qamdo, the coupling coordination among social, environmental, and infrastructure resilience is significantly higher, whereas the coordination degree of economic resilience in Garzê has the highest degree of coupling coordination between environmental and infrastructure resilience, while Qamdo has the fastest degree of coupling coordination between social resilience and environmental resilience.

5.3 Resilience correlation

The analysis of urban resilience trends and coupling coordination reveals that the development and evolution of economic resilience and social resilience are relatively similar to the evolution of urban resilience as a whole, whereas environmental and infrastructure resilience reflects unique characteristics. We can therefore validate them using Pearson correlation analysis and gray correlation analysis. Figure 7 displays the results of the Pearson correlation coefficient calculation, which demonstrates that economic and social elements have a stronger relationship with urban resilience. Moreover, the correlation coefficients between economic and social resilience are extremely high, indicating that they interact closely. The correlation between environmental and infrastructure resilience and other resilience factors is weak, suggesting that their roles are relatively independent of overall urban resilience. Figure 8 depicts the findings of additional correlation analysis among the indicators. Among all evaluation indicators, those about city finances, residents' lives, and social services have the highest correlation with city resilience. And there are mostly certain connections between city economic and social resilience indicators. The majority of urban environmental and infrastructure resilience indicators do not correlate significantly with economic and social resilience indicators, and their internal correlation is similarly modest.

By doing a gray correlation study between each indicator and urban resilience as a whole, we may gain a deeper understanding of the magnitude of the driving power of each indicator on the urban resilience of underdeveloped cities, as detailed in Table 3. Indicators related to the urban economy and resident's lives, such as bank deposit balance *per capita* and GDP *per capita*, as well as

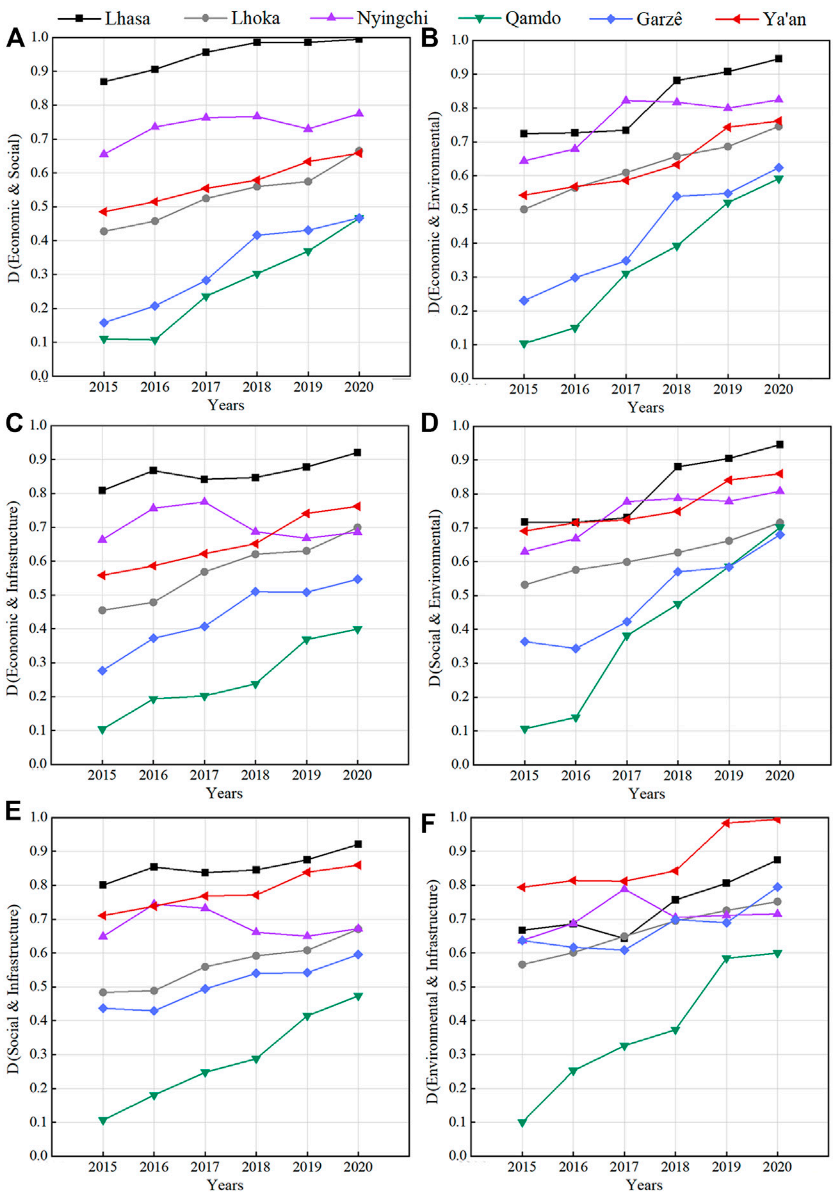

FIGURE 6
Trends in the evolution of aspects of resilience coupling coordination. **(A)** Economic & social. **(B)** Economic & environmental. **(C)** Economic & infrastructure. **(D)** Social & environmental. **(E)** Social & infrastructure. **(F)** Environmental & infrastructure.

indicators related to public services, such as the number of mobiles *per capita*, have a higher degree of correlation with urban resilience. Indicators of urban environmental resilience and infrastructure resilience have a relatively lower correlation with urban resilience, which is essentially consistent with the results.

6 Discussion

6.1 Influencing factors of urban resilience

The urban resilience of cities in underdeveloped regions is inadequate, but under the influence of significant construction projects and national aid policies, diverse resources pour fast into these cities, resulting in constant improvement. Lhasa, Lhoka, Nyingchi, and Ya'an, in which railway subjects are under construction or already in operation, have significantly higher urban resilience (especially economic and social resilience) than Qamdo and Garzê, in which railway construction is not yet complete. While their urban resilience tends to increase significantly at the beginning of the railroad construction and opening to traffic, such as Nyingchi and Lhoka at the beginning of the railway operation period. However, not all indicators of urban resilience maintain continuous growth after the construction or operation of major projects, such as Nyingchi after a period of railroad construction (2017–2020), when all its resilience levels begin to decline and are difficult to improve further. Whereas for other cities and states, economic, social, environmental, and

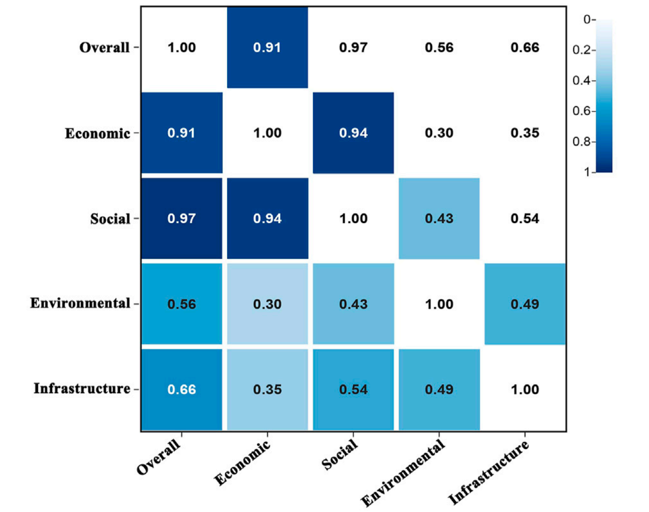

FIGURE 7
Pearson correlation coefficient for each aspect.

infrastructure factors do not have the same influence on urban resilience. Consequently, based on the comprehensive assessment of urban resilience, the effect of each component on the overall resilience of cities should be assessed separately in order to explore the characteristics and trends of urban resilience's evolution in a focused manner.

6.1.1 Economic resilience

The degree of urban economic development is the basis of sustainable urban development and a crucial determinant of urban resilience (Sabatino, 2016; Feng et al., 2023). When cities resist external disturbances, greater economic resilience enables them to accumulate sufficient material reserves and maintain basic operational efficiency to quickly compensate for the direct losses and indirect impacts of the disturbances (Wang S et al., 2022). And after the external disturbances have subsided, cities with greater economic resilience can also establish themselves more quickly, allowing them to quickly regain or even surpass their prior development position.

Improving the economic resilience of cities in underdeveloped regions is essential for enhancing the living standards of residents, promoting harmonious and stable social development, enhancing the living environment, and promoting the construction of urban and rural infrastructure, thereby making these cities and towns less susceptible to collapse in the face of external disturbances. For cities and states along the Sichuan-Tibet Railway, differences in economic resilience are caused by factors such as urban location, attributes, and transportation infrastructure conditions. Regardless of whether it is Lhasa with high resilience or other cities transitioning from low to medium resilience, economic development is steadily improving. With the completion and gradual opening of the Sichuan-Tibet Railway, external human, logistics, information, technology, and capital flows will accelerate into the surrounding towns and cities, thereby accelerating the economic development of these cities, which must adhere to a path of sustainable development and prevent structural disorders and ecological damage caused by excessive urban development.

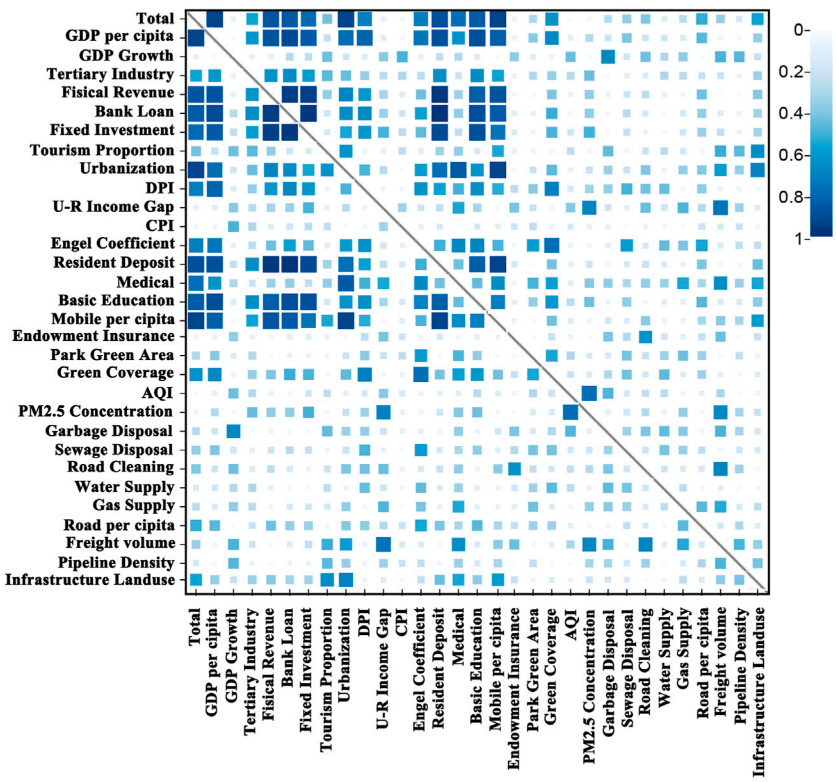

FIGURE 8
Pearson correlation coefficient for each indicator.

TABLE 3 Grey correlation of each indicator.

Indicator	*Correlation*	Rank	Indicator	*Correlation*	Rank
Bank balance *per capita*	0.89	1	Road freight volume	0.786	16
GDP *per capita*	0.88	2	Average air quality index	0.786	17
Urbanization rate	0.858	3	Gas supply penetration rate	0.784	18
Mobiles *per capita*	0.857	4	GDP growth	0.78	19
Compulsory education resources	0.856	5	Government revenue *per capita*	0.772	20
Medical resources	0.843	6	Share of infrastructure land	0.771	21
Disposable income *per capita*	0.84	7	Density of water & drainage pipes	0.762	22
Sewage disposal rate	0.83	8	Park green space *per capita*	0.75	23
Government revenue *per capita*	0.823	9	Engel coefficient	0.738	24
Share of tertiary industry	0.82	10	Road area *per capita*	0.736	25
Government revenue *per capita*	0.82	11	Road cleaning rate	0.733	26
Fixed asset investment per cipita	0.81	12	Share of tourism revenue	0.728	27
Water supply penetration rate	0.809	13	Consumer price index	0.714	28
Green coverage in built-up area	0.805	14	Urban-rural income ratio	0.713	29
Domestic waste disposal rate	0.8	15	Average PM2.5 concentration	0.682	30

6.1.2 Social resilience

The social system of a city is a complex system comprised of numerous areas of life, healthcare, education, management, and culture, and its level of resilience is an essential component of urban overall resilience (Maclean et al., 2014; Saja et al., 2019). A higher level of social resilience implies, on the one hand, that urban residents have a higher standard of living and that households and communities have sufficient resources and capacity to withstand losses from external disturbances, on the other hand, that cities have a higher level of public services to meet the sharply rising demand for social services and grassroots management during external disturbances.

The low degree of social development is one of the defining characteristics of underdeveloped cities, and the big wealth disparity and major public service gaps pose significant threats to the development of urban resilience. In the event of severe natural disasters or outbreaks of infectious diseases, it will be difficult to mobilize social resources, and without the timely influx of external resources, significant societal losses will occur (such as the Wenchuan and Ya'an earthquakes). Due to this, the construction of the Sichuan-Tibet Railway had the most evident impact on the social resilience of the communities along the route. After the completion of the large-scale project, the living income and employment level of residents in the towns along the route will continue to increase, thereby bolstering social resilience; in the event of external disturbances, external resources can also be imported quickly *via* rail, thereby enhancing the buffer capacity and recovery speed of the cities.

6.1.3 Environmental resilience

The environmental resilience of cities encompasses urban ecology, resources, and environmental health, and is an inherent factor that supports the regular operation and sustainable growth of cities (Alberti and Marzluff, 2004; Perrings, 2006). The maintenance and transformation of urban environmental benefits and urban economic and social development interact in a dynamic equilibrium, and adherence to ecologically coordinated green development is conducive to enhancing the quality of urban economic development, as well as promoting the improvement of the human habitat and the living standards of urban residents (Pickett et al., 2014). Greater environmental resilience can reduce the risk of the spread of infectious diseases in urban areas while also enabling cities to obtain more suitable ecological buffers and a wealthier supply of resources in the face of natural disasters, thereby ensuring that cities can resist disturbances and recover rapidly from them.

Due to a lack of comprehensive social governance capacity and reasonable urban planning, environmental sanitation conditions in underdeveloped regions cannot meet the needs of inhabitants. Nevertheless, the environmental resilience basis of cities varies widely, and climate, geology, hydrology, and resources are all characteristics that have the potential to become significant limiting factors for their development. The development of large-scale projects in underdeveloped regions would, on the one hand, stimulate the expedited construction of sanitation projects and increase the quality of urban sanitation, but it will also represent a significant threat to their delicate urban ecological environment. It is vital to closely regulate the environmental degradation and resource consumption caused by the project's construction, to maintain a balance between economic and environmental benefits, and to support the green and sustainable development of the communities along the route.

6.1.4 Infrastucture resilience

This research focuses primarily on the infrastructure (such as water supply and drainage, power supply and heating, gas, road construction, network communication, etc.) that maintains the operation of cities, and the construction and maintenance of these facilities are closely related to the economic and social development of cities as well as the resource utilization and environmental protection

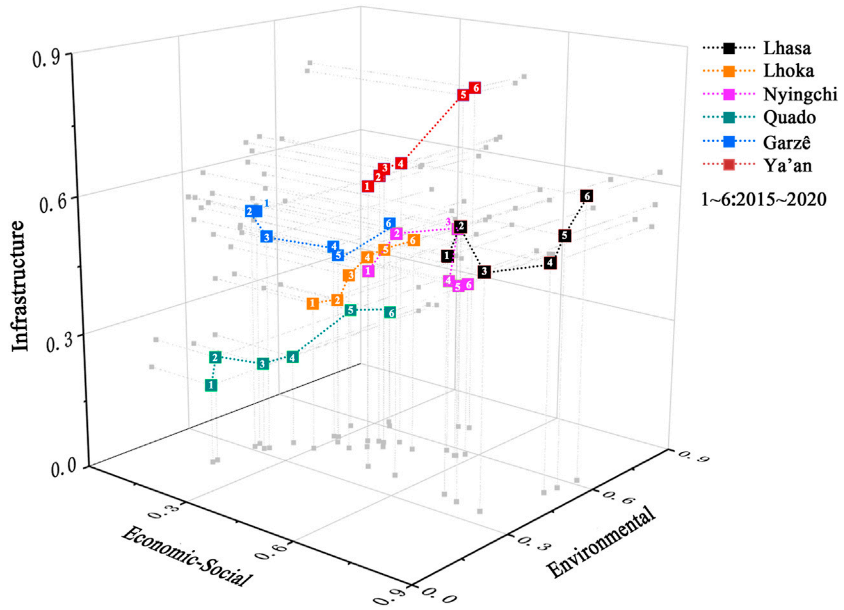

FIGURE 9
Three-dimensional evaluation model of urban resilience.

requirements. Therefore, improving the resilience of urban infrastructure is a process of continuously fulfilling the new demands of urban development, which is typically a sluggish and lagging process. High infrastructure resilience is the fundamental guarantee for urban operation in the face of external shocks (Alderson et al., 2015; Labaka et al., 2016; Liu and Song, 2020), hence urban crises produced by inadequate infrastructure resilience are more severe than those caused by other resilience aspects (e.g., insufficient urban power supply and road damage caused by natural disasters).

Due to the weak economic and social foundations of cities, infrastructure development in underdeveloped regions lags substantially behind that of economically developed regions, yet towns in these regions are also relatively less dependent on infrastructure. The speed of infrastructure construction in cities along the Sichuan-Tibet Railway has accelerated steadily due to the construction of large-scale projects, but this will be a protracted and ongoing process that cannot be completed overnight. To achieve the coordination of urban growth pace and development quality in less-developed areas, it is vital to maintain the synchronization of infrastructure construction with economic and social development and improvement of the human living environment.

6.2 Evolutionary paths of urban resilience

The combination of urban resilience evaluation, coupled coordination degree analysis, and correlation analysis can determine the evolution process and coordination relationship of each dimension of urban resilience. And the multidimensional evaluation model combining economic, social, environmental, and infrastructure can then determine the path and mode of urban resilience evolution from an overall standpoint. Since economic and social resilience are correlated, whereas environmental and infrastructure resilience is rather independent, a three-dimensional model for assessing urban resilience can be developed by incorporating economic-social resilience as one of the dimensions (Figure 9). We categorize the results of the city resilience evaluation into three levels: high resilience (>0.6), medium resilience (0.3–0.6), and poor resilience (0.3) to evaluate the evolution of urban resilience in each dimension. When the economic-social resilience level of a city is significantly lower than the environmental and infrastructure resilience levels, it indicates that economic and social development momentum is insufficient. Therefore, the city should accelerate the introduction of external resources and activate the leading industries in order to accelerate economic and social development. When environmental resilience is significantly lower, it indicates that excessive development and pollution levels are unsustainable. When infrastructure resilience is significantly lower, it indicates that urban infrastructure construction is lagging behind urban development and it is vital to strengthen infrastructure investment and encourage high-quality urban development. When all aspects are maintained at a high level, the economic and social development of a city is coordinated with the urban environment and the construction of infrastructures. It means overall resilience is high.

Figure 10 depicts the evolution of urban resilience development in each city and state along the Sichuan-Tibet Railway. By evaluating the evolution pattern of resilience in various cities and states, we may determine their resilience development path and current state of development and then anticipate and direct their future development.

(1) Lhasa's overall resilience demonstrates a pattern of prioritizing economic development and limiting the improvement of environmental and infrastructure resilience, which then transitions to a sustainable development path of slowing economic and social development and prioritizing environmental and infrastructure construction, and then enters a phase of high resilience development.

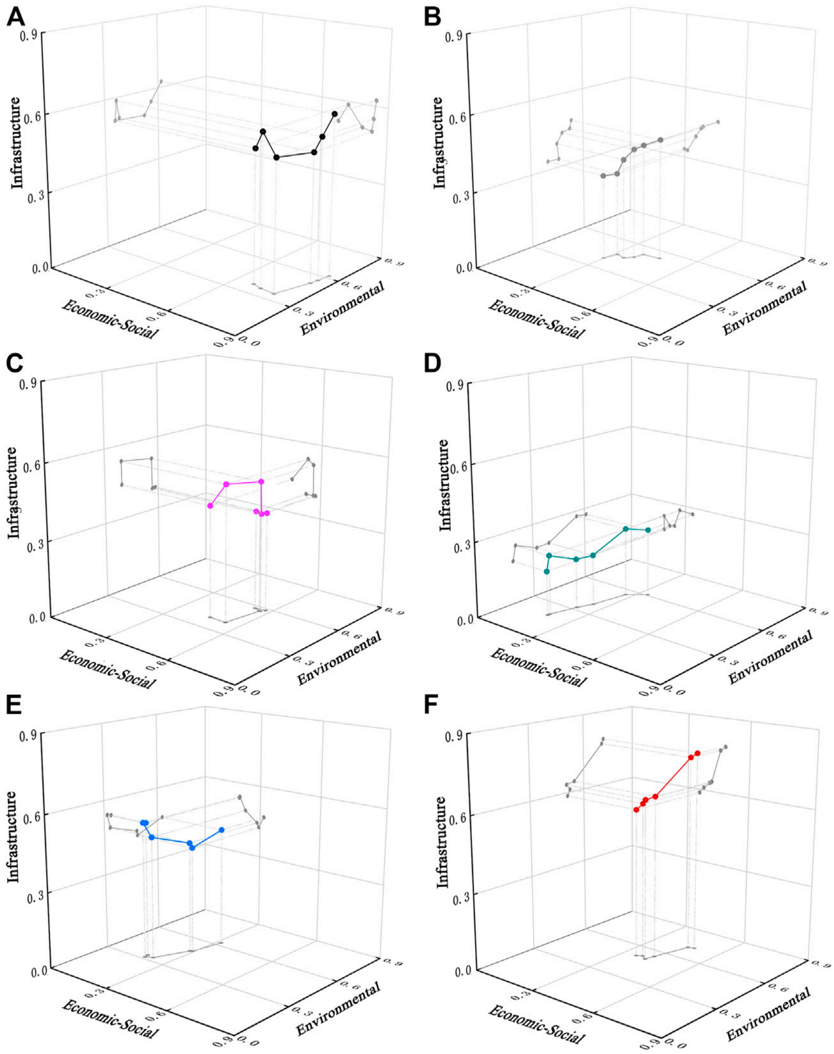

FIGURE 10
Evolutionary paths of urban resilience of each object. **(A)** Lhasa. **(B)** Lhoka. **(C)** Nyingchi. **(D)** Qamdo. **(E)** Garzê. **(F)** Ya'an.

(2) Lhoka remains at the medium resilience development level, with balanced development of all aspects and progressive overall improvement, and moves gradually to the high resilience development level.
(3) Nyingchi's resilience in all dimensions has plateaued after an early period of strong growth, and it is difficult to break past the bottleneck of medium resilience development; the city urgently needs new external development momentum.
(4) Qamdo's urban resilience level exhibits a gradual progression from low resilience to medium resilience, but the resilience foundation is weak and the deficiencies of urban infrastructure construction are evident.
(5) In Garzê, the construction of infrastructure has resulted in the improvement of economic, social, and environmental resilience, but its infrastructure resilience is limited and requires future infrastructure construction improvement to maintain the urban growth trend.
(6) Ya'an's urban resilience demonstrates an opposite evolutionary path to that of Lhasa, with slow growth in economic and social resilience, while environmental and infrastructure resilience has increased significantly, further driving economic and social development and assisting the city in shifting to a high resilience development level.

7 Conclusion

Extremely sensitive to external shocks are cities in underdeveloped locations with severe natural environmental limits and insufficient foundations for their own economic and social growth. How to improve the overall urban resilience and boost the resistance, adaptation, and recovery capacity of at-risk cities is one of the development challenges faced by these cities, and the evaluation and characterization of urban resilience serve as the foundation for the related activity. This study proposes a quantitative evaluation framework that combines the TOPSIS entropy method, coupled coordination model, and correlation analysis to determine the evolutionary path and trend of urban resilience by assessing the resilience of underdeveloped cities and analyzing the coupled coordination relationships between their intrinsic factors. The study's results can aid in clarifying urban development strategies and give quantitative evidence for relevant policy ideas and planning activities.

This study's methodology and findings provide a certain reference value for urban planning work, and its originality is demonstrated primarily in the following. Firstly, this study selects cities in underdeveloped regions as the research objects. Although these cities have a weak resilience foundation, the inner system composition is simpler, and the resilience evolution characteristics are more evident than in developed cities, so it is easy to judge their resilience development pattern and evolution direction. Secondly, this study also combines multiple evaluation and analysis methods. Based on the evaluation and analysis results, explore the internal linkages and the degree of coordination of subsystems. Thirdly, this study proposes a three-dimensional model to determine the development state of urban resilience, from which we can analyze the pattern and development direction of each city's resilience evolution to suggest guiding ideas for various cities. Each city's pattern of resilience evolution and development path can be analyzed, allowing us to suggest guiding principles for its qualities.

The city is a complex large-scale system, and urban resilience is influenced by a variety of internal and external elements, as well as dynamic interactions between subsystems. Simultaneously, the key causes of urban resilience vary from city to city, as do the variables that impede urban development in cities in underdeveloped regions. This paper presents a universal framework for assessing urban resilience in underdeveloped locations, although it has certain practical limits. The evaluation indicators of the study have yet to be further enriched to make them more relevant to underdeveloped regions. Moreover, the linear thinking of the TOPSIS model has some limitations in evaluating the non-linear development process of urban resilience. Therefore, we believe that the research based on this evaluation method must further investigate the interactions of various subsystems and determine the dominant factors affecting urban resilience. When assessing and analyzing the resilience of a specific city, appropriate evaluation indicators and methods must be chosen following the city's characteristics, and the effects of climate, ecology, topography, religion, humanities and other factors must be taken into account. It can make evaluation results and strategies for urban development more targeted. Moreover, future study should also focus on urban resilience prediction and proposes strategies for specific construction aspects.

Data availability statement

The raw data supporting the conclusion of this article will be made available by the authors, without undue reservation.

Author contributions

RZ: Formal analysis, methodology, and writing. YY: Conceptualization, funding acquisition, and supervision. BW and XL: Review and editing. All authors contributed to the article and approved the submitted version.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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Moving to a healthier city? An analysis from China's internal population migration

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A healthy urban environment is considered as an important issue for the amenity and equity of migrants. China has one of the largest internal population movements in the world, and the environmental health of its migrants becomes a growing concern. Based on the 1‰ microdata from the 2015 1% population sample survey, this study uses the spatial visualization and spatial econometric interaction model to reveal intercity population migration patterns and the role of environmental health in China. The results are as follows. First, the main direction of population migration is toward economically developed high class cities, especially the eastern coast where the intercity population migration is most active. However, these major destinations are not necessarily the healthiest areas for the environment. Second, environmentally friendly cities are mainly located in the southern region. Among them, the areas with less serious atmospheric pollution are mainly distributed in the south, climate comfort zones are mainly located in the southeastern region, but areas with more urban green space are mainly distributed in the northwestern region. Third, compared with socioeconomic factors, environmental health factors have not yet become a major driver of population migration. Migrants often place higher value on income than on environmental health. The government should focus not only on the public service wellbeing of migrant workers, but also on their environmental health vulnerability.

KEYWORDS

environmental health, intercity population migration, spatial pattern, influencing factor, China

1. Introduction

Throughout the history of human development, population migration and population distribution have always tended to favor areas with suitable environments, which are suitable for human survival and also improve human health and life expectancy (1–3). With the onset of the industrialization period, socioeconomic factors became important drivers of changing population migration patterns. Migrants have a stronger need for job opportunities, income levels and social and public services (4–6). However, in recent years, with the emergence of climate change, environmental pollution and ecological damage, more and more studies have focused on the relationship between population migration and environmental health (7–9). On the one hand, migrants, especially migrant workers, are considered as a vulnerable group in the city. Concerns have been raised about the equity of migrant health in urban environments. On the other hand, as the level of socio-economic development has increased, a healthy urban environment has become an important consideration for migrants in making migration decisions. Some new terms, including amenity migration and lifestyle migration, are emerging (10, 11). Therefore, the role of migrants should not be overlooked when discussing the urban environment and health issues. However, existing studies have focused more on forced migration due to environmental changes but less on active migration. Moreover, no consensus conclusion has been reached on the effect of environmental health on population migration.

To compensate for these shortcomings, this study selects China, the country with the highest population and the most prominent scale of internal migration, to explore in-depth the impact of environmental health factors on population migration. Since the reform and opening up of China in 1978, a massive transfer of surplus rural labor to the cities has occurred. Some of the migrants have settled in cities and become urban residents. However, a large number of migrants remain who are only workers in the cities, and this group is known as the floating population in China (12). According to the data of the seventh national census, China's current floating population is 376 million, and the proportion of the floating population in the total urban population has reached 41.6%. Unlike local urban residents, the floating population does not have complete urban social security and is often separated from other members of the family (13). The government has actively introduced policies to strongly improve the social welfare level of the floating population. However, compared with social vulnerability, the environmental health equity vulnerability of floating population has long been neglected. Chinese cities face many environmental challenges, including air pollution, green space shortages and water scarcity (14). Although most of the floating population treat the destinations as a place of work, and many are even still willing to return and settle in their hometown, they are permanently exposed to the environment of the destination cities. Focusing on the environmental health of the floating population is a topic of health equity for those who move and the long-term development of a healthy city (15).

This study focuses on whether urban environmental health factors influence migrants' migration decision and destination choice. The spatial patterns of intercity migration flows and the strength of their environmental health factors are investigated, taking China as an example. The second part gives a systematic literature review in which we summarize the research frontiers on the patterns and drivers of population migration, with a focus on the impact of environmental health factors. The third section presents the research methodology of this study. The fourth part is the structure of the analysis, including the spatial pattern of intercity population migration in China, the spatial pattern of environmental health factors in Chinese cities, and the mechanism of the effect of environmental health factors on population migration. The fifth part is the discussion. The sixth part concludes.

2. Literature review

2.1. Patterns of population migration

Numerous theoretical and empirical studies have shown that migrants tend to move to larger commercial or industrial centers, and the great body of migrants only proceed a short distance. In developing countries, population migration is dominated by rural-urban migration, while in developed countries, reverse urbanization has occurred. Inter- and intra-city migration will become mainstream during the developed society period. The laws of migration also pointed out that migration from counties surrounding big cities such as London and Manchester leaves gaps in the rural population, which are subsequently filled by migrants from more remote districts, thus net migration flows were upward alone the urban hierarchy, and the biggest inflow for any level is that for its exchanges with units of the next smaller size (16, 17). This step migration is still predominant in today's developing countries. However, the US's hierarchical migration is strongly contrasting, many of the major movements are flows down the urban hierarchy (18), which has become the norm in some developed countries.

Unlike most countries, population migration in China is characterized by the hukou system, which is the nation's household registration institution (19). Hukou is a type of permit that allows migrants to enjoy social welfare as local citizens do. In other words, a migrant who lacks the hukou in the destination cannot be an honest citizen like those residents who possess the hukou (20). Owing to the hukou, a unique feature of population migration in China is its two-track system, consisting of permanent migration and temporary migration (21). The former refers to movements that are accompanied by hukou change, while the latter refers to movements that are not associated with hukou change (22). Temporary migrants are known as floating population or no-hukou migrants; they are mainly rural-urban individuals and cannot enjoy the benefits and rights of permanent migrants and local residents in destination cities, such as social securities, health care and education opportunities (23). Recently, no-hukou migrants have become the main body of urbanization and citizenization and deserve more attention. Thus, the population migration in this study mainly refers to no-hukou migration.

Since the reform and opening up, China adopted a coastal development strategy which allowed some coastal areas to develop first, resulting in a reversal in the direction of migration: more migrants moved from the western and central to the eastern, from inland to coastal areas (24–26). The pattern of population migration in China is relatively concentrated. Three major developed urban agglomerations in the Yangtze River Delta, Pearl River Delta and Beijing–Tianjin–Hebei were the main centers of migration destination, while the less developed central regions were the main migration sources (27). Some scholars believed that this spatial polarization was continuously strengthened, indicating gainers gaining more and losers losing more population from net migration (28). However, some others argued that this polarization began to decline in the 21st century, with a trend of decentralization and landization (29, 30). Recently, many interior areas have undergone a tide of industrialization and received many labor-intensive industries transferring from coastal regions, potentially heralding a decrease in eastward migration and an increase in backflow in the coming decades (31). Evidence also shows that settling permanently in the destination city is difficult for the vast floating population; thus, most of them adopt a circular flow pattern to travel between the origin and destination cities (32).

China has a large number of intra-provincial instead of inter-provincial no-hukou migrants, accounting for 66.8 and 33.2% in 2020, respectively (33). However, due to the limitation of data acquisition, the studies on migration patterns in China are mainly limited to the inter-provincial scale (34, 35). The intra-provincial scale, especially the inter-city level, which may have a greater impact on urbanization and regional development, has gained little attention (36). Recently, some studies have realized the importance of scale and tried to study migration patterns at the prefecture-level city scale (37–39), but they mainly used big data to study short-term daily mobility, which is essentially different from population migration. Migration, rather than mobility, has a greater impact on the urban system and urbanization process and is thus more worthy of study. Only in recent years has the literature begun to examine intercity population migration in China. For example, Liu et al. (40) studied the stability and change in China's geography of intercity migration based on a complex network approach, finding that the migration network is stable but also becomes significantly dispersed due to the increasing short-distance and intra-provincial migration. Mu et al. (41) revealed an emerging reversal from a predominantly upward pattern (e.g., most of the net flows move to high-level cities) to a downward one (e.g., from super-large/extra-large cities to large cities).

2.2. Drivers of population migration and environmental health factors

Traditional migration theory generally believed that economic factors play a decisive role in population migration. The laws of migration considered migration as an inseparable part of economic development, and the major cause of migration is economic (16). Neoclassical theory considered migration as a function of geographical differences in the supply and demand for labor. The resulting wage differentials encourage workers to move from low-wage, labor-surplus areas to high-wage, labor-scarce areas (42). Migration network theory believed that population migration is a path-dependent process; already settled migrants often act as a "bridgehead" (43), reducing the risks and costs of subsequent migration and settlement by providing information, organizing travel, finding jobs and housing and assisting in adaptation to a new environment, thereby promoting more migration. According to the gravity law and the radiation model (44), population size and distance are also the main factors influencing population migration.

Environmental migration is an issue that is often considered as new or a part of future trends. In fact, it is a long-standing phenomenon (45). Environmental factors ranked highly in the first systematic theories of migration. In Ravenstein's "the laws of migration," he mentioned unattractive climate (46). Semple (47) pointed out that the search for better land, milder climate and easier conditions of living starts many a movement of people which, in view of their purpose, necessarily leads them into an environment sharply contrasted to their original habitat. However, with the onset of the industrialization period, socioeconomic factors became important drivers of changing population migration patterns; references to the environment as an explanatory factor gradually disappeared from the migration literature. Theoretical publications, such as migration transition theory, neoclassical theory and ecological models, gave the most central place to socioeconomic factors but did not mention environmental factors (17, 48, 49). This is because with economic development and technological advances, the influence of nature on population migration and distribution continued to diminish. Petersen (50) even believed that environmental migration as a primitive form of migration is bound to decline as human beings gradually increase their control over their environment.

However, with the emergence of climate change, environmental pollution and ecological damage, more and more studies have refocused on the relationship between population migration and environmental health. These studies mostly started with amenity migration, focusing on natural amenities such as climate and air quality. For example, Graves (51, 52) argued that under the assumption that individual utility of labor is uniform, the differences in labor wage between regions are compensations for amenity, thus, migration is essentially based on the need for regional amenity rather than wage differences. Gottlieb (53) argued that urban amenity is often seen as a commodity, with non-tradable and place-specific characteristics, and people choose residential migration to satisfy the demand for such goods. In recent years, as developed countries enter the post-industrial era, lifestyle migration, residential tourism and retirement migration have become the focus of academic attention (54). These migrations are mostly White residents of the Global North moving part- or full-time to "their" paradise in the Global South, not motivated primarily by economic need but by a desire to consume a particular set of amenities critical to an imagined recreational lifestyle unavailable or unaffordable in their home country. The U.S. migration-pattern regime also shows that many of the major movements in the system of domestic migration are flowing down the urban hierarchy (18), one of the main reasons is the desire for a healthy environment for some migrants as they change over the life cycle.

In China, numerous empirical studies confirm economic incentives and socio-cultural conditions, such as differences in wages, living standards, job opportunities, public facilities and services, are important determinants of migration decisions and destination choices (55). However, migrants are not only economic people pursuing economic benefits but also social people pursuing better quality of life, that is, when the physiological or material needs of migrants are satisfied, they will breed the demand for high quality of life. With the transition of young, high-quality migrants and the family-oriented migration mode, the literature has begun to focus on environmentally driven amenity migration studies, and environmental health begins to become a concern as an influencing factor for population migration in China. For instance, Cao et al. (27) found that the natural environment gradually became an attractive factor that migrants considered. Liu and Yu (56) found that there is a significant and negative effect of air pollution on migrants' interest in settling down. Liu and Shen (31) suggested that China's skilled people prioritize their career prospects over the quality of life; climatic amenities exert a strong influence on skilled migration but have a positive effect on less-skilled migration at the origin and no effect at the destination.

In terms of methodology, the gravity law and radiation model are the prevailing framework to predict population movement (44). The size of migration flows mainly depend on the push and pull factors of the origin and destination and the distance attenuation effect but has nothing to do with other migration flows, which ignore the spatial dependence between migration flows, and cannot disclose the multilateral spillover mechanism in the migration process (57). On this basis, Griffith and Jones (58) proposed the idea of using the spatial lag of the dependent variable or error term to capture spatial dependence. Lesage and Pace (59) extended the gravity model by introducing the spatial lag of explained variable and proposing a spatial econometric interaction model, which provides an effective analytical tool for quantitatively analyzing the "multilateral effect" of migration flows. In addition, some scholars tried to use a spatial filtering model to filter out network autocorrelation (60). These methods have effectively reduced the deviation of parameter estimates and significantly improved the model's accuracy, but they often filter out some meaningful information, such as spatial spillover effects.

3. Methodology

3.1. Study area

This study focuses on the population migration flows between cities in China. The term "city" in this study refers to 341 prefecture-level or above administrative units, comprising 4 municipalities (Beijing, Shanghai, Tianjin and Chongqing), 15 sub-provincial cities, 17 general provincial capital cities, 300 general prefecture-level cities and 5 provincial-controlled divisions. It is officially designated administrative territory, not physical territory. Except for Qingdao, Dalian, Ningbo, Xiamen and Shenzhen, the remaining sub-provincial cities are also provincial capital cities. Taiwan and Sansha in Hainan Province are not included due to unavailable data. According to the National Bureau of Statistics, these cities are grouped into four economic regions: eastern, central, western and northeastern (Figure 1).

This study also uses the natural breaks slice method to divide cities into five levels of hierarchy based on the economic scale of each city, that is, A, AA, AAA, AAAA and AAAAA cities, representing low, lower-middle, medium, upper-middle and high income cities, respectively. The economic scale can reflect a certain level of development, and the use of economic scale to classify city hierarchy can not only examine the direction and internal structure of hierarchical migration, but also reflect the relationship between the structure of hierarchical migration and the level of development from the side. The number of A, AA, AAA, AAAA and AAAAA cities was 7, 27, 49, 119, and 138, respectively, presenting a pyramid structure.

3.2. Models and variables

3.2.1. Spatial econometric interaction model

Lesage and Pace (59) summarized the spatial dependence relationship between population flows into three types. The first is "destination-based" spatial dependence, that is, the flows from origin A to destination B will change with the flows from the same origin A to the surrounding areas of destination B. The second type is "origin-based" spatial dependence, that is, the flows from origin A to destination B will change with the flows from the surrounding areas of origin A to the same destination B. Third is "origin-to-destination-based" or "flow-based" spatial dependence, that is, the flows from origin A to destination B will change with the flows from surrounding areas of origin A to the surrounding areas of destination B. On this basis, three network weight matrices (W_d, W_o, W_w) are used to construct the spatial lag form of the dependent variable (W_dy, W_oy, W_wy), to form the spatial autoregressive form of the gravity model, that is, the spatial OD model, also called the spatial econometric interaction model. Its general expressions are as follows:

$$y = \rho_d W_d y + \rho_o W_o y + \rho_w W_w y + \alpha\tau_N + X'_d\beta_d + X'_o\beta_o + \gamma g + \epsilon$$

The model contains $n^2 = N$ pairs of OD migration flows, y represents the $N\times1$ column vector of intercity migration flow. W_dy, W_oy, W_wy are the "destination-based", "origin-based" and "origin-to-destination-based" dependent variables spatial lag, representing the weighted average flows to the destination neighbors, from the origin neighbors, and from the origin neighbors to the destination neighbors, respectively. ρ_d, ρ_o, ρ_w represent the corresponding spatial dependence parameters, respectively, reflecting the intensity of three types of spatial autocorrelation effect. When spatial autocorrelation is not considered ($\rho_d = \rho_o = \rho_w = 0$), the spatial OD model becomes the gravity model. τ_N is a $N\times1$ column vector whose all elements are 1. α is the constant term coefficient of τ_N. X is the $n\times k$ explanatory variable matrix, repeating X n times to obtain an $N\times k$ destination explanatory variable matrix X'_d and repeating each row of X n times to obtain an $N\times k$ origin explanatory variable matrix X'_o. β_d, β_o are the corresponding influence coefficients. g is the $N\times1$ distance matrix between cities. γ is the distance friction coefficient. ϵ is an $N\times1$ error perturbation term, which obeys the standard normal distribution.

3.2.2. Explanatory variables of intercity population migration

The environment is closely related to people's health, and a suitable environment is beneficial to human survival and health. In this study, the environmental factors affecting human health are defined as environmental health factors, among which the influence of natural environment is particularly prominent. Therefore, the term "environment" in this study mainly refers to the natural environment, namely, the total of various inartificial and artificially modified natural factors that affect human survival and development. It follows that environmental health factors are environmental factors related to population health, are part of environmental conditions/factors, and sometimes it can also refer to healthy environmental factors. This study selects air quality, climate comfort and green space as proxy variables for environmental health factors. The air quality index and climate comfort index are two negative indicators. The larger the value, the worse the air quality and climate comfort.

In addition, socio-economic factors as well as gravity factors are also important factors influencing intercity population migration; they are included in the model as control variables. Among them, economic level, wage income, job opportunity and living cost are selected as proxy variables for economic factors. Social network, education level, medical level and cultural service are selected as proxy variables for social factors. Population size, spatial distance and temporal distance are selected as proxy variables for gravity factors. The same explanatory variables are selected for each city as origin and destination; "_o" and "_d" are added after the variables to distinguish the two roles. The variable descriptions, expected effects and data sources are shown in Table 1.

3.3. Data sources

The data used in this study are mainly aggregated intercity population migration flows, including size and direction. Intercity population migration refers to the migration process in which the "current residence" and "domicile place" are not in the same city for more than half a year. These data can be gathered from

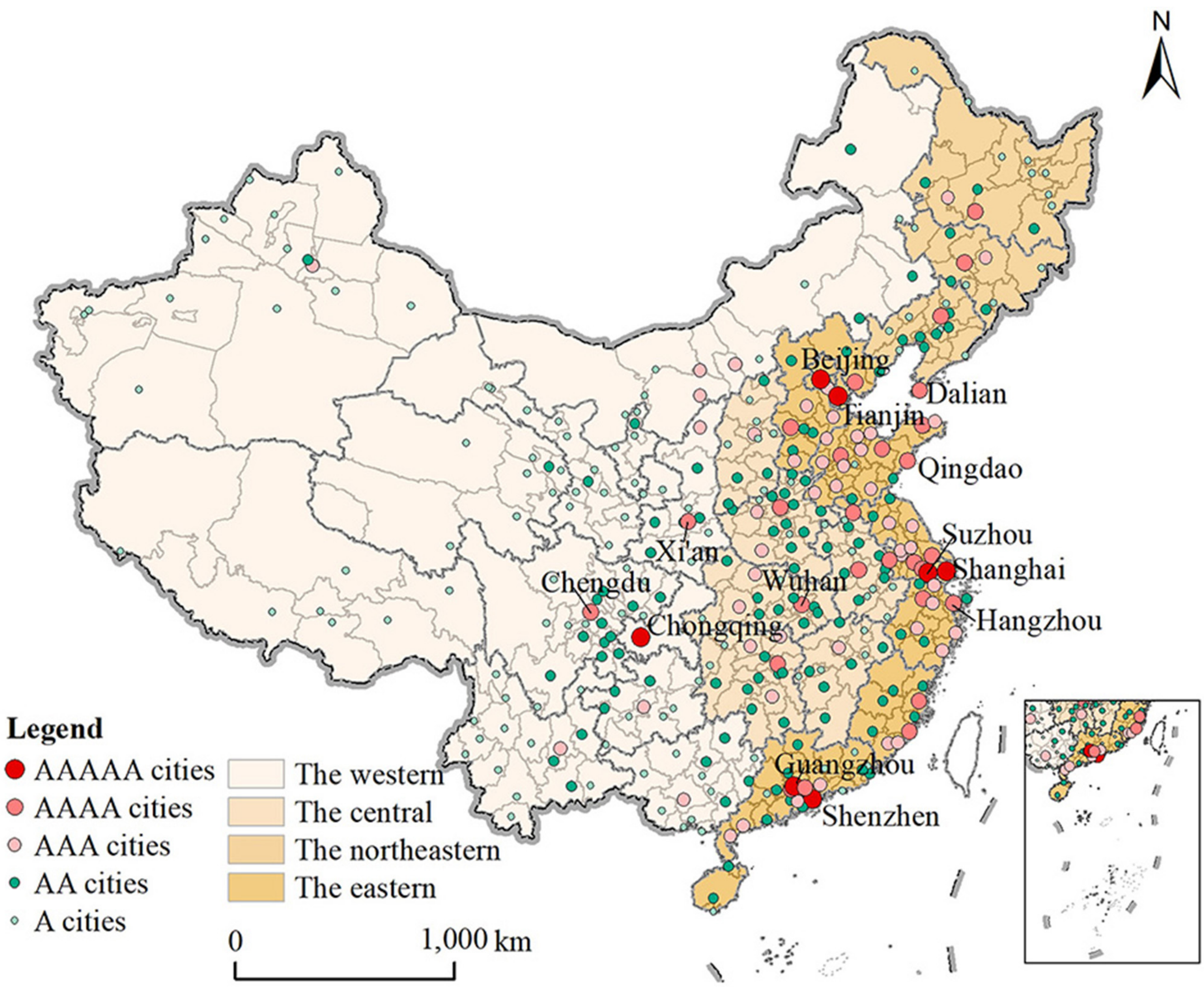

FIGURE 1
The geographic location of four economic regions and the city hierarchy classification.

the 1‰ micro-database of the 2015 1% population sample survey (thereafter, 2015 microdata), which includes 1.37 million personal records, accounting for 1‰ of the total population in China. After weighting, the data of each region has been converted according to the national uniform sampling ratio to ensure the samples' composition represents that of the actual population. Thus, the data can be directly compared. In addition, the data sources of influencing factors are detailed in Table 1.

4. Results

4.1. Patterns of intercity population migration in China

4.1.1. Spatial heterogeneity of migration flows

There are 15,472 intercity migration flows in China, carrying a total of 153 million intercity floating population, with an average of 9,900 people per flow and a maximum flow of 641,000 people. In space, intercity migration flows show obvious spatial heterogeneity (Figure 2). Firstly, there are 138 first-level flows, accounting for 0.89% of total flows. These stronger migration flows basically distribute in the southeast half of China, especially between the core cities and their surrounding cities in three major developed coastal urban agglomerations: the Yangtze River Delta, the Pearl River Delta and the Beijing–Tianjin–Heibei regions. Next are the two major developed inland urban agglomerations, the Chengdu–Chongqing City Cluster and the Triangle of Central China, whose core cities, Chengdu and Wuhan, are also important destination cities that attract a large number of migrants within the province. Chongqing is an important outflow city, showing long-distance migration to developed eastern coastal cities, such as Dongguan, Quanzhou, Wenzhou and Shanghai.

Then, there are 782 second-level flows, accounting for 5.05% of total flows. The core cities in three major developed coastal urban agglomerations continue to expand their hinterland range, covering most of the southeastern half of China. The population gathering capacity of sub-provincial cities and general provincial capital cities are gradually prominent, such as Jinan, Qingdao, Xi'an, Kunming, Xiamen and Harbin. Flows in the northwestern half of China began to appear, such as the flows between Urumqi, which is the provincial capital city of Xinjiang, and its surrounding cities.

TABLE 1 The variables system of influencing factors of inter-city population migration.

Variables	Descriptions	Expected effect	
		_o	_d
(1) Environmental health factors			
Air quality	Air quality index (AQI)[a]	+	-
Climate comfort	Climate comfort index (THI)[b]	+	-
Green space	Per capita park green area (PARK, km²/person)[c]	-	+
(2) Economic factors			
Economic level	Per capita GDP (PGDP, ten thousand Yuan)[c]	-	+
Wage income	The average wages of employees (WAGE, ten thousand Yuan)[c]	-	+
Job opportunity	The proportion of employees in secondary and tertiary industries (PJOB, %)[c]	-	+
Living cost	The house price-to-income ratio (COSH, %)[c]	+	-
(3) Social factors			
Social network	Migration stock (SOC)[d]	+	
Education level	The number of teachers per primary and secondary students (EDU)[c]	-	+
Medical level	The number of tertiary hospitals (HEAL)[c]	-	+
Cultural service	The number of books in the public library per 100 people (CUL)[c]	-	+
(4) Gravity factors			
Population size	The size of permanent population (POP, million people)[e]	+	+
Spatial distance	The straight-line distance between two cities (DIS, km)[f]	-	
Temporal distance	The shortest time spent on the closest route and fastest means of transportation (TDIS, h)[f]	-	

Sources: [a]https://www.aqistudy.cn/historydata/. [b]THI = |T-0.55(1-RH)(T-58)-65|, T is temperature(°F), RH is relative humidity(%), temperature and humidity data are from the Resource and Environment Science and Data Center. [c]China city statistical yearbook in 2016. [d]SOC = the number of migrants from city *i* to city *j*/the total number of migrants from city *i*. [e]Tabulation on the 2015 1% population sample survey. [f]Calculated by Network Analyst Tools in ArcGIS based on traffic network data, which are from Practical Atlas of China.

Finally, there are 14,551 third-level connections, accounting for 94.06% of total flows, implying that intercity migration flows are dominated by weak intensity flows. These flows still mainly occur in the southeastern half of China, but the coverage has expanded to the national scope.

It follows that intercity population migration flows still tend to move from less developed cities to developed cities and has formed a "three big and two small" polycentric spatial pattern. Three big centers refer to the regions of Beijing–Tianjin–Hebei, the Yangtze River Delta and the Pearl River Delta, while the two small centers mainly refer to the Chengdu–Chongqing City Cluster and the Triangle of Central China. Unlike the inter-provincial migration pattern from the central and western to the eastern, the regional distribution of intercity migration flows is mainly within the eastern cities, with a total of 36.58 million people (Table 2), followed by the migration from the central and the western to the eastern, reaching 35.65 and 21.92, respectively. This is because the majority of high-intensity migration flows are mainly within the three major eastern urban agglomerations, clustering from peripheral cities to a few core cities, such as Beijing, Shanghai, Shenzhen, Dongguan and Guangzhou.

4.1.2. Hierarchical migration pattern

Intercity population migration has the characteristics of hierarchical migration, that is, intercity net migration flows go up the development-based city hierarchy (Figure 3), with net migration from lower-income cities to higher-income cities and lower-income cities attracting migrants from poorer cities. This result agrees with Ravenstein's migration system, where labor gaps left by people leaving semi-peripheral areas to central areas are filled by migrants from even more peripheral areas, which is also called replacement migration. However, unlike Ravenstein's migration system where the largest net flows are the step migration between adjacent levels of hierarchy, namely, the biggest inflow for any level is its exchanges with units of the next lower level, intercity population migration in China is a type of cross-level jump migration. Here, the largest net flows are the jump migration from AA cities to AAAA cities, accounting for 25.2%, followed by migration from AA cities to AAAAA and AAA cities, accounting for 21.1 and 11.4%, respectively.

It follows that intercity population migration still conforms to the economic law of migration, moving up the urban economic hierarchy, but it is a jump migration from lower-medium-income cities to higher-income cities. It is noteworthy that most intercity net migration flows neither come from the poorest cities nor from the poorest segments of the population, which can be explained by the aspiration-capabilities model (61). Migration involves significant costs and risks. Although people in the poorest cities have high migration aspirations, their migration capabilities sometimes can not afford these migration costs and risks, such as funds for travel, housing and living expenses. However, development in low-income cities boosts migration because improvements in income, infrastructure and education typically increase people's capabilities and aspirations to migrate. Lower-middle income cities therefore tend to be the most migratory, and migrants predominantly come from relatively better-off sections of origin populations.

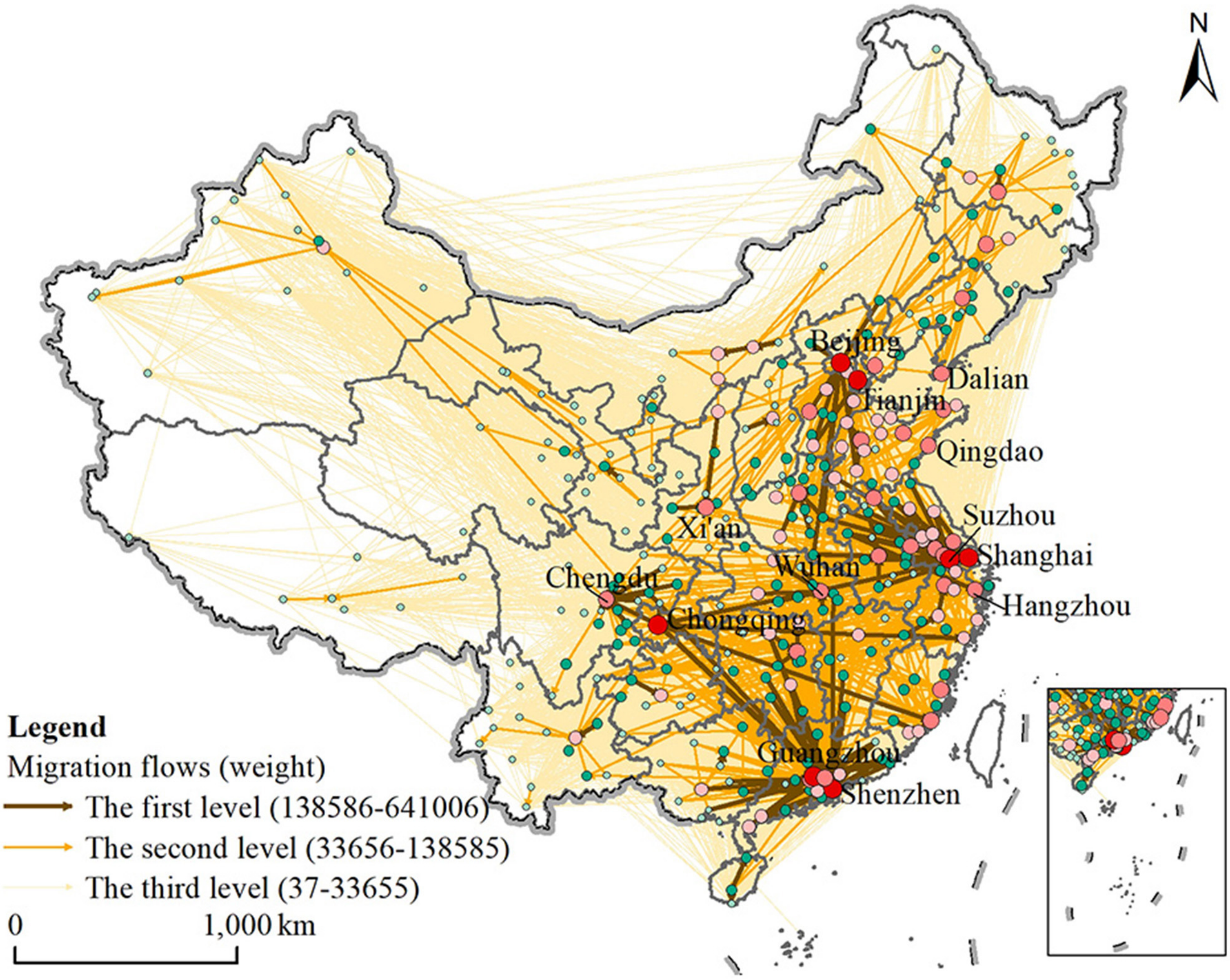

FIGURE 2
The spatial pattern of intercity migration flows at different levels in China.

TABLE 2 The statistics of intercity migration flows between four economic regions (million).

Regions	The eastern	The central	The western	The northeastern
The eastern	36.58	3.00	3.26	0.52
The central	35.65	15.74	3.23	0.44
The western	21.92	1.68	21.85	0.41
The northeastern	3.45	0.27	0.56	4.54

4.2. Spatial differences in environmental health in Chinese cities

Environmentally friendly cities are mainly located in the southern region. Here, the air quality index (AQI) shows a spatial pattern of "high in the north and low in the south" (Figure 4A), which means that the air quality condition in the south is better than that in the north. On the one hand, the high AQI areas are mainly in the northern regions: the Beijing–Tianjin–Hebei region and its neighboring Shandong Province and Henan Province, as well as the central and western regions of the Xinjiang Autonomous Region. Their industrialization level is relatively high and the industrial structure is relatively heavy, generating a large amount of waste gas, slag and wastewater, resulting in serious environmental pollution problems. However, core cities in these regions, such as Beijing and Tianjin are important destinations for migrants. On the other hand, the low AQI areas are mainly located in the south, especially in the southwest, where the industrial development is mainly commercial and service industries, with a relatively light industrial structure, high precipitation and high forest coverage. The air quality conditions are good.

The climate comfort index (THI) shows a spatial pattern of "high in the northwest and low in the southeast" (Figure 4B), which means that the climate comfort condition in the southeast is higher than that in the northwest. On the one hand, the high THI areas are concentrated in the three northeastern provinces, Qinghai–Tibet Plateau region and Xinjiang Autonomous Region, Inner Mongolia Autonomous Region and Gansu Province in the northwest. They are relatively unsuitable for human habitation due to their location at higher latitudes or high altitudes and extremely low temperatures in winter. On the other hand, the low THI areas are mainly located in the southern region, especially the cities in the central Hunan Province, Jiangxi Province and the eastern Fujian Province; their temperature and humidity are relatively moderate in the four seasons and more suitable for human habitation. However, the majority of cities in these provinces are important origins for migrants.

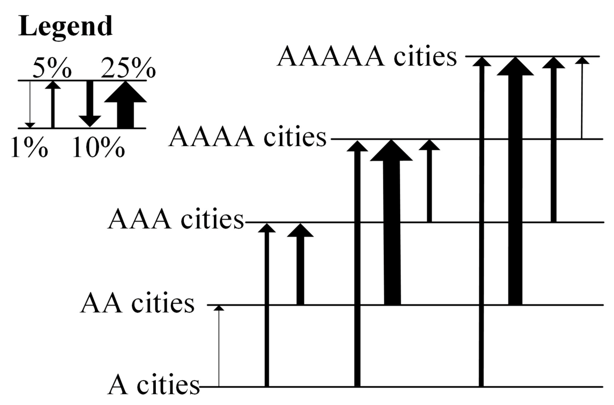

FIGURE 3
The net migration flows up the city hierarchy. The arrow of the line indicates the direction of net migration, and the width of line indicates the percentage of total net migration between all levels of the hierarchy.

The per capita park green area (PARK) shows a spatial pattern of "high in the northwest and low in the southeast" (Figure 4C), meaning that the ecological environment in the northwest is relatively better than that in the southeast. On the one hand, the high PARK areas are mainly located in the Qinghai–Tibet Plateau region and the Xinjiang and Inner Mongolia Autonomous Regions in the northwest. These cities are economically underdeveloped but have high forest coverage and sparse populations, resulting in larger per capita green space areas and good ecological environments. On the other hand, the low PARK areas are mainly located in the central, eastern and northeastern regions. These cities have relatively high levels of urbanization, and the development of the urban built environment has crowded out a large amount of ecological space, together with a large population, leading to a low per capita park green area. Some cities even face the dilemma of lacking ecological public space.

4.3. Impact of environmental health factors on intercity population migration in China

4.3.1. Environmental health factors

The impact of AQI on intercity population migration is not in line with expectations. In general, if the AQI increases by 1%, its

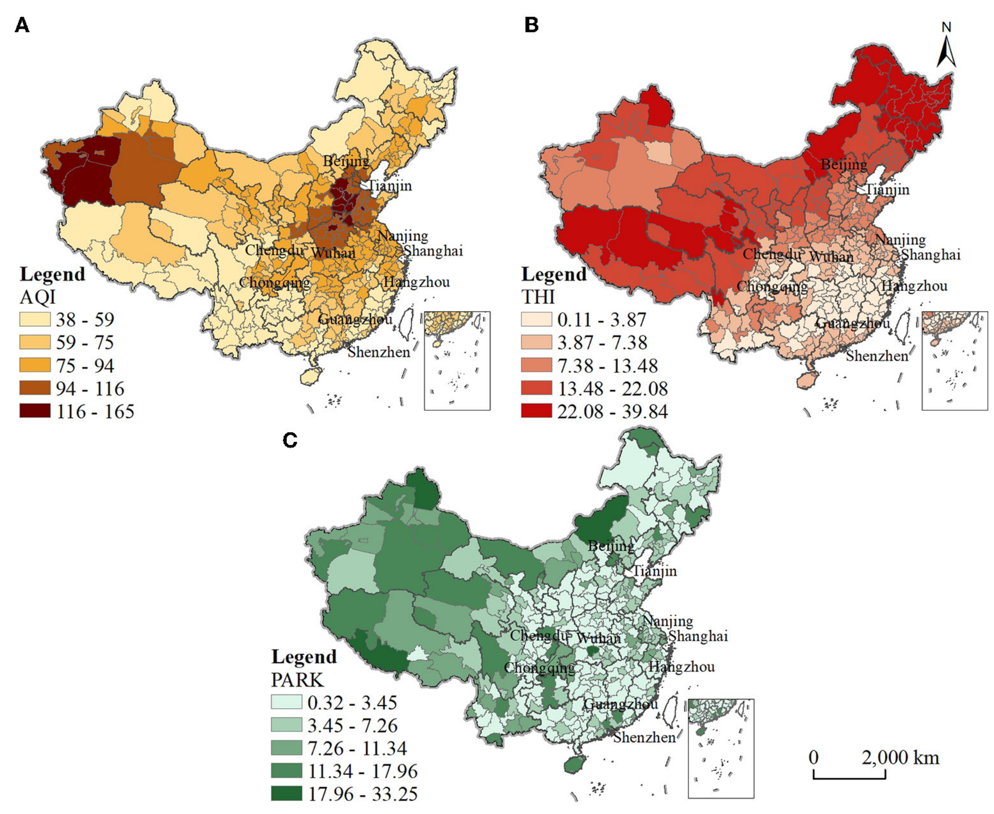

FIGURE 4
The spatial pattern of three environmental health factors. **(A)** Air quality index. **(B)** Climate comfort index. **(C)** Per capita park green area.

inflows will significantly increase by 0.04%, and its outflows will significantly reduce by 0.37% (Table 3), indicating that the more serious air pollution in the city is, the more migrants it attracts and the less local people it moves out. The reason may be related to the level of industrialization. The spatial distribution of AQI shows that important migration destinations, such as Beijing and Tianjin, tend to have higher levels of industrialization but relatively serious air pollution. By contrast, most of the southern cities with lower levels of industrialization but better air quality are important sources of migrants, leading to statistically more migrants moving into cities with more serious air pollution, and from cities with better air quality. Thus, air quality has minimal effect on intercity population migration.

THI has a significant pulling effect on the inter-city inflows, but the impact on the outflows does not meet expectations. Generally, if the THI increases by 1%, its inflows will significantly reduce by 0.08%, but its outflows will significantly reduce by 0.86%, showing obvious asymmetry. This means that the more comfortable the urban climate is, the more floating population it attracts but the more population outflow it promotes. This radiation effect is far greater than the attractive effect. This is mainly because the vast majority of cities located in the southeast with a comfortable climate are also important sources of emigration, leading to a statistically more comfortable climate with more emigrants, reflecting perspective that climate is not an important consideration in the migration decision of migrants. However, the attraction of climate comfort in the choice of migration destination is beginning to emerge.

The impact of PARK on intercity population migration is not in line with expectations. In general, if the PARK increases by 1%, its inflows will increase by 0.0005% but are not significant, and the outflows will increase by 0.01%. That is, a good ecological environment does not attract more floating population but will push more local people to move out. This is mainly because the cities with higher PARK are mostly small and medium-sized cities in the northwestern half of China with lower population density, plot ratio, and economic development level. They are often accompanied by more emigration, resulting in a better ecological environment with statistically more emigrants. Cities with lower PARK are mostly located in the southwest half of China, including both important emigration and immigration cities, resulting in statistical insignificance, reflecting the perspective that green ecological space is also not an important factor for intercity population migration.

4.3.2. Other influencing factors

The impact of per capita GDP, the proportion of employees in secondary and tertiary industries, and the average wages of employees are in line with expectations. Generally, if these three indicators increase by 1%, their inflows will increase significantly by 0.02, 0.03, and 0.01%, respectively, and their outflows will decrease significantly by 0.04, 0.19, and 0.18%, respectively. This means that migrants still tend to move to (from) cities with higher (lower) economic development levels, more (fewer) job opportunities and higher (lower) wage incomes. In addition, the increase in living cost can significantly reduce the desire of migrants, but it has not formed a push force for the local population to flee the city. If the housing price-to-income ratio of a city increases by 1%, its inflows will decrease significantly by 0.05%, but the outflows will also decrease significantly by 0.12%. This may be because a higher house price-to-income ratio often means a higher economic development level, facilitating the retention of local people in the city.

The migration stock has a significant positive effect on intercity migration with the highest regression coefficient. If the migration stock increases by 1%, the migration flows will increase significantly by 0.94%, indicating that the closer the social relationship, the greater the population migration. Migrants can establish social networks through family, friendships, colleagues and geo-relationship, promoting more migrants by providing them with help such as employment information, housing and transportation guidance. If the number of teachers per primary and secondary student, the number of tertiary hospitals and the number of books in the public library per 100 people increase by 1%, their inflows will increase by 0.04%, increase by 0.02% and drop by 0.009%, respectively, and their outflows will increase by 0.23%, reduce by 0.04% and reduce by 0.30%, respectively. This means the improvement of education and medical care can enhance the city's attractiveness, but cultural facilities cannot. Medical and cultural facilities can retain local people and reduce emigration, but education improvement can accelerate population exodus.

Population size has a significant positive effect on intercity population migration. If population size increases by 1%, its inflows and outflows will increase significantly by 0.01 and 0.88%, respectively, showing obvious asymmetry, meaning the influence of population size is dominated by push force. The impact of geographic distance doesn't meet expectations, but temporal distance has a significant negative impact. If the geographic distance and temporal distance increase by 1%, its migration flows will increase significantly by 0.02% and reduce significantly by 0.03%, respectively, indicating that the greater the geographic distance and the shorter the temporal distance, the greater the inter-city migration flows. This is because migrants do not choose the nearest cities as destinations but prefer cities that are provincial capitals and above with a higher economic development level. With the improvement of high-speed railways and airports, traditional spatio-temporal distance has been greatly compressed, enabling long-distance migration. The hindering effect of geographic distance is gradually weakening, while the friction effect of temporal distance remains significant.

4.3.3. Network autocorrelation

Significant "destination-based," "origin-based" and "origin-to-destination-based" spatial autocorrelation or spatial dependence relations are observed because ρ_d, ρ_o and ρ_w are not significantly equal to 0. Among them, ρ_d and ρ_o are significantly >0, indicating a positive multilateral spillover effect. The migration flows from the same city tend to gather in a certain destination city and its surrounding cities. The migration flows moving to the same city also tend to come from a certain origin city and its surrounding cities, reflecting the spatial emulation behavior of migration flows. However, ρ_w is significantly <0, indicating a negative multilateral spillover effect. The flows from the origin city to the destination city will inhibit the flows from surrounding cities of origin to surrounding cities of destination, reflecting the spatial competition behavior of migration flows. Notably, the spatial competition effect of migration flows is too small ($\rho_w = -0.0029$) and even negligible, thus, the spatial emulation

TABLE 3 The estimation results of gravity model and spatial econometric interaction model.

Log (variables)	Gravity model		Spatial econometric interaction model	
	Coefficient	t value	Coefficient	t value
Const	7.3840***	46.824	6.8599***	119.434
lAQI_o	−0.4041***	−27.284	−0.3579***	−66.477
lAQI_d	−0.0049	−0.312	0.0343***	6.050
lTHI_o	−0.8559***	35.463	−0.8640***	98.799
lTHI_d	−0.1136***	4.391	−0.0799***	8.481
lPARK_o	0.0171***	3.196	0.0116***	6.018
lPARK_d	0.0010	0.186	0.0005	0.268
lPGDP_o	−0.0510***	−5.487	−0.0385***	−11.503
lPGDP_d	0.0392***	4.272	0.0149***	4.462
lWAGE_o	−0.1904***	−9.806	−0.1880***	−10.438
lWAGE_d	0.0351**	2.324	0.0347**	2.435
lJOB_o	−0.1849***	−20.613	−0.1810***	−56.142
lJOB_d	0.0218**	2.389	0.0120***	3.628
lCOSH_o	−0.1176***	−9.183	−0.1156***	−25.086
lCOSH_d	−0.0263**	−2.332	−0.0506***	−12.392
lSOC	0.9226***	336.681	0.9030***	874.790
lEDU_o	0.2228***	16.001	0.2225***	44.438
lEDU_d	0.02287	1.533	0.0428***	7.960
lHEAL_o	−0.0407***	−6.489	−0.0427***	−18.927
lHEAL_d	−0.0002	−0.037	0.0173***	7.967
lCUL_o	−0.3051***	−51.523	−0.2917***	−136.200
lCUL_d	0.0137**	2.311	−0.0085***	−3.916
lPOP_o	0.9200***	139.589	0.8822***	355.467
lPOP_d	0.0180***	2.925	0.0149***	6.629
lDIS	−0.0087	−1.205	0.0219***	8.207
lTDIS	−0.0491***	−6.562	−0.0326***	−12.013
ρ_d	-	-	0.0252***	40.581
ρ_o	-	-	0.0146***	26.498
ρ_w	-	-	−0.0029***	−3.353
AIC	12,633.53	-	12,034.56	-

*** and ** indicate passing the significance tests of 1% and 5%, respectively.

effect is dominant, emphasizing the important influence of social networks or path dependence on intercity population migration.

The Akaike info criterion (AIC) of the spatial econometric interaction model is smaller than that of the gravity model ($AIC_{spatialODmodel} = 12,034.56 < AIC_{gravitymodel} = 12,633.53$), implying that compared with the traditional gravity model, the spatial econometric interaction model not only considers the spatial dependence between flows, but also improves the fitting level of the model. In addition, the absolute values of the estimated coefficients of the spatial econometric interaction model are generally smaller than the gravity model, implying that the role of factors on population migration is often exaggerated when network autocorrelation is not considered.

5. Discussion

5.1. Economically developed cities remain the main destinations for population migration

Consistent with the results of existing studies, intercity population migration still tends to cluster in a few economically developed cities, especially the core cities of developed urban agglomerations, forming a "three big and two small" polycentric spatial pattern. The three big centers refer to the Beijing–Tianjin–Hebei, the Yangtze River Delta and the Pearl River Delta region, and the two small centers refer to the Chengdu–Chongqing City

Cluster and the Triangle of Central China. The high-intensity migration flows occur mainly within the three major developed urban agglomerations in the eastern, moving from the peripheral cities to the core cities. Thus, the main direction of intercity migration flows is from the eastern to the eastern, which is different from the inter-provincial migration pattern. In central and western China, migration flows tend to gather in relatively developed provincial capital cities, such as Chengdu, Wuhan, Kunming, Xian and Urumqi.

This study also found that intercity population migration in China has the characteristics of hierarchical migration. Net migration flows go up the urban hierarchy, validating the economic law of migration to cities with high economic development levels again. However, it is a jump migration rather than Revenstein's step migration, with the largest inflows for any level being its exchanges with lower-middle level cities, rather than the next lower level. It is worth noting that net migration flows move upward the city hierarchy do not mean that all migration flows do as well; there are still a small number of downward migration flows that are likely to be related to environmental or amenity migration, especially for high-skilled and highly educated talent, they tend to have a tendency to flee from the high-class large cities because of unhealthy natural and social environment.

In addition, this case study from China has shown that destination cities with large number of migrants and high economic development levels are not necessarily the healthiest areas for the environment, which can be seen by the spatial pattern of environmental health factors. Environmentally friendly cities are mainly located in the southern region, and most of them are important origin cities for the floating population. While important destination cities for the floating population in developed eastern region tend to have relatively poor environmental conditions. Therefore, there is a spatial mismatch between the migrant gathering space and the good environmental space.

5.2. Environmental health factors have not yet become a determinant of population migration

Different from some existing research, this study found the effect of environmental health factors, such as air quality, climate comfort and ecological space, are inconsistent with expectations. Environmental health factors have not yet become a major consideration in migration decisions. However, socioeconomic factors remain the determinants in intercity migration, meaning that migrants pay more attention to economic needs rather than environmental health. This is because of China's development stage and the fact that most of China's floating population are low-skilled migrant workers who migrate more for economic purposes. On the one hand, different from developed countries, China is the largest developing country in the world. The development of industrialization exposes the cities themselves to many unhealthy environmental exposures, and migrants are willing to pay the price of environmental health to earn more money. On the other hand, the vast majority of the low-skilled migrant workers are poorly educated, have a heavy family livelihood burden, and do not have a high level of awareness of environmental health themselves. However, some studies have shown that highly educated and high-skilled migrants are increasingly concerned about environmental health (39, 62). They often have the ability to obtain satisfying jobs in large cities. On the basis of meeting basic economic needs, they are more concerned about air quality, climate comfort and other environmental health issues.

This study also found that except for economic factors such as wage income and job opportunities, social factors such as social networks, education and health care are also important influencing factors of intercity population migration. On the one hand, already settled migrants often act as a "bridgehead," reducing the risks and costs of subsequent migration and settlement by providing information, organizing travel, finding jobs and housing and assisting in adaptation to a new environment, thus promoting more migration. The spatial emulation behavior among migration flows proves this path-dependent process. On the other hand, after satisfying basic material life needs, migrants also breed a demand for high levels of public service such as education and medical care. More and more migrants prioritize their quality of life over career prospects, especially for high-quality talents. In addition, the friction effect of geographic distance on intercity migration is not significant, while the friction effect of time distance is significant, indicating that migrants pay more attention to time distance rather than geographic distance.

Based on the existing literature and empirical studies in this paper, the internal mechanism of the impact of environmental health factors on population migration is summarized: Environmental health factors, together with socioeconomic factors, gravity factors and other factors, contribute to the process of population migration decisions and destination selection. When environmental changes threaten people's lives and property security, people will move passively, and their destination selections are more determined by the government or living conditions, such as ecological migrants or refugees. When environmental changes are not sufficient to threaten people's lives and property, people may choose not to migrate or to migrate voluntarily. For low-skilled migrant workers, the environmental health factors often do not play a decisive role. Although the environment may affect their health, they often make destination choices at the expense of environment quality to pursue stable employment and economic income. However, for high-skilled talents, the environmental health factors sometimes play a decisive role, poor environmental conditions may make them decide to leave or not to move in.

5.3. Policy implications

Owing to the hukou system, the floating population cannot enjoy the benefits and rights of permanent migrants and local residents in the destination city, such as social securities, health care and education opportunities. Thus, migrants face social vulnerability in the destination cities. Recently, the government has been aware of this problem and has relaxed hukou restrictions in large cities to actively promote the citizenship of the agricultural transfer population and the equalization of basic public services. However, the environmental health vulnerability of migrants has long been overlooked. Migration is generally followed by behavioral, lifestyle and environmental changes that can significantly increase the risk of disease in the early generations of migrants (63), and affect migrants' health. Thus, the government should pay attention not only to the social vulnerability of migrants, but also to their environmental health vulnerability.

The environmental health problems faced by China's population migration can provide policy implications for other developing and underdeveloped countries. Large cities with high immigration should pay more attention to environmental health issues and follow an environmentally friendly and sustainable development path in the process of urbanization, potentially increasing people's health wellbeing. Specifically, to focus on ecological construction, and expand ecological space such as parks, green spaces and forests. To strengthen environmental protection and governance, and reduce pollutant pollution. To promote green development, and develop circular economy and clean production.

This study also found that most migrants neither come from the poorest cities nor the poorest segments of the population. This is because migration involves significant costs and risks that the poorest generally cannot afford. This also means that people in poor cities benefit very little from the urbanization and migration process. Therefore, the government should pay more attention to the migration barriers of poverty areas and poverty population, and provide them with more labor export opportunities and migration cost subsidies. The government should also vigorously implement the rural revitalization strategy, increase industry cultivation and support and promote local urbanization.

6. Conclusion

Based on the 1‰ micro-database of the 2015 1% population sample survey, this study used the spatial visualization method and spatial econometric interaction model to examine the spatial patterns of intercity population migration and environmental health factors in China, and focus more on the impact of environmental health factors on intercity population migration. The conclusions are as follows.

First, the main direction of intercity population migration is still toward economically developed high class cities, especially the core cities of three major urban agglomerations in the eastern coast where the floating population is most active. However, these major destinations are not necessarily the healthiest areas for the environment. Second, environmentally friendly cities are mainly located in the southern region. The areas with less serious atmospheric pollution are mainly distributed in the south, climate comfort zones are mainly located in the southeastern region, and the areas with more urban green areas are mainly distributed in the northwestern region, all of which are not necessarily the main destination cities for floating populations. Third, compared with socioeconomic factors, environmental health factors have not yet become a major driver of population migration; migrants tend to place a higher value on income than on environmental health.

The contributions of this study are as follows. It found that economically developed cities are still the main destination for population migration. Then, it proved that environmental health factors have not yet become a determinant of population migration. This study also suggested the government should focus not only on the public service wellbeing of migrant workers but also on their environmental health vulnerability, contributing to the construction of a healthy city.

However, this study is not free from limitations. The first is that the data sample is biased. This study uses the 1‰ microdata, including a large number of zero flows, which does not mean that cities did not have migration flows but rather they were not collected when sampling. The second limitation is the selection of environmental health indicators. This study only selects three variables that are currently of most concern for the environmental health development in Chinese cities. In the future, more attention should be paid to the research on the relationship between more comprehensive environmental health factors and population migration based on individual migrant surveys.

Data availability statement

Publicly available datasets were analyzed in this study. This data can be found at: https://microdata.stats.gov.cn/.

Author contributions

PG was responsible for data processing, graph production, and paper writing and revision. WQ provided important insights and was responsible for paper revision. SL and ZL participated in paper revision. ZP was responsible for collecting and processing data. All authors contributed to the article and approved the submitted version.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Publisher's note

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Determining the ecological security pattern and important ecological regions based on the supply–demand of ecosystem services: A case study of Xuzhou City, China

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The supply–demand for ecosystem services (ESs) is the bridge between ecological security patterns (ESPs) and human wellbeing. This study proposed a research framework of ESP of "supply–demand–corridor–node" and took Xuzhou, China, as a research case, providing a new perspective for the construction of ESPs. The framework was divided into four sections: identifying the ecological source based on the ESs supply; utilizing multi-source economic-social data to characterize the demand of ESs and constructing a resistance surface; defining the ecological corridor in the study area by employing the Linkage Mapper; and identifying crucial ecological protection/restoration areas along the ecological corridor. The results showed that the area of the supply source of ESs in Xuzhou City is 573.89 km^2, accounting for 5.19% of the city's total area. The spatial distribution of 105 ecological corridors revealed that there were multiple and dense ecological corridors in the middle of the city, but few in the northwest and southeast. A total of 14 ecological protection areas were located primarily in the south of the urban area, and 10 ecological restoration areas were located primarily in the middle and north of the urban area, with a total area of 4.74 km^2. The findings of this article will be useful in developing ESPs and determining important ecological protection/restoration areas in Xuzhou, China. The research framework could potentially be used in other areas.

KEYWORDS

ecological security pattern, important ecological regions, supply-demand of ecosystem services, circuit theory, research framework

1. Introduction

In recent years, global climate change and the growth of human activities have caused a number of problems between people and the natural environment, such as ecological patch fragmentation, biodiversity loss, the heat island effect, and soil erosion (1–3). These problems have seriously threatened regional and national ecological security and slowed down sustainable development. In this situation, ecological security patterns (ESPs) offer a practical way to keep the balance between local environmental protection and economic growth. This has become a hot topic of research around the world, especially in China, which is urbanizing quickly (4).

The ESPs are primarily spatial control methods to coordinate natural ecosystems and socio-economic systems, derived from landscape ecology theories and methodologies (5–7). By identifying the significance of ecological processes and functions in various landscape patches, ESPs can delineate significant ecological areas and build a network system that can maintain the continuity of ecological processes and the integrity of regional ecosystems, preventing the disruption caused by urban growth (8). Several advances have been made in the study of ESPs, including their genesis and development mechanisms (9), design and optimization (10), protection of biodiversity (11), allocation of land to the most productive uses (12), and ecological planning of landscapes (13).

With a growing understanding of natural ecological functions, research on regional ESPs based on ESs has gained prominence in recent years. ESs serve as a link between ecosystems and human welfare. The dynamic process by which ESs flow from ecological systems to human-social systems is constituted by the supply–demand of ESs. The supply–demand for ESs research can improve the ESPs' practical integrity and scientific measurement (14), as well as expand its connotation (10). More and more scholars use ESs supply to identify ecological sources. For example, Li et al. (15) determined the ecological source based on the ESs assessment (carbon storage, water retention, soil retention, and habitat quality) and morphological spatial pattern analysis (MSPA) model; Zhang et al. (16) selected three typical indicators, namely soil conservation, water yield, and carbon fixation, to measure the supply of ESs in the Yellow River basin, and used them as important indicators to identify ecological sources; Wang et al. (17) selected eight indicators, such as water conservation, waste disposal, gas regulation, and climate control, to measure the value of ESs, and took areas with high value of ESs as ecological sources.

Nevertheless, the coupling and coordination between ecosystems and economies/societies are dependent not only on the supply capacity of ESs but also on the human demand for ESs (18). Some research combines the supply and demand of ESs to determine ecological sources. For instance, Zhang et al. emphasized that the ability of ESs demand is the key to identifying ecological sources, so human needs were included in the assessment of ESs in the Beijing-Tianjin-Hebei region of China (19, 20); Jiang et al. (21) identified ecological sources through comprehensive ecological supply–demand ratio by combining the ecological background of the Greater Bay Area of Guangdong, Hong Kong, and Macao in China; Cui et al. (22) analyzed both the ESs supply potential and the human demand potential to determine the ecological source. Nevertheless, the expansion of ESs from the source to other units would be influenced by factors such as accessibility, cost, and the degree of economic and social development, which are frequently reflected in the human demand for ESs. Existing research on the application of ESs demand to construct the resistance surface of ESs flow is limited. Therefore, it is appropriate and important to construct a resistance surface based on the measurement results of the resistance value of ESs demand to reflect the potential for dissipation in the process of ESs delivery.

In addition, the current research concentrates on the development of overall ESPs but disregards the identification of crucial protection/restoration areas. Priority management of key areas can improve the overall function of the regional ecosystem at a lower cost, helping to reach the goal of comprehensive optimization of ecological, economic, and social benefits (23, 24). Important ecological protection areas are generally the core nodes of the regional ESPs, which can effectively conserve the region's most influential flagship species (8, 25). Important ecological restoration areas generally restore damaged ecosystem areas by combining policies and technologies in order to increase the circulation of ecological sources (16, 26). The academic contribution of this study is to construct ESPs that consider the supply–demand for ESs and to precisely identify crucial locations for ecological conservation/restoration around the ESPs. This study has three objectives: establishing a research framework of "supply–demand–corridor–node"; utilizing multi-source economic-social data to characterize the demand of ESs and constructing a resistance surface; and using the circuit theory model to identify the key ecological protection/restoration regions within the study area.

2. Study area

Xuzhou is an important node city of China's "Belt and Road" initiative, situated in the northwest of Jiangsu Province between E116°22'−118°40' and N33°43'−34°58', with a total land area of 11,258 km^2. Except for a few hills in the middle and east, most of the terrain is plain landform. Affected by the temperate monsoon, the annual mean temperature is 14°C and the annual precipitation is 800–930 mm. By the end of 2021, Xuzhou has a permanent population of 9.028 million, with a GDP of 811.744 billion, comprising five districts and five counties (Figure 1). With the rapid development of urbanization and industrialization, Xuzhou is facing the challenge of ecologically sustainable development. Scientific construction of ESPs and accurate identification of ecological restoration/protection areas are of great practical significance for the transformation, development, and ecological restoration of Xuzhou.

3. Research framework and data sources

3.1. Research framework

Figure 2 displays the research framework. The ESPs research framework not only helps academics in related fields understand the basic technical logic behind their work but also helps government officials understand how to carry out projects. Based on the supply–demand of ESs, this article designs a research framework of "supply–demand–corridor–node."

3.1.1. Identify the ecological source through the supply of ESs

In the past, identifying ecological sources was primarily done by directly choosing natural reserves, historical sites, and land use types (27), or by constructing numerical models using pertinent indicators, such as the quantitative ecological importance evaluation system and MSPA (28). Natural ecosystems provide the resources required for human survival and development. As a result, employing ESs supply evaluation to select the ecological source is more in accordance

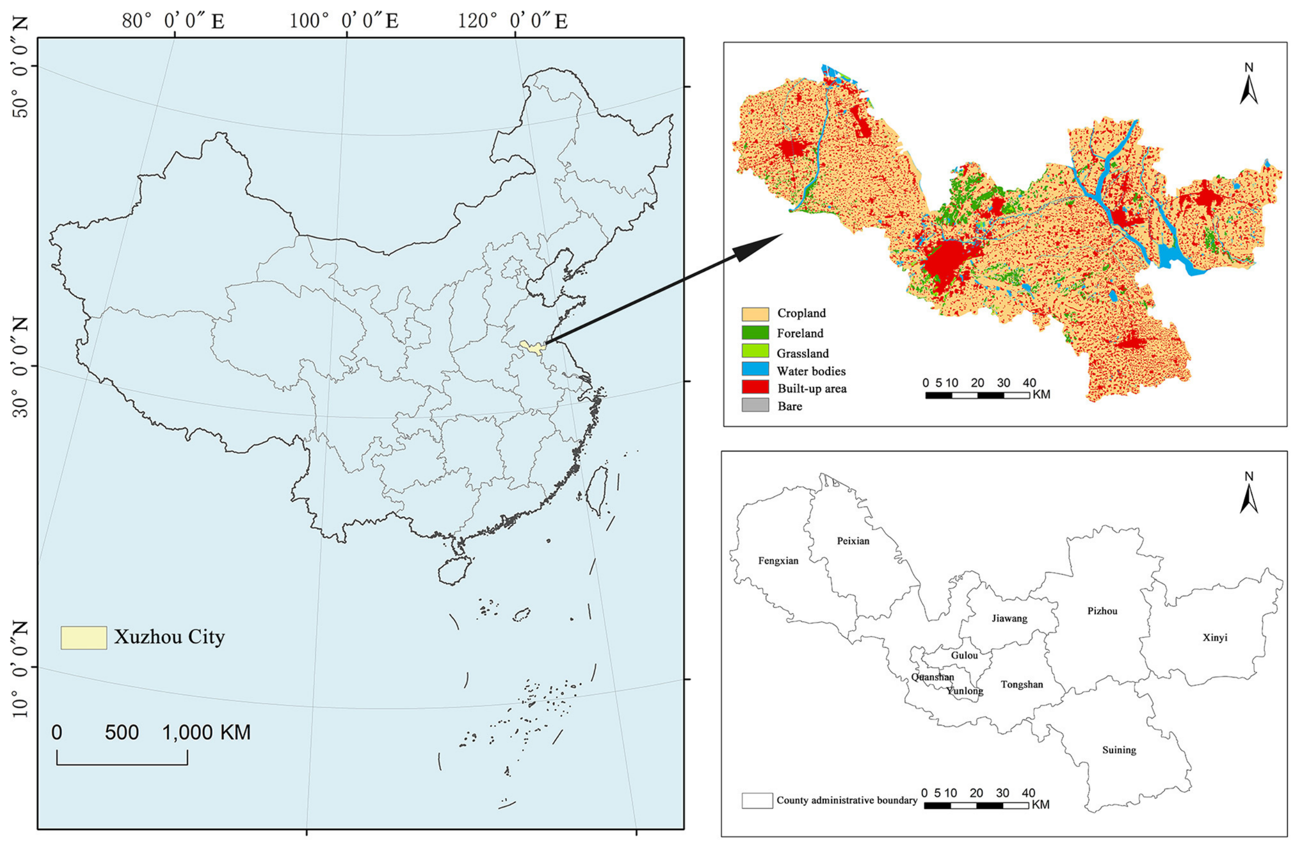

FIGURE 1
Geographical location and distribution of land cover types in Xuzhou.

with humanity's actual demands. To acquire the ecological source, we use the InVEST model with four ESs, namely, carbon storage, soil conservation, water yield, and habitat quality, to quantitatively evaluate the ESs supply (29–32).

3.1.2. Construct resistance surface through human demand of ESs

In the past, resistance surface was generated by assigning values to different land use types, superimposing other economic and social factors, and combining the habitat risk assessment model or analytic hierarchy process (AHP) to weigh multiple factors (25, 33). The resistance surface of ESs demand in this article refers to the fact that when ES functions deliver services from an ecological source to other regions, the transmission and transformation of ESs are hampered by the constraints of natural geographical conditions and socio-economic conditions. In essence, it is a potential consumption of ESs.

3.1.3. Identify ecological corridors based on the supply—demand of ESs and build ESPs

The ecological corridor is the passage of ecological flow, ecological process, and ecological function in the region. The ecological corridor maintains the stability of the ecological function and ensures the continuity of the ecological process (10, 31). The methods used to build corridors are also diversifying, with the minimum cumulative resistance (MCR) model, the graph theory method, and circuit theory being the prominent examples (34). The MCR model can identify the direction of the biological flow and the best path among them, but it is unable to establish the size of the ecological corridor or the important ecological nodes (3). Circuit theory effectively bridges this gap by simulating biological flow across different resistance surfaces. The size of the current shows how much organisms can move between different patches, and the areas with high current values are important for movement and diffusion (35).

The open-source modeling tool Circuitscape, which is based on circuit theory, determines ecological pinch points and ecological barrier points to represent, respectively, significant areas of ecological protection/restoration. Ecological pinch points are proposed by Mcrae et al. (36) based on circuit theory to represent the key areas that affect the connectivity of the landscape. The identification of ecological pinch points can prevent the degradation or change of ecological sources, so we take ecological pinch points as the key areas of ecological protection. Ecological barrier points are regions where organisms' migration between ecological sources is hindered. Eliminating these spaces will improve communication among ecological sources. This research views ecological barrier points as major areas in need of

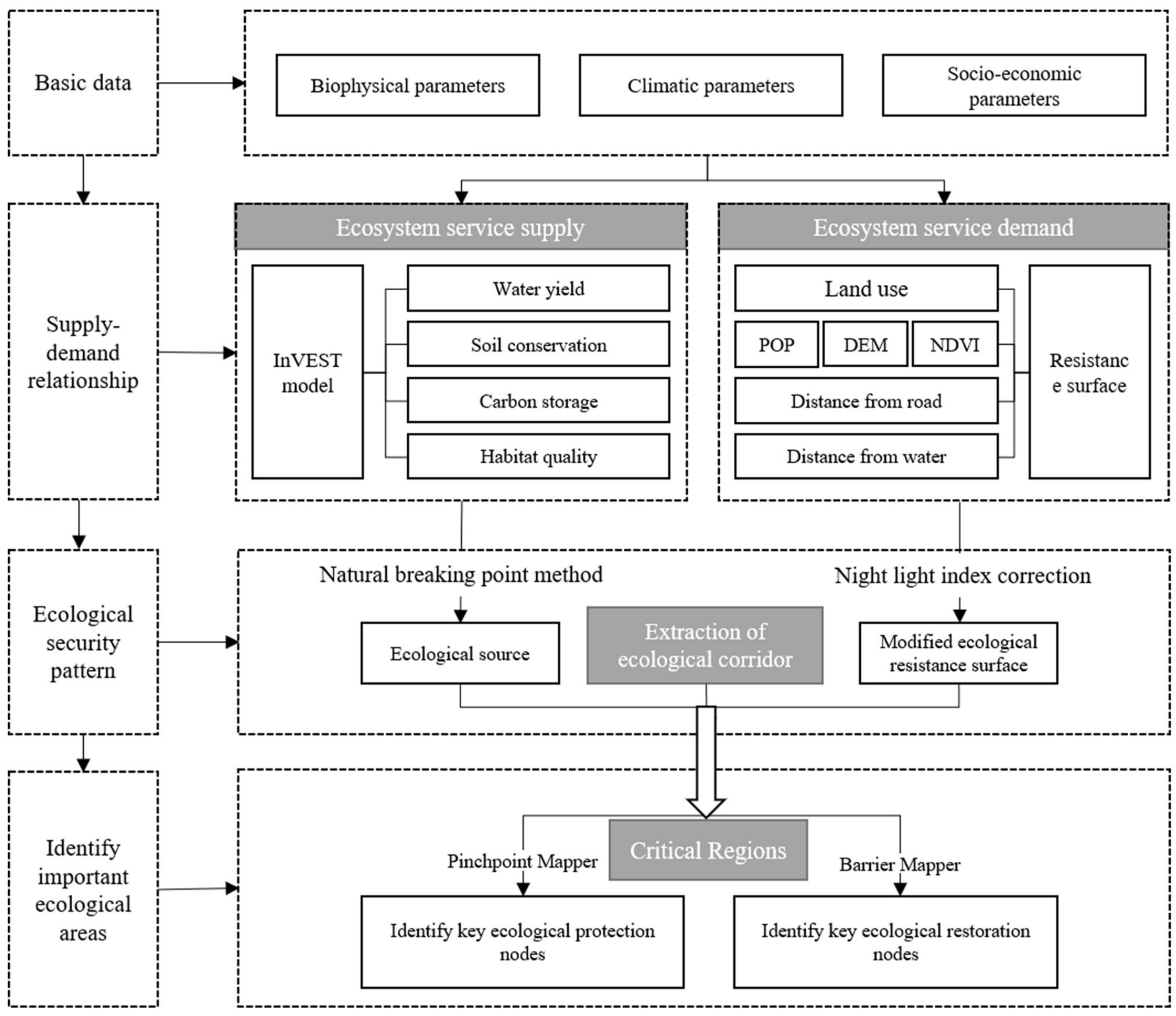

FIGURE 2
Research framework.

ecological restoration. Precisely formulate relevant policies and technologies for the identified key protection/repair areas to overcome their internal flaws and external threats. Important area restoration/protection measures are much more effective than those implemented randomly.

3.2. Data sources

The main types of data in this study are the administrative scope of the study area, the basic data for calculating the supply of ESs in Xuzhou based on the InVEST model, and the diverse natural and social basic data needed for calculating the demand for ESs in Xuzhou (Table 1). Simultaneously, to maintain data uniformity and correctness, all data are unified to a 30-m spatial resolution under the same coordinate system using Arcgis10.5.

4. Method

4.1. Quantifying the supply of ESs

4.1.1. Water yield

Water yield services measure the capacity of an ecosystem to hold rainwater under the combined action of plants and soil. In this article, the Water Production module of the InVEST model was used to obtain the spatial distribution of water production in Xuzhou. Based on the principle of water balance, the module defines water production as the amount of water remaining after subtracting plant transpiration and surface evaporation from the precipitation within the grid. It also assumes that the water production of the grid unit will eventually reach the watershed outlet through the surface and underground runoff. The water production was estimated from parameters such as precipitation, potential evapotranspiration, root

TABLE 1 Data sources.

Data type	Source	Explain
Xuzhou administrative boundary	National Geographic Information Resources Directory Service System (https://www.webmap.cn/commres.do?method=result100W)	The Ministry of Natural Resources gives the national geographic information resources directory service system permission to let people download 1:1,000,000 full-layer elements for free
Land use data of Xuzhou in 2020	Resource and environment science and data center, Chinese Academy of Sciences (http://www.resdc.cn)	The land is put into six groups: cultivated land, forest land, grassland, water area, construction land, and unused land
Digital elevation model	Geospatial data cloud platform (http://www.gscloud.cn)	A solid ground model that shows the height of the ground as a set of ordered arrays of numbers. It is also the basic information you need to figure out the slope
Precipitation data	China Meteorological Data Service Center (http://data.cma.cn)	Using the Kriging interpolation tool, the average annual rainfall can be found
Soil data	Data from global soil data provided in the World Soil Database (HWSD) constructed by the Food and Agriculture Organization of the United Nations (FAO) and the International Institute for Applied Systems (IIASA), Vienna	This data is a grid with a spatial resolution of KM. Each grid point has information about its soil type, soil phase, soil's physical and chemical properties, and more
Potential evapotranspiration data	From CGIAR-CSI GeoPortal (http://www.csi.cgiar.org)	It means how much water can be lost through evaporation from the area covered by plants on the surface below
Demographic and economic data	From the resource and environment science and data center of Chinese Academy of Sciences (http://www.resdc.cn)	Mainly including road traffic data and population density of Xuzhou
NDVI data	From geospatial data cloud (https://www.gscloud.cn)	It is a MOD13Q1 item with a 250 m resolution
Night light data	Adopt NPP-VIIRS data (https://www.ngdc.noaa.gov)	This information is preprocessed and corrected 2020 data that has been algorithmically produced

system, and soil depth, and finally, the raster water yield of the watershed was calculated. The model's algorithms are as follows:

$$Y_{xj} = \left(1 - AET_{xj}/P_x\right) \times P_x \quad (1)$$

$$\frac{AET(x)}{P(x)} = \frac{1+w_x R_{xj}}{1+w_x R_{xj}+1/R_{xj}} \quad (2)$$

where Y_{xj} represents the water yield of the x-th grid of land use type j ($m^3 \cdot hm^{-2}$); AET_{xj} represents the annual actual evapotranspiration of the x-th grid of land use type j (mm); P_x represents the annual average precipitation of the x-th grid (mm); R_{xj} represents the dryness index of the x-th grid of land use type j; and w_x represents the available water content of vegetation. The details of each coefficient are shown in Supplementary Table A1.

4.1.2. Soil conservation

Soil conservation services are the function of ecosystems to maintain soil by reducing erosion from rainfall through the forest canopy and root system to increase soil erosion resistance, thereby reducing soil erosion and soil loss. The soil in Xuzhou is primarily brown and cinnamon type, with poor water storage conditions and relatively low vegetation coverage (37). It is the key prevention and control area of soil erosion in Jiangsu Province and a plain sand protection area. Therefore, soil conservation is an important indicator to measure the water and soil conservation of the ecosystem in Xuzhou. The SDR module in the InVEST model was utilized in this article to evaluate soil conservation in Xuzhou (26). According to the potential soil loss equation, soil conservation was obtained by reducing actual soil erosion with potential soil erosion as follows:

$$SC_i = RKLS_i - USLE_i \quad (3)$$

$$RKLS_i = R_i \times K_i \times LS_i \quad (4)$$

$$USLE_i = R_i \times K_i \times LS_i \times C_i \times P_i \quad (5)$$

where SC_i is soil conservation; $RKLS_i$ is the potential erosion amount; $USLE_i$ is the actual erosion amount; R_i is Rainfall Erosivity Factor; K_i is soil erodibility factor; LS_i is the slope length factor; C_i is the vegetation cover management factor; and P_i is the factor of water and soil conservation measures. The details of each coefficient are shown in Supplementary Table A2.

4.1.3. Carbon storage

The carbon storage service of an ecosystem is the absorption of carbon dioxide from the atmosphere by plants through photosynthesis, which is converted into carbohydrates such as glucose and fixed in the form of organic carbon in the plant or soil. Xuzhou is an example of a historic industrial city in our country. The city's growing industrialization has made it a prominent area for the combustion of chemical fuels. Xuzhou's carbon stock has become an important indicator, affecting the regional climate and the security of the regional ecosystem. In this article, the Carbon module of the InVEST model was used to calculate the amount of carbon stored in Xuzhou, and the amount of carbon currently stored was estimated based on the data of land use types and their corresponding storage in the four carbon pools. The following is the formula:

$$C_{total} = C_{above} + C_{below} + C_{soil} + C_{dead} \quad (6)$$

where C_{tota} is the total carbon storage; C_{above} is aboveground carbon storage; C_{below} refers to underground carbon storage; C_{soil} is soil carbon storage; and C_{dead} is the carbon storage of dead organic matter. The unit is $t{\cdot}hm^{-2}$. The details of each coefficient are shown in Supplementary Table A3.

4.1.4. Habitat quality

In recent years, heavily urbanized human activities have had an impact on Xuzhou's biodiversity. As a result, habitat quality can evaluate ecosystems' potential to retain and sustain genetic, species, and ecosystem variety, which is the most essential supporting function offered by ecosystems. In this article, the InVEST model's Habitat Quality module was used to assess the biodiversity of the study region and simulate the influence of human activities on the habitat. The more people do, the more the habitat is threatened; the lower the quality of the habitat, and the lower the level of biodiversity. In contrast, the fewer people do, the higher the quality of the habitat and the higher the level of biodiversity. The birth quality is derived by combining the sensitivity of different land use types to threat factors and the degree of external threats as follows:

$$Q_{xj} = H_j \left[1 - \left(\frac{D_{xj}^z}{D_{xj}^z + K^z} \right) \right] \tag{7}$$

where Q_{xj} represents the habitat quality of the x-th patch of land use type J; D_{xj}^z represents the habitat stress degree of the x-th patch of land use type j; H_j indicates the habitat suitability; and K^z is the semi-saturation constant. The details of each factor are given in Supplementary Table A4.

The biophysical parameters used in the following model development are mostly drawn from earlier studies (38–40). To eliminate the dimensional effects among the four indicators, the results of the ES assessment were unified and normalized, using the method of natural break point; the four ESs were divided into three grades, namely, extremely important, medium important, and unimportant, specifically, with levels 1 and 2 are low-value zones (not important), levels 3 are medium value zones (medium important), and levels 4 and 5 are high-value zones (extremely important).

4.2. Quantifying the demand for ESs

The expansion of ESs from the source to other units is influenced by factors such as accessibility, cost, and the degree of economic and social development, which are often reflected in the human demand for ESs. Therefore, it is reasonable to construct the resistance surface based on the resistance value of ESs demand to reflect the dissipation potential in the process of ESs supply. Due to different types of natural land cover and different levels of human activity interventions, the movement processes of species between regions show differentiated characteristics, including the mobility and transmission of ecological functions. Quantifying the demand for ESs is based on two main perspectives: the natural influences on the generation and transmission of ESs and the degree of demand in human activity areas.

Referring to previous studies and combining with the natural and economic conditions of the study area (41–45), this article selects six factors, namely, land use types, population density, DEM, NDVI, distance from the road, and distance from water, to characterize human demand of ESs (Table 2). The elevation can determine the flow of ESs by regulating the distribution of water and heat; NDVI can directly affect local climate, biodiversity, soil conservation, and other services; population density, water, and road traffic distribution are important for the development or decline of the region; land use type is a concentrated expression of human activities, which is both an influencing factor and an important carrier of various ESs (Figure 3).

Since human disturbance is one of the important resistances to species dispersal, and nighttime light data can represent the intensity of human activities in the whole region, the higher the value of nighttime light intensity represents the stronger the development vitality of the region (46). Therefore, this article then uses the

TABLE 2 Resistance factor and its resistance value.

Resistance indicator	Classification	Resistance value	Weight
Types of land use	Water	1	0.4
	Woodland	2	
	Grassland	3	
	Cultivated land/bare land	4	
	Construction land	5	
Population density	<1.42	1	0.2
	1.42–4.74	2	
	4.74–12.10	3	
	12.10–24.20	4	
	>24.20	5	
DEM(m)	<31	1	0.1
	31–49	2	
	49–78	3	
	78–127	4	
	>127	5	
NDVI	<0.46	1	0.1
	0.46–0.61	2	
	0.61–0.73	3	
	0.73 – 0.82	4	
	>0.82	5	
Distance to road(m)	<1,500	1	0.1
	1,546–3,092	2	
	3,092–4,638	3	
	4,638–6,184	4	
	>6,184	5	
Distance to water(m)	<3,475.68	1	0.1
	3,475.68–6,951.36	2	
	6,951.36–10,427.04	3	
	10,427.04–13,902.71	4	
	>13,902.71	5	

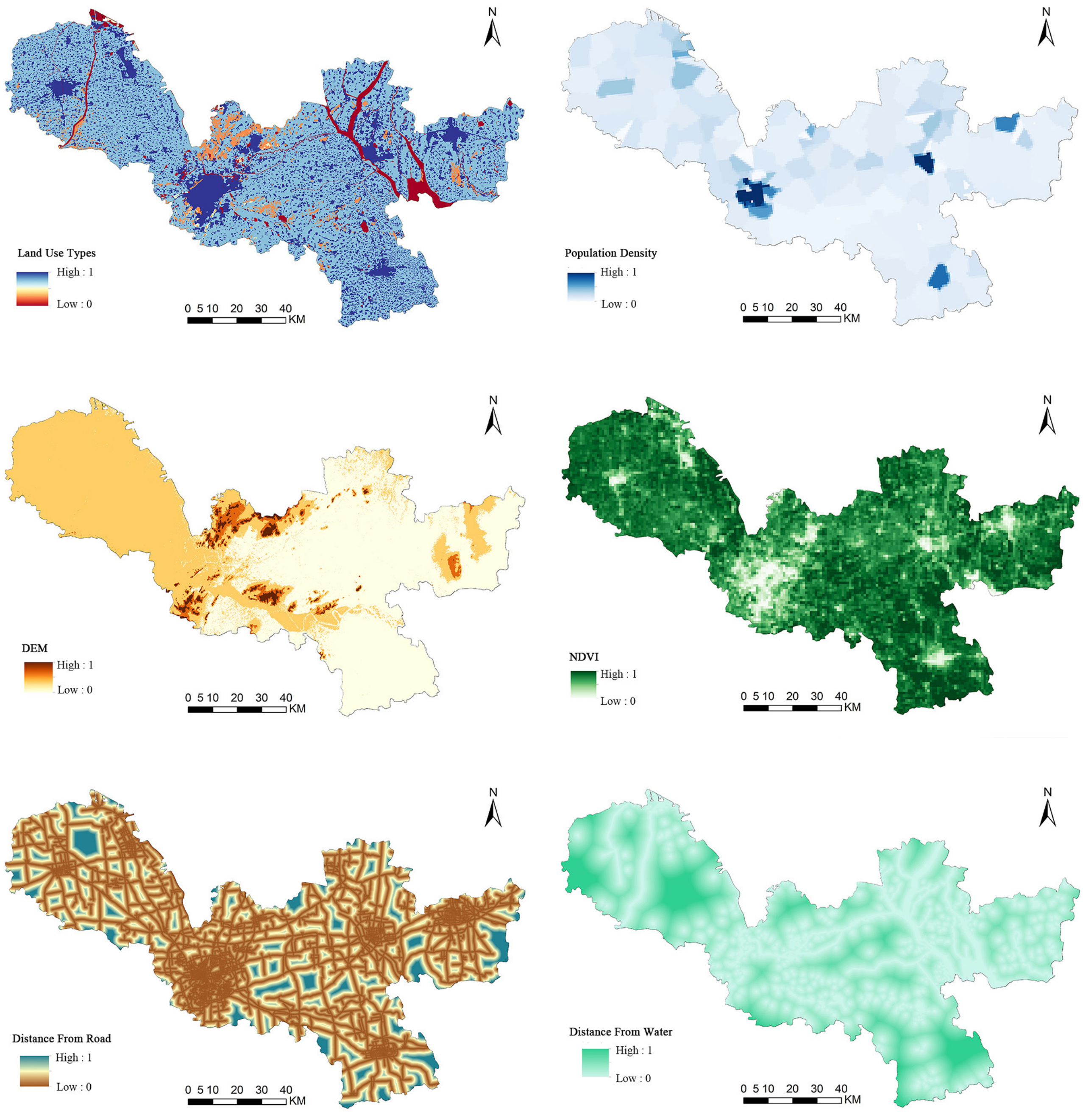

FIGURE 3
Spatial distribution of ecosystem service demand in Xuzhou.

nighttime light index to modify the ecological resistance coefficient to construct the resistance surface as follows:

$$R^{*} = \frac{TLI_i}{TLI_a} \times R_o \qquad (8)$$

where R* is the corrected grid resistance coefficient; TLI_i is the night light intensity value of grid I; TLI_a is the average night light intensity value of land type a; and R_o is the base resistance value of grid i.

4.3. Extraction of an ecological corridor

The circuit theory simulates the migration and diffusion process of species by using the characteristic of the random walk of electrons in the circuit. This scheme can relatively accurately simulate the diffusion path of species in a heterogeneous landscape, even in the absence of species migration data (36). At present, the ecological corridor has been used as a tool to connect the natural ecological source and the needs of human society (44). This article uses the Linkage Pathways Tool module to identify the ecological corridor, which can draw the lowest cost link between core patches according to the core patch and resistance grid. At the same time, the contribution degree of landscape connectivity can be determined through centrality analysis. The greater the centrality of an ecological patch indicates that it can have sufficient material, energy, and information exchange with other patches and that it is easy to establish contact with other patches in the face of disturbance. Therefore, its ability to resist disturbance is relatively strong. The Centrality Mapper tool is used to calculate the flow centrality of the optimal ecological corridor and quantitatively analyze the importance level of the ecological corridor.

4.4. Identify ecological protection and restoration nodes

Ecological pinch points represent areas with high-flow density in the ecological network, that is, areas with a high probability of species migration or no alternative path. Priority should be given to protecting such areas during the construction of the ecological network (47). In this article, Pinchpoint Mapper is used to identifying ecological protection areas. Pinchpoint Mapper combines the Circuitscape algorithm with the base map generated by Linkage Mapper to achieve the research purpose. Ecological barrier points refer to areas where the migration process of species between source areas is greatly hindered (48). Taking ecological barrier points as ecological restoration nodes can significantly improve the connectivity between ecological sources. The operation of the Barrier Mapper tool is based on the extraction of ecological corridors by the Linkage Mapper tool. This tool can not only detect the complete obstacle points that hinder the migration of species but also detect the obstacle areas that have some obstacles but do not completely affect the migration of species. This article considers only the areas that have complete obstacles to the migration of species.

5. Results

5.1. The spatial pattern of supply—demand of ESs

Figure 4 shows that the water yield service decreases gradually from east to west. This was related to the local precipitation, soil properties, and evapotranspiration. The high-value area was distributed in the northeast of Xuzhou City, which was an important water conservation area. Soil conservation services were distributed spatially in Xuzhou in a zonal and dot-overlapping pattern. High-value areas were mainly concentrated in the northern Jiawang District and the peripheral areas of the central urban area, while the rest are mostly low-value areas. Xuzhou's carbon storage service generally presented a pattern of low in the center and high on the edge, high in the north, and low in the south. High-value areas were

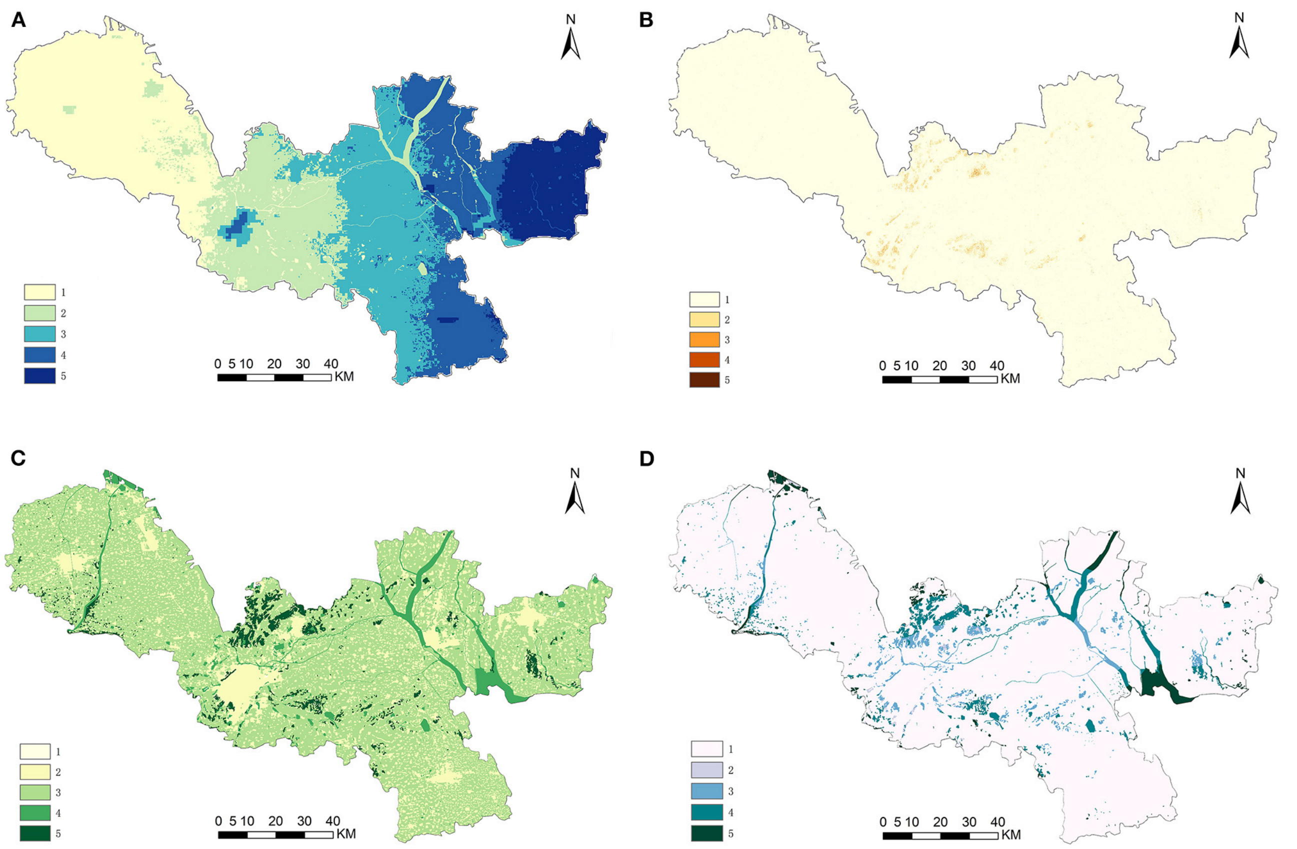

FIGURE 4
Four types of ESs supply in Xuzhou **(A)** water yield, **(B)** soil conservation, **(C)** carbon storage, and **(D)** habitat quality.

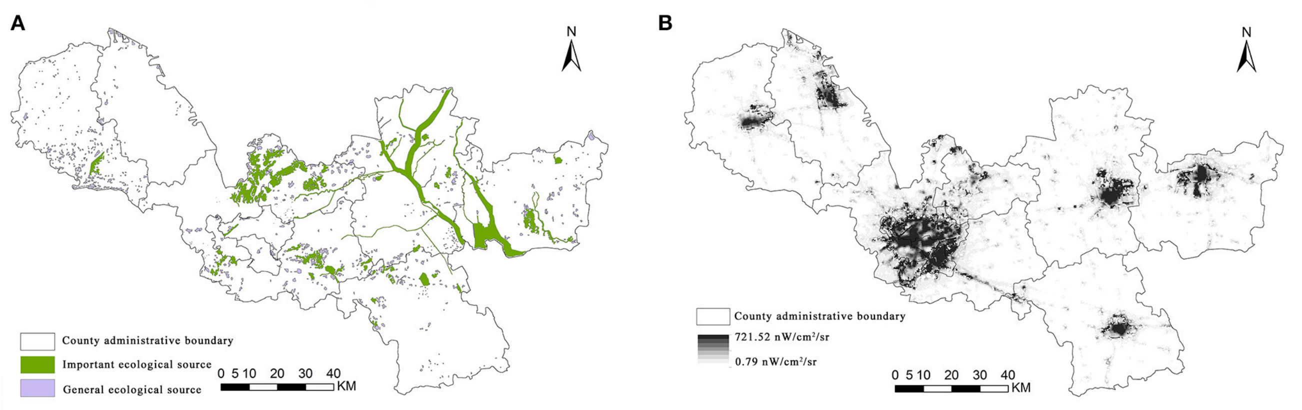

FIGURE 5
Spatial distribution of ecological sources **(A)** and resistance surface **(B)** in Xuzhou.

mainly distributed in Jiawang District in the north of Xuzhou City, Luoma Lake Basin in the east, Dasha River Basin in the northwest, and the green area around the city outside the central urban area. The high-value areas of habitat quality were mainly distributed in areas where forests and lakes were concentrated.

A total of 1,107 important ecological sources were extracted from the classification of extremely important regions. If all ecological sources were included in the scope of ESPs, it would lead to fragmentation of the ecological space, which was not conducive to the overall regional optimization strategy. Referring to previous studies (49, 50), this article further extracted patches with an area of more than 0.8 km^2 as the ESs supply source, representing the main areas with strong ESs formation and supply capacity in Xuzhou. Finally, 47 patches were chosen as ecological sources. The overall area of the ecological source was 573.89 km^2, accounting for 5.19% of the city's total area. The greatest ecological source patch covered 152.26 km^2. The ecological source areas, as illustrated in Figure 5A, were concentrated in places where the mountain and water systems are adequately maintained. For instance, the southern part of Fengxian County, the northern part of Jiawang District and Tongshan County, and the Luoma Lake water system in Xinyi. Figure 5B depicted the demand for ESs in Xuzhou, which was identified as a barrier to the supply of ESs. The average ecological resistance was 18.60 $nW/cm^2/sr$, with a maximum of 721.52 $nW/cm^2/sr$ and a low of 0.79 $nW/cm^2/sr$. The ecological resistance depicts the collective predicament in space. The ecological resistance represented the predicament of humanity in space. Among them, regions with high resistance values were typically more populated, with a concentration in urban cores such as Quanshan District, Gulou District, Yunlong District, and others. Moreover, urbanized regions such as Fengxian County, Peixian County, Pizhou City, Xinyi City, and Suining County had high resistance values.

5.2. Extraction of an ecological corridor

The ecological corridor was calculated using Linkage Mapper and superimposed with the study area's source and resistance surface (Figure 6). The ecological corridors in Xuzhou were interconnected in a network, showing that the overall ecological quality was good but connectivity was limited. The article identified 105 ecological corridors that were distributed in a crisscross network. In the central portion of the study area, there were numerous and dense corridors, whereas there were few ecological corridors in the northwest and southeast. The ecological corridors in Xuzhou were overlapped, connected, and blocked each other. At the same time, the ecological corridor had a considerable curve, which could generate a more varied environment and was favorable for increasing the corridor's species richness.

5.3. Identification of ecological protection/restoration nodes

On the basis of realizing ecological corridor extraction, the key nodes in the corridor were further identified by combining Pinchpoint Mapper and Barrier Mapper tools (Figure 7). The main urban area's southern region was where 14 significant ecological protection nodes had been found in this article, with a sparse distribution in Jiawang District, Tongshan District, Pizhou City, and Xinyi City. The pinch point was the area in the ecological corridor that needs to be protected. The connectivity between ESs would be impacted if the pinch point's function was lost or damaged. Obstacle points were the places that hindered the connection of ecological patches. The connection between the landscape and ecological stability could be greatly enhanced by the restoration of barrier points. The existing corridor had 10 barriers, and the most of which were found in Tongshan District, Quanshan District, and Gulou District. Key ecological protection/restoration areas in Xuzhou City covered a total area of 4.74 km^2.

6. Discussion

6.1. The relationship between supply—demand of ESs and ESPs

Ecological security is the manifestation of ESs, and the supply–demand of ESs is the bridge between ecological security and

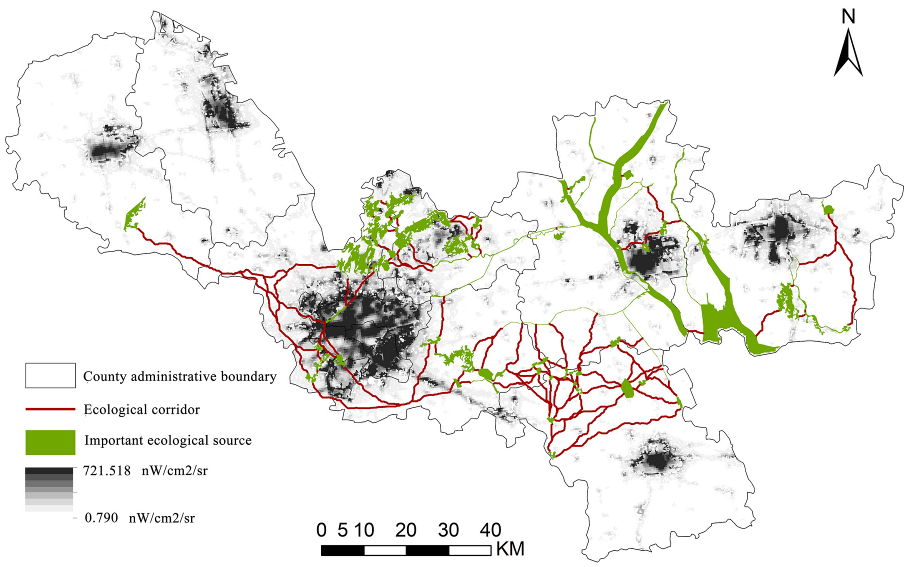

FIGURE 6
Spatial distribution of ecological corridors in Xuzhou.

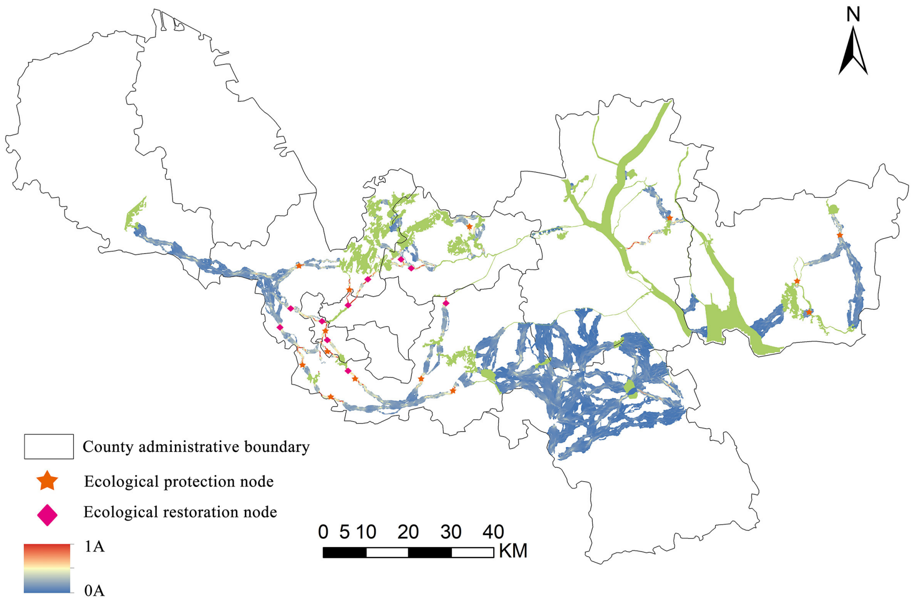

FIGURE 7
Critical ecological protection/restoration areas in Xuzhou.

human wellbeing. Ecological security is an abstract concept that refers to the ecological environment in which humans live and develop being entirely or partially free of risks and having the capacity to address important ecological issues. The objective of the creation of the ESP is to ensure the survival requirements of human society and to realize the sustainable growth of humans and the ecological environment. Its evaluation is centered on the stress and reaction between the ecosystem and human health. The supply–demand of ESs also emphasizes the relationship between the ecosystem and human wellbeing, which is the various benefits that mankind obtains from the ecosystem. Ecological security, on the one hand, is a representation of ESs. ESs supply will fail as a result of economic and social development harming the ecological environment, which will reduce human demand for ESs. For example, due to the long-term discharge of agricultural, industrial, and domestic sewage along the coast of China's Taihu Lake, the breakout of the blue-green algae crisis in Taihu Lake in 2007 directly resulted in a water shortage of millions of people. On the other hand, the balance between the supply and demand of ESs is the link between ecological security and human wellbeing. For instance, urban heat island, air pollution, and other problems are the result of an imbalance between the supply and demand of ESs, which has severely impacted the human and ecological environment's sustainable growth.

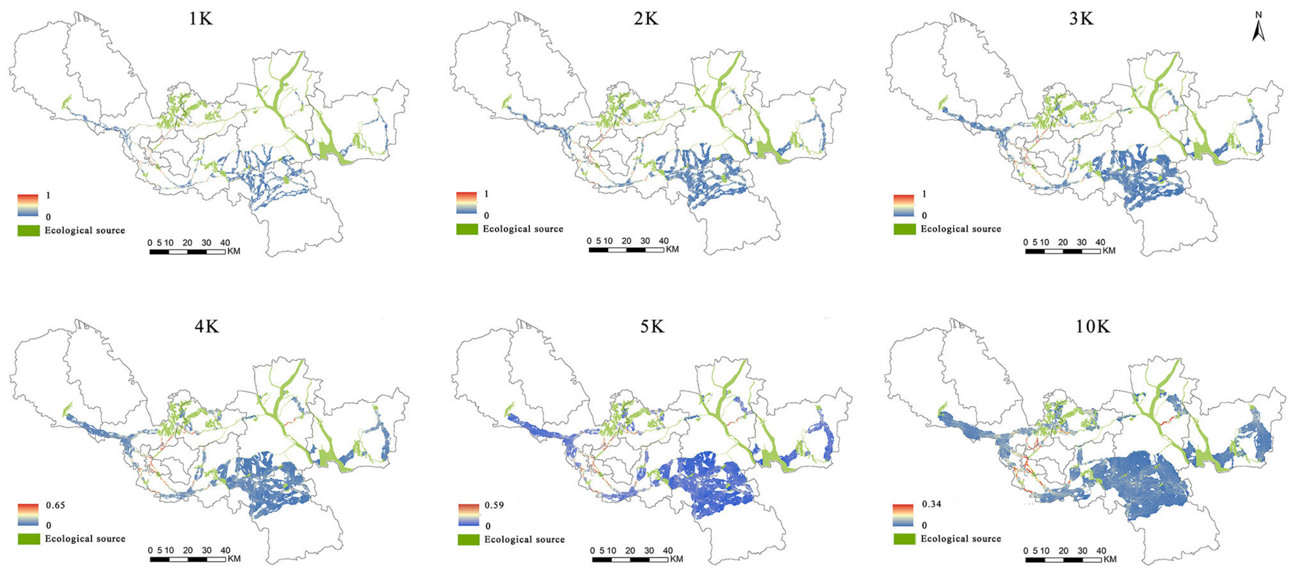

FIGURE 8
Ecological corridor extent and cumulative proportion at different thresholds (K for thousands and the number in each image represents the distance threshold for corridor recognition).

The introduction of the perspective of supply and demand for ESs provides crucial theoretical guidance for the development of ESPs. Internationally, this article seems to be the first time to use ecosystem service demand to build the resistance surface of ESP. The supply of ESs from the source to other units is influenced by factors such as accessibility, cost, and the level of economic and social development, which are frequently reflected in human demand for ecological services. This concept offers novel insights for the construction of ESPs.

6.2. Influence of resistance threshold on the ecological corridor

The main function of an ecological corridor is to connect different ecological source areas to maintain ecological processes. The spatial scope of the corridor directly affects the supply and demand of ESs (31, 51). The extent of an ecological corridor can be identified by cumulative resistance with a specific threshold, but there is still no consensus on the best approach (8). The distribution of ecological corridors in the study area showed spatial heterogeneity. In the areas with little change of slope and elevation and little human influence, the resistance of species migration and energy flow is small, and the spatial range of the ecological corridor is long. In contrast, in cultivated land and construction areas with high slope, high altitude or more man-made impacts, it is difficult to have appropriate circulation channels for ecological elements (10).

The ecological function of a corridor is closely related to its spatial scope, which plays a significant part in maintaining ecology. The corridor range distribution was examined in this study using various resistance thresholds, which revealed identical spatial distribution and various width ranges (52). This study attempted to define the spatial extent of the ecological corridor by raising the cumulative resistance threshold from 1 to 10 K (Figure 8). Although the total area of the ecological corridor has increased, the location of pinch points and obstacle points has not changed significantly, indicating that the model is effective for the judgment of the protection/restoration area (16). The larger the threshold value is set, the wider the ecological protection/restoration area will be, and the more expensive the actual protection and restoration will be. This study considers that Xuzhou has a large urban area and a limited budget for ecological protection/restoration. At the same time, under the control of territorial space planning, the oversized ecological network will encroach on a large number of permanent basic farmland and existing construction space, resulting in great difficulty in coordination and thus reducing operability. It is assumed that the funds and policies for ecological protection and restoration can only support 20% of the whole research area (16, 31). Therefore, 3 K is selected as the threshold range.

6.3. Policy suggestions on crucial regions of ecological protection/restoration in Xuzhou

Our overall approach to the ecological protection/restoration proposal in Xuzhou is to take into account the supply and demand of ESs, focus on corridor connectivity, and carry out ecological conservation/restoration at key nodes. This is because the most important function of ecological protection or restoration nodes is to be able to achieve focus on key locations within ecologically fragile areas. Combined with the research results, we found that ecological protection nodes are concentrated in the inter-patch corridor and the internal corridor in the south of Jiawang District and Tongshan District, while ecological restoration nodes are mainly distributed in Quanshan District and Gulou District, mostly concentrated in densely populated built-up areas and related development and construction projects.

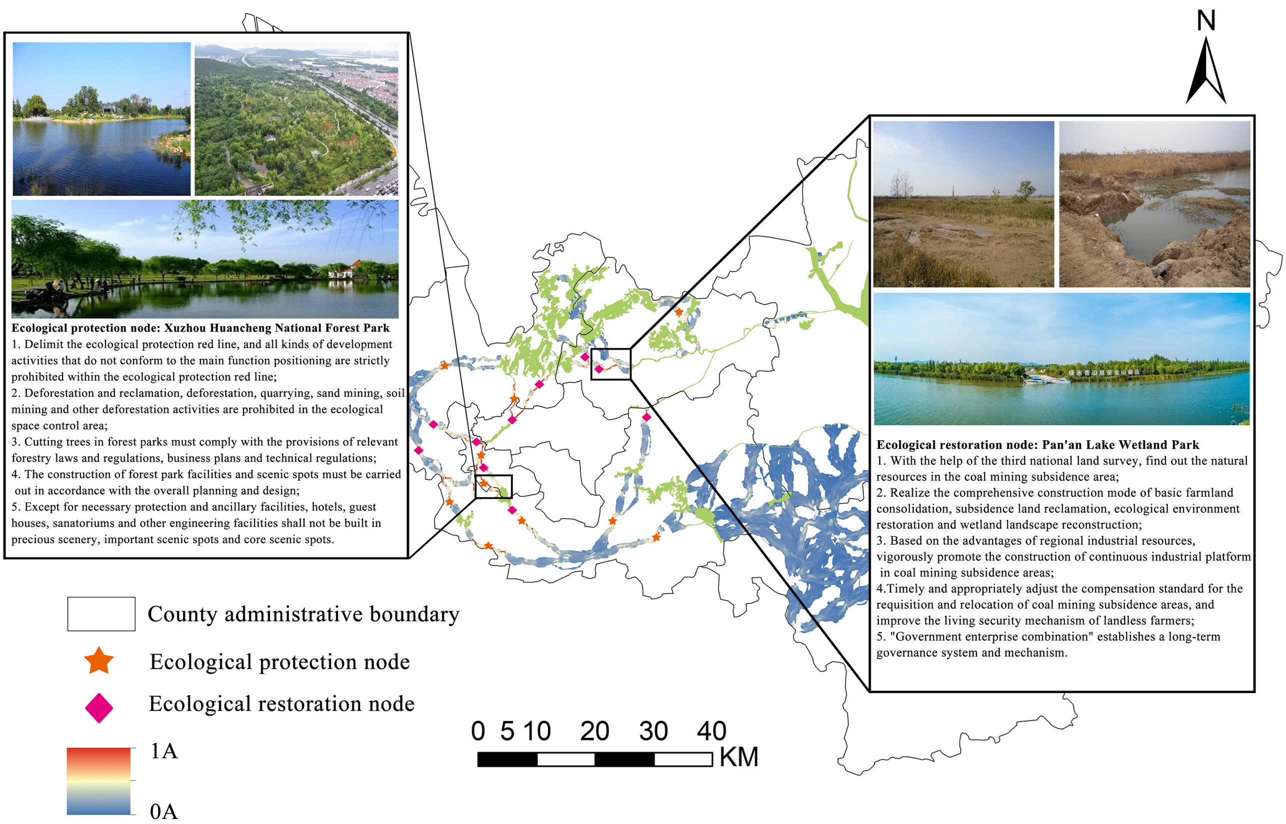

FIGURE 9
Two cases of key ecological protection/restoration areas in Xuzhou.

First of all, the protection of the ecological source should consider delimiting the core area, ensuring the habitat of the population and the intact natural landscape, and establishing the buffer zone outside the core area, so as to reduce the disturbance of human activities to the natural nature of the ecological source area as far as possible (19, 53). Second, ecological corridors are defined at different spatial and temporal scales to connect ecological sources and improve habitats by building forest road networks or building ecological bridges with local ecosystems. Finally, for the main supply areas of ESs such as nature reserves, forest parks, and reservoirs, it is necessary to develop tourism resources and eco-cultural industries to promote the realization of the value of ecological products.

The identification of ESP can determine the overall situation of regional ecological protection/restoration. However, the ecological protection and restoration oriented to the implementation of the project need to determine the specific nodes. We selected two nodes that represent typical patterns of ecological protection and restoration (Figure 9).

For the ecological protection node, we chose Xuzhou Beltway National Forest. Xuzhou Ring City National Forest Park has a beautiful natural landscape and rich animal and plant resources. The region should, therefore, be protected through the establishment of regulatory measures. For example, through China's ecological red line policy, to limit the ecological red line of different types of development activities, including deforestation reclamation and deforestation quarrying, sand mining, and soil mining. For the ecological restoration node, we chose Pan'an Lake, Xuzhou. The area was once Xuzhou's largest coal-mining subsidence area, with an area of 12.6 km^2. Such areas are typical of Xuzhou. On the one hand, the restoration of this kind of area should be done through the water system, construction of wetland ecological conservation area, and implementation of ecological interception and other ecological projects. On the other hand, a series of standards have been developed to regulate ecological restoration projects, such as "the technical standards for ecological restoration in North China Plain coal-mining subsidence areas."

7. Conclusion and limitations

Ecological security is the manifestation of ESs, and the supply–demand of ESs is the bridge between ecological security and human wellbeing. The research has three possible contributions: (1) coupling the supply–demand theory of ESs with the construction of ESPs, (2) proposing a research framework for the ESPs of "supply–demand–corridor–node," and (3) using the circuit theory model, the important ecological protection/restoration areas in the study area were identified. The results showed that the area of the supply source of ESs in Xuzhou City is 573.89 km^2, accounting for 5.19% of the study area. The greatest ecological source patch covered 152.26 km^2. The spatial distribution of 105 ecological corridors revealed that there were multiple and dense ecological corridors in the middle of the city, but few in the northwest and southeast. In all, 14 ecological protection areas were located primarily in the south of the urban area, and 10 ecological restoration areas were located primarily in the middle and north of the urban area, with a total area of 4.74 km^2. The findings of this article would be useful in developing ESPs and determining important ecological protection/restoration areas in Xuzhou, China. This article shows that the supply and demand assessment of ESs not only integrates ecological processes and ecological functions but also fully considers the needs of economic society for ecology. The introduction of the perspective of supply—demand of ESs provides important theoretical guidance for the construction of ESPs.

There are still some limitations to this study. First of all, we did not consider the trade-offs and synergies between different ESs. Therefore, when we extract important ecological patches by superimposing a variety of ESs, duplication may occur (54, 55). Second, there are challenges in methods and standards when using ESs demand as the resistance surface. This article is only a preliminary exploration, which needs to be studied more systematically in the future. Finally, it is difficult to distinguish the supply and demand of ESs. For example, food production is not only the material supply of ESs but also the demand of human beings for ESs. More scientific index selection needs further research.

Data availability statement

The original contributions presented in the study are included in the article/Supplementary material, further inquiries can be directed to the corresponding authors.

Author contributions

ZW: writing—original draft and data curation. JZ: data curation and software. JC: editing and supervision. HG: supervision and writing—review and editing. JL: supervision. ML: writing—review and editing. All authors have read and agreed to the published version of the manuscript.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

The reviewer YM declared a shared affiliation with the author JL to the handling editor at the time of review.

Publisher's note

Supplementary material

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/fpubh.2023.1087588/full#supplementary-material

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Dynamic evolution characteristics and driving factors of tourism ecosystem health in China

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Tourism ecosystem health is key to high-quality tourism development. China is now promoting sustainable development and high-quality transformation and upgrading of regional tourism; thus, the research on tourism ecosystem health is of practical significance. Based on the DPSIR model, an evaluation index system of tourism ecosystem health in China was constructed. Then the entropy weight method, spatial autocorrelation analysis, Markov chain analysis, and quantile regression were used to explore the dynamic evolution characteristics and driving factors of tourism ecosystem health in China from 2011 to 2020. The following conclusions were drawn: (1) The tourism ecosystem health in China showed an M-shaped fluctuation process as a whole, with significant spatial correlation and spatial difference. (2) There was a "path-dependent" and "self-locking" effect on the type transfer of tourism ecosystem health, and the type transfer was mainly between adjacent types in successive transfers, with the probability of downward transfer higher than upward transfer, and the geospatial background played a significant role in its dynamic evolution process. (3) In provinces with low tourism ecosystem health type, the negative effect of technological innovation capacity was more significant, and the influence coefficient of the positive effect of tourism environmental regulation and information technology level was larger, while in provinces with high tourism ecosystem health type, the negative effect of tourism industry agglomeration was more significant, and the influence coefficient of the positive effect of tourism industry structure and tourism land-use scale was larger.

KEYWORDS

tourism ecosystem health, dynamic evolution, Markov chains, quantile regression, China

1. Introduction

The tourism business, like other industries, has a paradoxical connection with the ecological environment due to the dual industrial qualities of environmental dependence and resource consumption (1–3). With the rapid growth of tourism and the advent of "mass tourism", health issues affecting the industry's ecosystem have gradually surfaced (4, 5). Phenomena like excessive resource consumption, ecosystem degradation, biodiversity loss, and rising environmental pollution limited the resilience of sustainable tourism development (6–8). It has become a paramount practical concern to find a solution to integrate the interaction between ecological protection and tourism development and sustain the health of the tourism ecosystem. Exploring sustainable tourism development models has emerged as the most crucial challenge in China's tourism development as one of the nations with the fastest global tourist growth rates (9, 10). The report of the 20th CPC National Congress and the 14th Five-Year Plan for Tourism Development both place "promoting harmonious coexistence between man and nature" at the top of the overall agenda under the new development concept of "innovation, coordination, green, openness, and sharing", and tourism ecosystem health has also grown to be a significant research area of high-quality tourism development. The research on tourism ecosystem health, with a particular focus on spatial and temporal dynamic evolution as well as driving factors, is thus crucial to the improvement of sustainable development and the high-quality transformation and upgrading of regional tourism in China.

Rapport, a Canadian scholar, introduced the concept of ecosystem health—which connects human health, human activity, and ecosystem change—into the field of ecosystems in 1979 (11). Since tourism ecosystems are stable, dynamic, and sustainable, the term "tourism ecosystem health" refers to the capacity of a system to maintain its own structural and functional integrity in the face of disturbances, such as those caused by human tourism activities (12, 13). It is widely acknowledged that a healthy tourism ecosystem is one in which the ecosystems themselves function in an orderly manner, satisfy the material and ecological needs of visitors and locals (14–16), and are capable of self-regulation and stress resistance (17, 18). The study of tourism ecosystem health, which concentrated on coordinating man-land connections, proliferated and flourished vigorously in the 1990s with the explosion of tourism sustainable development research and the International Society for Ecosystem Health (19–24). Previous studies have investigated tourism ecosystem health from the perspectives of disciplines such as geography, management, tourism, environment, and ecology (13, 25), including conceptual connotations, measurement and evaluation, spatial and temporal evolution characteristics, coordination status, trend prediction, influencing factors, and optimization paths (13, 25–29). Regarding research scales, tourism ecosystem health has been calculated at regional, urban, scenic, lakes, nature reserves, wetlands, and islands scales (25, 28–34). For the index system and measurement methods, the academic circles have started from the definition and characteristics of tourism ecosystem health, constructed a tourism ecosystem health evaluation index system based on the pressure-state-response (PSR) framework model, the drive-pressure-state-impact-response (DPSIR) framework model, and the vigor-organization structure-restoring force-service function-community crowd health-education level (VORSH) framework model (25, 28, 29, 31, 33), and then used the least squares method, the entropy weight method the fuzzy mathematical method and the analytic hierarchy method (AHP) to quantitatively measure tourism ecosystem health (26, 28, 31, 33). In recent years, constant attention has been given to analyzing factors influencing tourism ecosystem health. Most studies have used the gray correlation fuzzy assessment model, the obstacle degree model, the geographic detector model, etcetera (13, 29, 30).

To sum up, the existing studies have comprehensively examined tourism ecosystem health. They have produced a variety of findings that may be utilized as references in this paper. However, there are still several issues that need to be explored. First, there was broad agreement that the PSR model, the DPSIR model, or the VORSH model could be used to construct a tourism ecosystem health evaluation index system, but the coverage of specific indicators needed to be expanded and strengthened. Second, most previous studies used the traditional panel data model, which conforms to the normal distribution conditional mean, to identify the factors influencing tourism ecosystem health. Consequently, the possibility of different influencing factors in different regions of the tourism ecosystem health level was ignored. In addition, given the higher strategic value of sustainable tourism development and high-quality transformation and upgrading, little attention has been given to the spatial correlation and dynamic transfer of tourism ecosystem health at the national scale in the results of the available study, which are mostly focused on the dimensions of specific areas and economic zones. This paper attempts to deepen the previous research further based on these three deficiencies. Therefore, we selected 30 provinces (excluding Tibet, Hong Kong, Macao, and Taiwan) in China as the research subjects, then constructed a tourism ecosystem health evaluation index system based on the DPSIR model and used the entropy method to assess that health from 2011 to 2020. Meanwhile, the dynamic evolution characteristics of the tourism ecosystem health were explored through the entropy weight method, spatial autocorrelation analysis, and Markov chain analysis. Moreover, the panel quantile regression model was used to identify the driving forces behind the shifting trends in tourism ecosystem health under various quantile conditions. The research findings of this paper are intended to comprehensively understand the dynamic evolution characteristics and driving factors of tourism ecosystem health in China and provide a theoretical basis and decision-making reference for provinces with different levels of tourism ecosystem health so that it can promote the coordinated development of tourism and the eco-environment.

2. Materials and methods

2.1. Entropy weight method

The subjective assignment approach introduces the impact of human factors. However, the entropy weighting method uses the original information of the indicators as the foundation for assigning weights, which can adequately reflect the significance of each indicator in the comprehensive index. The entropy weight method calculated the evaluation index weight of tourism ecosystem health. The following are the specific steps for implementation (35):

The first step is to standardize the evaluation indexes.

$$\text{Positive index}: x_{ij}' = \frac{x_{ij} - \min x_{ij}}{\max x_{ij} - \min x_{ij}} \tag{1}$$

$$\text{Negative index}: x_{ij}' = \frac{\max x_{ij} - x_{ij}}{\max x_{ij} - \min x_{ij}} \tag{2}$$

In Formulas (1) and (2), x_{ij}represents the original index j in the region i; x_{ij}'represents the index after standardization processing; maxx_{ij} and minx_{ij}represent the maximum and the minimum values of index j, respectively.

The second step is to calculate the weight. In Formulas (3) and (4), $w_{ij}$is the proportion of index j under the region i; e_j is the entropy value of index j, and ϕ_j is the index weight. The specific

TABLE 1 Tourism ecosystem health level standard.

Health state	Unhealthy level	Sub-healthy level	Generally healthy level	Very healthy level
Health type	I	II	III	IV
Health value	(0,0.30]	(0.30,0.40]	(0.40,0.55]	(0.55,1]

Formula is as follows:

$$w_{ij} = \frac{x'_{ij}}{\sum_{i=1}^{m} x'_{ij}},\ e_j = -\frac{1}{\ln m}\sum_{i=1}^{m} w_{ij} \times \ln w_{ij} \quad (3)$$

$$\varphi_j = \frac{(1-e_j)}{\sum_{j=1}^{m}(1-e_j)} \quad (4)$$

The third step is a comprehensive evaluation index of tourism ecosystem health (TEH_i).

$$TEH_i = \sum_{j=1}^{m} \varphi_j \times w_{ij} \quad (5)$$

Integrating the results of the actual measurement of tourism ecosystem health in China and the synthesis of existing studies (28, 33), the tourism ecosystem health of 30 provinces in China was divided into four types: non-healthy level, sub-healthy level, generally healthy level, and very healthy level (Table 1).

2.2. Global spatial autocorrelation analysis

Global spatial autocorrelation analysis, frequently measured by the global Moran's I index, is used to evaluate the overall spatial dependency between different geographical areas (36). In this paper, the global Moran's I index can reflect the spatial autocorrelation of tourism ecosystem health in China as a whole. The Formula for calculating the global Moran's I index is:

$$Global\ Moran's\ \mathrm{I} = \frac{n\sum_{i=1}^{n}\sum_{j=1}^{n} W_{ij}(x_i-\bar{x})(x_j-\bar{x})}{\sum_{i=1}^{n}\sum_{j=1}^{n} W_{ij}\sum_{i=1}^{n}(x_i-\bar{x})^2} \quad (6)$$

In Formula (8), n represents the total number of provincial samples, which is 30 here; $x_i$and $x_j$represent the tourism ecosystem health measures of provinces i and j, respectively; x is the arithmetic means of the tourism ecosystem health of all provinces; W_{ij} is the adjacency weight matrix, which indicates the adjacency relationship between two provinces, and W_{ij}= 1 when provinces i and j are adjacent, otherwise it is 0. The value of global Moran's I index is $[-1, 1]$. The more the value of this index tends to 1, the stronger the correlation in the tourism ecosystem health space. The value of this index tends to 0, which indicates spatial decorrelation and random distribution in space.

2.3. Markov chain analysis method

The Markov chain, a transition matrix and the simplest stochastic model has been extensively used for state change studies at various spatial scales (37). In this paper, the Markov chain analysis method was used to calculate the initial and transfer probability of different states of tourism ecosystem health, and the trend over time was determined. Assuming that $M_t = [\ M_{1,t}, M_{2,t}, M_{3,t}, \ldots\ M_{k,t}]$ is a vector of $1 \times k$ state probability distributions in year t, the transfer between various types of tourism ecosystem health in different years can be represented by a Markovian transfer probability matrix of order $z \times z$:

$$P = \begin{pmatrix} p_{11} & \cdots & p_{1k} \\ \vdots & \ddots & \vdots \\ p_{k1} & \cdots & p_{kk} \end{pmatrix} \quad (7)$$

In Formula (9), p_{ij} represents the probability of a random process transitioning from state type i in year t to state type j in year $t+1$, and it can be calculated as α_{ij}/α_i; α_{ij} represents the number of provinces of type i in year t transferred to type j in year $t+1$ and α_i represents the number of provinces of type i in all years.

To examine the relationship between the probability of transfer of tourism ecosystem health types and neighboring provinces, the spatial Markov chain analysis incorporated the spatial lag factors into the analytical framework based on the traditional Markov chain analysis (38). The traditional z-order transition probability matrix ($z \times z$) is broken and decomposed into n conditional transition probability matrices ($z \times z \times z$) by the spatial Markov chain transition probability matrix. In the z-th condition matrix, P_{zij} designates the probability that a province a that was in type i in year t transfers into type j in year t + 1, conditional on a spatial lag type of z. The spatial lag value for province a is a weighted average of the tourism ecosystem health of the province's spatial neighbors. The calculation Formula is:

$$Lag_a = \sum Y_b W_{ab} \quad (8)$$

In Formula (10), W_{ab} is the adjacency weight matrix, which indicates the adjacency relationship between two provinces, and $W_{ab} = 1$ when provinces a and b are adjacent; otherwise, it is 0. Y_b represents the tourism ecosystem health in province b; Lag_a represents the spatial lag value of province a, indicating the state of the neighborhood of province a. By comparing the traditional Markov chain matrix and the spatial Markov chain matrix, it is possible to determine the importance of the surrounding area on the probability of a particular spatial province's type transition.

2.4. Panel quantile regression model

Koenker and Basett proposed the quantile regression model to overcome the shortcomings of the traditional regression method, which can only obtain the average influence of the explanatory variables on the dependent variable (39). The difference in significance levels and regression coefficients at various quantiles in the quantile regression model can reflect the heterogeneity of the influence of the explanatory variables on the explained variables. Tourism ecosystem health varies from province to province, and explanatory variables affect those with high tourism ecosystem health differently than those with low tourism ecosystem health. Therefore, the quantile regression model can comprehensively, systematically, and dynamically reveal the effect of driving factors on tourism ecosystem health. For the panel data, the quantile regression model is set as follows (40):

$$Y_{it} = x_{it}^{T}\beta_i + \alpha_i + \mu_{it}, \quad (i = 1, 2, \cdots K;\ t = i = 1, 2, \cdots T) \tag{9}$$

$$Q_{y_{it}}(\tau | x_{it}, \alpha_i) = x_{it}^{T}\beta(\tau_q) + \alpha_i \tag{10}$$

In Formula (11) and (12), x_{it} represents the independent variable of province i in the $1\times k$ dimension of year t; β_i and $\alpha_i$are the parameters to be estimated, and μ is a random error; Q_{yit} represents the tourism ecosystem health at the quantile under the given explanatory variable conditions; τ represents the quantile points. The following Formula generally calculates the parameter β:

$$\beta = \arg\min_{\alpha,\beta} \sum_{q=1}^{Q}\sum_{t=1}^{T}\sum_{i=1}^{N} W_k\rho_\tau[y_{it} - x_{it}^{T}\beta(\tau_q) - \alpha_i] \tag{11}$$

In Formula (13), $\rho_\tau$represents the quantile loss function; W_k represents the weight coefficient of the k quantile; $\beta(\tau_q)$ represents the influence coefficient of the k quantile.

Based on the current state of China's tourism industry and data availability, six indicators were selected to quantify the factors driving the change process in the spatial and temporal patterns of tourism ecosystem health under multiple factors. These indicators include tourism industry structure, tourism industry agglomeration, tourism environmental regulation, information technology level, technological innovation capacity, and tourism land-use scale (Table 2).

TABLE 2 Variables and explanations of tourism ecosystem health influencing indicators.

Driving factors	Abbreviation	Definition
Tourism industry structure	TIS	Tourism industry structure rationalization index
Tourism industry agglomeration	TIA	Location quotient
Tourism environmental regulation	TER	Cost of pollution control/tourism revenue
Information technology level	INFO	Internet broadband access users
Technological innovation capacity	TIC	R&D expenditure
Tourism land-use scale	TLS	Tourism revenue/provincial area

2.5. Evaluation index system and data source

The PSR model served as the foundation for the DPSIR model, which was first proposed and utilized by the European Environment Agency (EEA) to provide a more thorough understanding of the interactions and feedback mechanisms between human activities and the biological environment (41). The DPSIR model for tourism ecosystem operations is as follows: for an extensive period, economic and social development and tourism demand act as driving forces (D) on the ecosystem, resulting in several pressures (P) on the environment and changing the health state (S) of the tourism ecosystem, which in turn has a variety of impacts (I) on individuals, nature, and society, forcing human society to respond to ecological changes (R). Combining the characteristics of tourism ecosystems and the concept of tourism ecosystem health, this paper constructs a set of indicators for assessing the tourism ecosystem health in China (13, 42), as shown in Table 3.

The data in this paper were mainly derived from the "China Statistical Yearbook", "China Tourism Statistical Yearbook", "China Culture and Tourism Yearbook", the yearbooks of each province, and the Statistical Bulletin of National Economic and Social Development of each province. Some missing data was supplemented using the linear interpolation method. Following data collection, panel data for 30 Chinese provinces from 2011 to 2020 were obtained.

3. Results

3.1. Spatial and temporal characteristics of tourism ecosystem health

3.1.1. Time-series evolutionary characteristics

According to Formula (1)–(7), the tourism ecosystem health of 30 provinces in China from 2011 to 2020 was evaluated based on the constructed evaluation index system of tourism ecosystem health, and the trend of change was plotted (Figure 1). During the study period, the tourism ecosystem health in China showed an M-shaped fluctuation process of "increasing-decreasing-increasing-decreasing", with a three-stage evolution. In the first stage (2011–2012), tourism ecosystem health rose from 0.164 in 2011 to 0.361 in 2012, an increase of 120.12%. China introduced the 12th Five-Year Plan in 2011, and the government has emphasized structural adjustment, energy conservation, emission reduction, and coordinated regional development. Moreover, the Opinions on Accelerating Tourism Development and the National Ecotourism Development Outline (2008–2015) have clearly defined initiatives to develop low-carbon tourism and green tourism, reinforcing the correlation between ecological protection and

TABLE 3 Tourism ecosystem health evaluation index system.

Dimension	Sub-dimension	Index (unit)	Positive/negative
Driving force (D)	Economic development	Per capita GDP (yuan)	Positive
		Disposable income per resident (yuan)	Positive
	Social life	Natural population growth rate (%)	Negative
		Urbanization rate (%)	Negative
	Tourism demand	Growth rate of tourists (%)	Negative
Pressure (P)	Ecological environment	SO_2 emission per unit area (t/hm^2)	Negative
		Sewage discharge density (m^3/hm^2)	Negative
	Social life	Per capita daily water consumption (m^3/person)	Negative
		Population density (person/hm^2)	Negative
	Tourism reception	Tourist traffic pressure (person times/km^2)	Negative
		Visitor density (person times/hm^2)	Negative
State (S)	Ecological environment	Proportion of good air quality days (%)	Positive
		Percentage of forest cover (%)	Positive
		Per capita arable land (hectare/person)	Positive
	Tourism resources	Tourism resources density (units/million km^2)	Negative
		Tourism resource taste (%)	Positive
	Tourism facilities	Density of star-rated hotels (units/million km^2)	Negative
		Travel agency density (units/million km^2)	Negative
	Tourism economy	Domestic tourism revenue (billion yuan)	Positive
		Tourism foreign exchange earnings (USD billion)	Positive
Impact (I)	Ecological environment	Decline rate of ecological land (%)	Negative
	Sudden environmental incidents	Rate of increase in sudden environmental incidents (%)	Negative
	Economic structure	Proportion of total tourism revenue in GDP (%)	Positive
		Proportion of tertiary industry in GDP (%)	Positive
Response (R)	Government regulation and control	Proportion of environmental investment in GDP (%)	Positive
		Number of college students per 100000 population (%)	Positive
	Environmental governance	Urban domestic sewage treatment rate (%)	Positive
		Harmless domestic waste treatment rate (%)	Positive

tourism development. Policy guidelines have promoted the green transformation and enhancement of China's tourism industry, resulting in a more substantial improvement in tourism ecosystem health. In the second stage (2012–2015), tourism ecosystem health declined slowly from 0.361 in 2012 to 0.328 in 2015, a decrease of 3.3%. The adverse effects of the crude growth of the tourism economy at this stage have gradually emerged. The intensification of resource and environmental constraints has diminished tourism ecosystem health. Tourism ecosystem health in the third stage (2015–2020) showed an inverted N-shaped trend. At the beginning of this stage, China's economy entered a period of new normal, with the deepening of the concept of ecological civilization and increased government efforts to combat environmental pollution, resulting in a rise in tourism ecosystem health. However, with the impact of the new crown epidemic (Covid-19) on both the supply and demand sides, tourism ecosystem health has gradually shifted toward a downward phase.

The kernel density of the Gauss kernel function, depicted by Matlab R2011b software in Figure 2, was estimated to define the time-varying process of the absolute differences in the tourism ecosystem health across provinces. Then, utilizing the distribution location, distribution trend, and distribution extensibility, the kernel density was estimated using the Gauss kernel function to illustrate the dynamic evolution of the tourism ecosystem health in China. The nuclear density distribution curve shifted first to the right, then to the left, then to the right, and finally to the left from 2011 to 2020. This indicates that the tourism ecosystem health in China has undergone the process of "increasing-decreasing-increasing-decreasing", which is in line with the trend analyzed above. The overall kernel density exhibited a right-trailing phenomenon concerning the extension of the distribution over time, indicating that the gap between China's tourism ecosystem health and the average has widened and that the types of provinces with high tourism ecosystem health levels were increasing faster

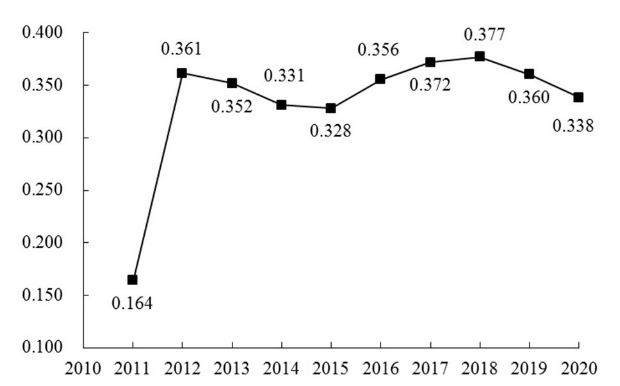

FIGURE 1
The trend of tourism ecosystem health in China from 2011 to 2020.

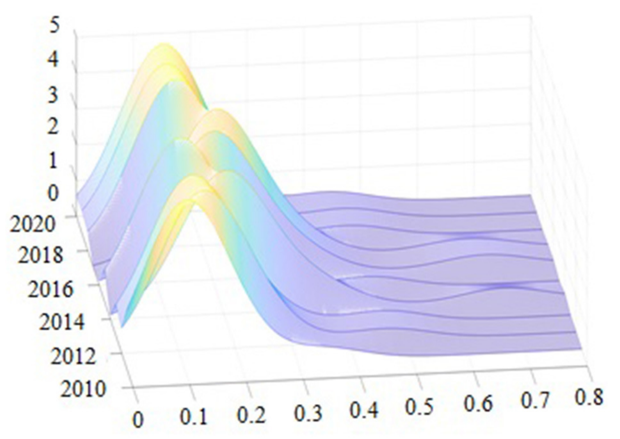

FIGURE 2
The Kernel density estimation of tourism ecosystem health in China.

while the types of provinces with low tourism ecosystem health levels were decreasing. From a morphological point of view, the overall kernel density curve did not show a decreasing peak or increasing width. However, the sample period was characterized by multiple peaks, implying a particular gradient of differences in the tourism ecosystem health in China.

3.1.2. Spatial differentiation characteristics

According to Formula (8), combined with the measured value of tourism ecosystem health, using the Rook spatial weight matrix (Hainan and Guangdong were set as neighbors to avoid the "island phenomenon"), the spatial autocorrelation of tourism ecosystem health in China is tested and analyzed, and the global Moran's I index test results were calculated using Stata 16.0 software (Table 4). It can be seen from Table 4 that the global Moran's I index of tourism ecosystem health in China from 2011 to 2020 was all positive and passed the statistical test, reflecting a solid spatial correlation. China's spatial distribution of tourism ecosystem health was not isolated and random. However, it showed apparent spatial dependence and agglomeration, such as convergence between provinces with high tourism ecosystem health level types, forming a "high-high" agglomeration pattern, and the convergence between provinces with low tourism ecosystem health level types, forming a "low-low" agglomeration pattern. From 2012 to 2020, Moran's I index of tourism ecosystem health continued to decline in fluctuation, showing a trend of weakening spatial dependence, which, to a certain extent, indicated that China's tourism ecosystem health was gradually showing a coordinated and linked trend of regional integration.

With the help of ArcGIS 10.2 software, the spatial distribution map of tourism ecosystem health in 2011, 2014, 2017, and 2020 was drawn, and the tourism ecosystem health was divided into four types, which were non-healthy level, sub-healthy level, generally healthy level and very healthy level from low to high (Figure 3). During the inspection period, the provinces with higher tourism ecosystem health levels were mainly concentrated in Beijing, Shanghai, Guangdong, Jiangsu, and Zhejiang, accounting for a small portion of the total. This showed significant regional differences in the tourism ecosystem health in China, which were out of balance. Specifically, 28 provinces with non-healthy tourism ecosystem health levels in 2011, except for Beijing and Guangdong. Compared with 2011, Jiangsu and Zhejiang joined the provinces with generally healthy tourism ecosystem health levels, while Liaoning, Shandong, Fujian, and other provinces withdrew from the non-healthy level. In 2017, the provinces of the very healthy level type remained unchanged. Tianjin and Fujian went up from the sub-healthy level to the generally healthy level. In contrast, the provinces of the sub-healthy level type further expanded, most of which were concentrated in the central and western regions. In 2020, the spatial pattern of tourism ecosystem health in China was similar to that in 2017, with only minor changes found in the type of some provinces. From the spatial distribution pattern, it can be seen that the tourism ecosystem health showed the distribution law of decreasing gradually from the eastern coastal regions to the central, western, and northeastern regions. The provinces with higher tourism ecosystem health levels, driven by both their location and policy advantages, have achieved high-quality growth in the tourism economy under the intensive mode while simultaneously optimizing the structure of the tourism industry and environmental management through advanced technological advantages. The provinces with lower tourism ecosystem health levels were mainly severely constrained by their tourism resource endowment and location conditions, which, together with their strong dependence on tourism resources, has led to bottlenecks in the development of the tourism economy.

3.1.3. Dynamic evolutionary characteristics

This section used the Markov chain method to investigate the state transition of provinces in the distribution of tourism ecosystem health. It attempted to explore the long-term dynamic change trend of the differences in tourism ecosystem health between the various provinces in China. According to the type classification, the tourism ecosystem health of provinces can be discretized into four state-level types. Namely, non-healthy level (0, 0.30], sub-healthy level (0.30, 0.40], generally healthy level (0.30, 0.40] and very healthy level (0.55, 1], the completeness intervals of these four state types can be represented by k = I, II, III, and IV,

TABLE 4 Global Moran's I index from 2011 to 2020.

Year	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020
Moran's I	0.298	0.305	0.254	0.230	0.240	0.224	0.190	0.176	0.192	0.133
Z-scores	2.819	2.879	2.472	2.262	2.337	2.219	1.927	1.808	1.957	1.439
P-value	0.002	0.002	0.007	0.012	0.010	0.013	0.027	0.035	0.025	0.075

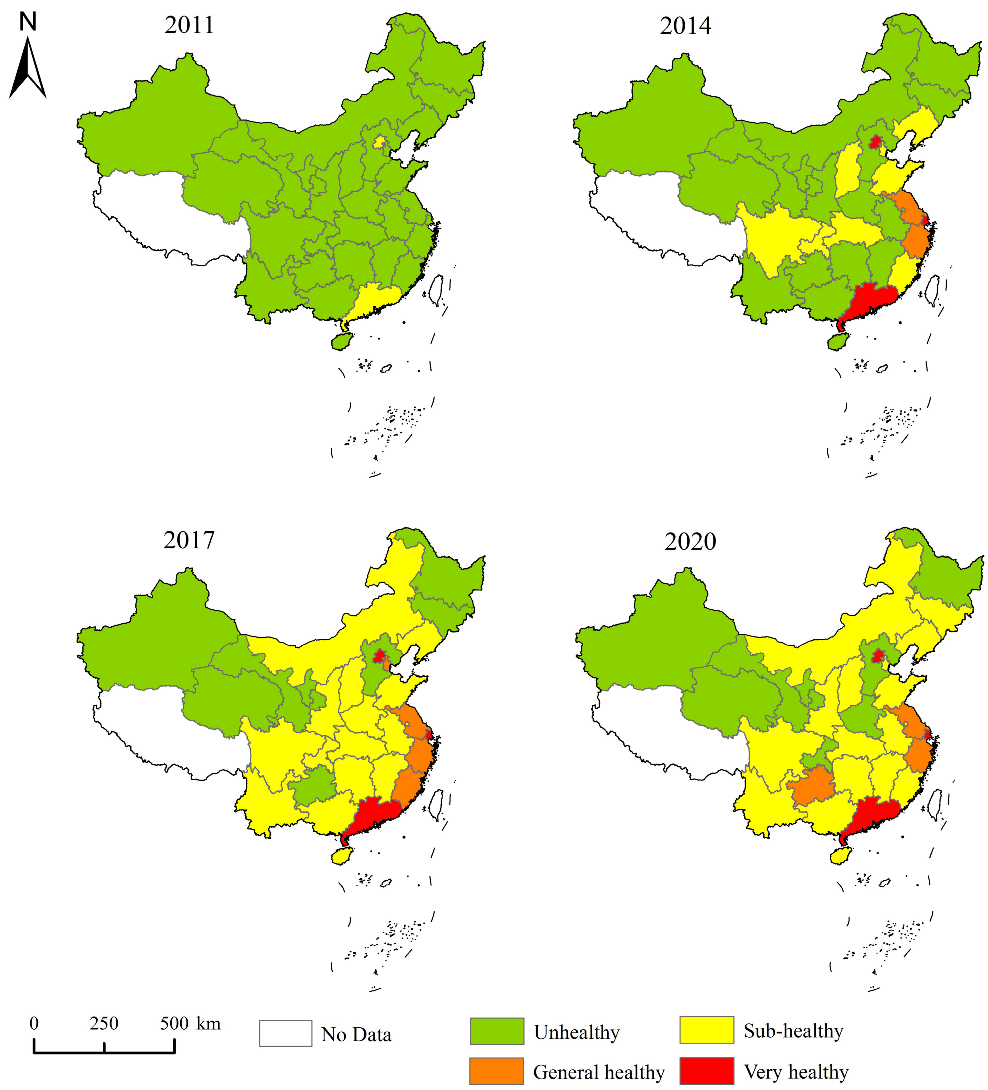

FIGURE 3
Spatial distribution patterns of tourism ecosystem health.

respectively. The definition of an upward transfer is from a low level to a high level, and the definition of a downward transfer is from a high level to a low level.

To further understand the dynamic evolution trend of tourism ecosystem health in China, the Markov transfer matrix of tourism ecosystem health in China was obtained using Matlab R2011b software (Table 5). The value on the diagonal line represents the possibility that the province will always remain at a particular state-level type. In contrast, the value on the off-diagonal line represents the probability that the various provinces will transition from one state-level type to another. Therefore, without considering the spatial effect, the dynamic evolution of tourism ecosystem health is characterized as follows: (1) The probability value on the diagonal line in the Markov transition matrix was significantly larger than those on the non-diagonal, with a minimum value of 72.41% and a maximum value of 100.00%. Under the above conditions, tourism ecosystem health attained at least 72.41% probability in the future development process and remained at the same state-level type. The probability of maintaining stability at each state-level type was greater than the probability of the upward transfer and the downward transfer, which reflected that the club convergence of tourism ecosystem health types was highly

TABLE 5 Markov transfer probability matrix for tourism ecosystem health types in China from 2011 to 2020.

t/t+1	*n*	I	II	III	IV
I	116	0.7241	0.2241	0.0431	0.0086
II	101	0.1188	0.8020	0.0594	0.0198
III	29	0.0000	0.2759	0.7241	0.0000
IV	24	0.0000	0.0000	0.0000	1.0000

TABLE 6 Spatial Markov probability matrix for tourism ecosystem health types in China from 2011 to 2020.

Geospatial background	t/t+1	*n*	I	II	III	IV
I	I	66	0.7273	0.1818	0.0758	0.0152
	II	22	0.0000	0.9091	0.0000	0.0909
	III	1	0.0000	1.0000	0.0000	0.0000
	IV	1	0.0000	0.0000	0.0000	1.0000
II	I	40	0.7250	0.2750	0.0000	0.0000
	II	57	0.1579	0.7895	0.0526	0.0000
	III	4	0.0000	0.5000	0.5000	0.0000
	IV	15	0.0000	0.0000	0.0000	1.0000
III	I	8	0.8750	0.1250	0.0000	0.0000
	II	16	0.0625	0.7500	0.1875	0.0000
	III	24	0.0000	0.2083	0.7917	0.0000
	IV	8	0.0000	0.0000	0.0000	1.0000
IV	I	2	0.0000	1.0000	0.0000	0.0000
	II	6	0.3333	0.6667	0.0000	0.0000
	III	0	0.0000	0.0000	0.0000	0.0000
	IV	0	0.0000	0.0000	0.0000	0.0000

stable, and its type transfer had a "path-dependent" and "self-locking" effect. (2) In terms of the probability value on both sides of the diagonal line, the probability of the non-healthy level type transitioning upward was 27.58%. It can be seen that the provinces with non-healthy level types were more likely to transfer upward, indicating that the tourism ecosystem health in the non-healthy level provinces was unstable and prone to state leapfrogging compared to other states. The probability of the sub-healthy level type transitioning downward was 11.88%, and the probability of the type transitioning upward was 7.92%. The probability of the downward shift of tourism ecosystem health at the sub-healthy level was more significant than the probability of the upward shift, which reflected that tourism ecosystem health still had a negative trend. The probability of the generally healthy level type transitioning downward was 27.59%, with the risk of a precipitous fall. (3) The probability values on both sides of the non-diagonal line were significantly smaller than those on both sides of the diagonal line, with a maximum value of only 0.86%, indicating that the improvement of tourism ecosystem health was a gradual process and that it was difficult to achieve leapfrogging in the short term.

The issue of spatial correlation is disregarded in the traditional Markov chain approach because it presumes that regions are independent of each other. This paper incorporated spatial lag into the traditional Markov chain analysis to investigate the neighborhood's influence and the probability that it will change among convergent groups. The results of the spatial Markov chain transition probability matrix of tourism ecosystem health in China from 2011 to 2020 are presented in Table 6.

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Through comparison with Tables 5, 6, the following spatial dynamic evolution characteristics of tourism ecosystem health could be obtained after considering the geospatial background: (1) Geospatial background played a significant role in the dynamic evolution process of tourism ecosystem health. The transfer probability of tourism ecosystem health varied against the neighborhood background, implying different levels of health. It also differed from that calculated using the traditional Markov probability transfer matrix. In particular, the probability of maintaining stability at the non-healthy level type in the traditional

Markov probability transfer matrix was 72.14%. In comparison, the probability of maintaining its original state-level type on different geospatial backgrounds was 72.73, 72.50, 87.50, and 0.00%, respectively, indicating a significant difference between the probability transfer of tourism ecosystem health with and without considering the geospatial background. (2) China's tourism ecosystem health exhibited a "spatial spillover" effect, with the tourism ecosystem health levels affecting each other between neighboring provinces. In general, the probability of the state-level type of province transferring downward would increase if it was adjacent to a province with a low tourism ecosystem health level. In contrast, the probability of the state-level type of province transferring upward would increase if it was adjacent to a province with a high tourism ecosystem health level. Specifically, as the state-level type of neighborhood tourism ecosystem health rose, the probability of the provinces of the non-healthy level type transitioning upward was 27.28, 27.50, 12.50, and 100.00%, showing a fluctuating upward trend; the probability of provinces of the generally healthy level type transitioning downward was 100.00, 50.00, 20.83, and 0.00%, showing a precipitous downward trend. This suggests that provinces with higher tourism ecosystem health levels have a radiation effect on their neighbors, whereas provinces with lower tourism ecosystem health levels may have an inhibition effect. Therefore, provinces with a high tourism ecosystem health level need to exploit their spillover effect actively and, through their radiation capacity, promote the health type of the surrounding provinces by leading from point to point.

3.2. Analysis of driving factors

In order to ensure the smoothness of the panel data time series and reduce heteroscedasticity in this paper, natural logarithms were taken as all non-percentage variables. At the same time, this paper employed both the LLC test, the Breitung test (which assumes a common unit root process), the IPS test, the Fisher-ADF test, and the Fisher-PP test (which assumes an individual unit root process) to probe the unit root properties of the study variables so that it could avoid problems such as multicollinearity and spurious regressions. According to the estimation results, every variable strongly rejected the null hypothesis that the panel had a unit root at a 1% significance level, indicating that the panel data were smooth and could be suitable for further regression analysis. This paper selected five representative quantiles for analysis, including 10, 25, 50, 75, and 90%. The Markov chain Monte Carlo (MCMC) method was adopted to estimate the driving factors of tourism ecosystem health to avoid possible endogeneity. The estimation results were presented in Columns (1) to (6) of Table 7. The changes in the quantile regression coefficients at different quantiles were displayed graphically in Figure 3. The estimated results were from stata16.0 software.

As shown in Table 7 and Figure 4, as a whole, tourism industry agglomeration and technological innovation capacity imposed negative influences on tourism ecosystem health, and tourism industry structure, tourism environmental regulation, information technology level, and tourism land-use scale were all significant in influencing tourism ecosystem health. However, the influence coefficients of each variable at different quantiles were significantly different.

(1) The results of the quantile regression of tourism industry structure (lnTIS) showed an M-shaped pattern, which was always positive and significant, indicating that the impact of tourism industry structure on tourism ecosystem health varies at different quantiles. The government should therefore transform the tourism economy and promote the integration of tourism industries to enhance tourism ecosystem health. It was important to note that the coefficient of influence of the tourism industry structure on the high quantile was relatively large. Therefore, the government should pay more attention to and strengthen the upgrading of the tourism industry structure in provinces with high tourism ecosystem health, thereby reducing duplicate construction and resource-consuming projects and increasing low-consumption, high-quality service projects, thereby promoting sustainable tourism development in these provinces.
(2) At the 10, 50, 75, and 90% quantiles, the absolute value of the coefficient of tourism industry agglomeration (lnTIA) had an increasing trend, indicating that tourism industry agglomeration was the main obstacle factor for provinces with high tourism ecosystem health in China, that is, the higher the level of tourism ecosystem health, the greater the pressure of tourism industry agglomeration on the ecosystem. Consequently, our results suggested that strengthening the centralization of resource use and the use of large-scale pollution control infrastructure in provinces with high tourism ecosystem health was one of the most effective ways to increase the resilience of sustainable tourism development in such provinces.
(3) Tourism environmental regulation (TER) significantly affected tourism ecosystem health at the lower quantiles, but this had no significant marginal impact as the quantiles increased. This may be because of the spatial mismatch between supply and demand in China's tourism resources and natural ecological background. The provinces with higher tourism ecosystem health types are generally more market-oriented regions, where the market itself can achieve an efficient allocation of resources through competitive mechanisms, price mechanisms, and supply and demand mechanisms. Too much macro-regulation is not conducive to forming environmental-economic systems such as green capital markets, green credit, ecological compensation, and other environmental-economic systems.
(4) The influence of technological innovation capacity (lnTIC) on tourism ecosystem health was negative, with a non-significant negative effect on technological innovation capacity at the higher quartiles (75% and 90%). All other quartiles showed a significant adverse effect at the 1% level. The absolute value of the coefficient of technological innovation capacity increased as the quantile decreased, with the negative effect reaching a maximum at the 10% quantile. According to our findings, the main obstacle factor for provinces with low tourism ecosystem health in China was a lack of technological innovation capacity.
(5) As the quantile changed, the value of the coefficient of information level (INFO) changed significantly, with the

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TABLE 7 The quantile regression model estimation results of driving factors of tourism ecosystem health.

Driving Factors	(1) OLS	(2) q10	(3) q25	(4) q50	(5) q75	(6) q90
ln TIS	0.037* (1.92)	0.125*** (3.49)	0.084*** (4.87)	0.059*** (3.25)	0.064*** (2.73)	0.131** (3.16)
ln TIA	−0.101*** (−5.52)	−0.008*** (−0.22)	−0.010*** (−0.59)	−0.023*** (−1.24)	−0.084*** (−3.49)	−0.103 (−2.45)
TER	0.003*** (3.97)	0.003*** (0.85)	0.016*** (0.81)	−0.003 (−0.19)	−0.003 (−1.03)	−0.005 (−1.09)
ln TIC	−0.015*** (−4.42)	−0.020*** (−1.67)	−0.012 (−2.20)	−0.010*** (−1.70)	0.003 (−0.04)	0.007 (0.48)
ln INFO	0.016*** (3.69)	0.018*** (1.32)	0.012 (1.78)	0.013** (1.89)	0.004 (0.37)	0.002*** (0.13)
ln TLS	0.070*** (12.41)	0.034*** (6.26)	0.033*** (12.31)	0.030*** (10.89)	0.035*** (9.63)	0.033*** (5.18)

t statistics in parentheses. $^{*}P < 0.05$, $^{**}P < 0.01$, and $^{***}P < 0.001$.

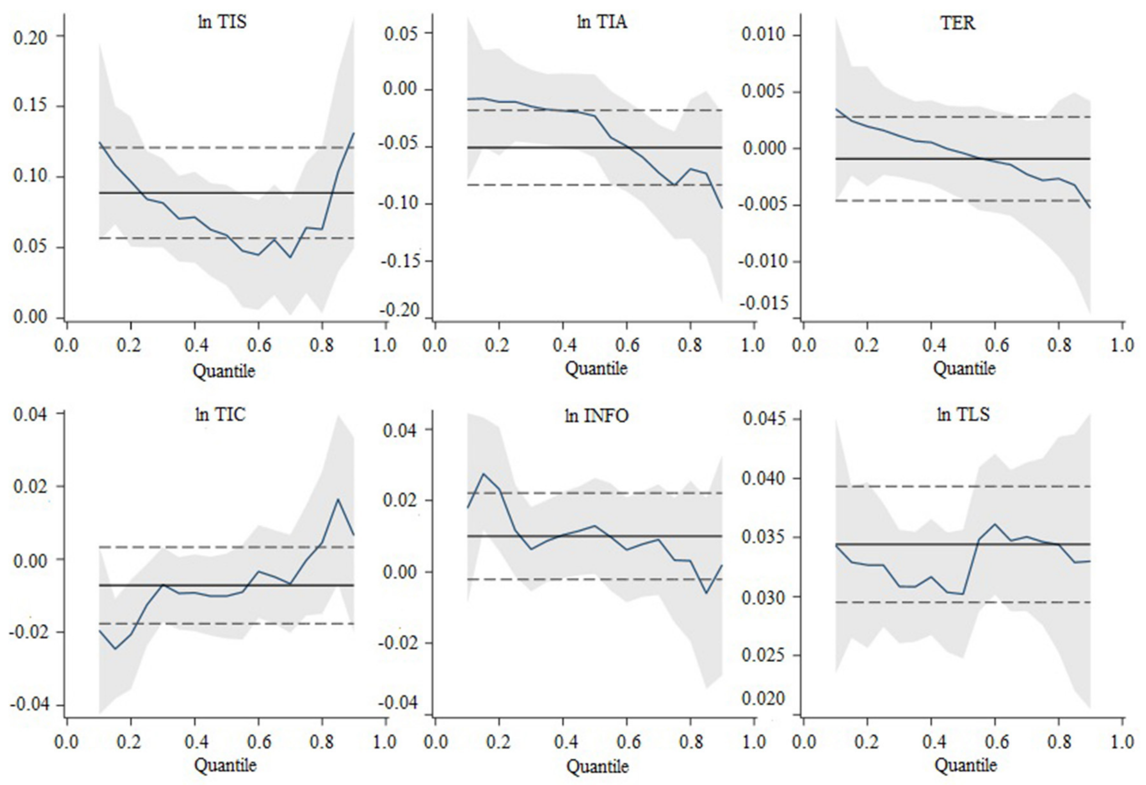

FIGURE 4
Changes in quantile regression coefficients for tourism ecosystem health.

coefficients for the first 50% of the quantile being significantly larger than those for the second 50% of the quantile. From the coefficients, the degree of impact of information infrastructure and information technology consumption was more substantial for provinces with low tourism ecosystem health. In contrast, for provinces with high tourism ecosystem health, the effect of increasing informatization was diminished.

(6) Tourism land-use scale positively affected tourism ecosystem health, with an inverted N-shaped trend. The panel quantile regression results showed that the tourism land-use scale had a significant and large positive effect on tourism ecosystem health at the high quantile. However, its positive effect decreased as the tourism land-use scale increased at this quantile. Despite the problems of waste of production factors such as land and capital and the excessive emission of pollutants in the process of the use of tourism land, the under-utilized tourism land has crowded out ecological land space. The ecosystem organization structure is under external stress. However, the resistance to external interference and self-repair functions of ecosystem services

does not exceed the reasonable carrying capacity of the tourism environment.

4. Conclusions and discussion

Based on the DPSIR model, we systematically constructed an evaluation index system to measure China's tourism ecosystem health. Then the dynamic evolution characteristics and driving factors of tourism ecosystem health in China from 2011 to 2020 were analyzed with the entropy weight method, spatial autocorrelation analysis, Markov chain analysis, and quantile regression. The main conclusions are as follows: (1) During the ten years from 2011 to 2020, the tourism ecosystem health in China showed an M-shaped fluctuation process as a whole, with three distinct stages of rapid increase (2011–2012), slow decrease (2012–2015), and fluctuating development (2015–2020). The kernel density exhibited a right-trailing phenomenon and multiple peaks, indicating that the gap between China's tourism ecosystem health and the average has widened and that there was a specific gradient of differences. Regarding spatial differentiation, the tourism ecosystem health in China was significantly spatially correlated, characterized by clustered and contiguous development, with significant regional differences in distribution. (2) There was a "path-dependent" and "self-locking" effect on the type transfer of the tourism ecosystem health in China. Type transfer generally occurs between adjacent types in successive transfers, while the probability of cross-type transfer is small, and the probability of downward transfer is higher than upward transfer. In addition, geospatial patterns played a significant role in the dynamic evolution process of tourism ecosystem health. Specifically, the probability of the state-level type of the province transferring downward would increase if it was adjacent to a province with a low tourism ecosystem health level, while the probability of the state-level type of the province transferring upward would increase if it was adjacent to a province with a high tourism ecosystem health level. (3) The tourism ecosystem health in China was driven by a combination of factors, including tourism industry structure, tourism industry agglomeration, tourism environmental regulation, information technology level, technological innovation capacity, and tourism land-use scale. Moreover, in provinces with low tourism ecosystem health type, the dampening effect of technological innovation capacity was more significant, and the influence coefficient of the positive marginal effect of tourism environmental regulation and information technology level was larger, while in provinces with high tourism ecosystem health type, the dampening effect of tourism industry agglomeration was more significant, and the influence coefficient of the positive marginal effect of tourism industry structure and tourism land-use scale was larger.

Under the new development concept of "innovation, coordination, green, openness and sharing", a systematic and in-depth study on the dynamic evolution of tourism ecosystem health in China and its driving factors are of great significance in promoting the sustainable development and high-quality transformation and upgrading of regional tourism. The main contributions of this paper are listed as follows: (1) The dynamic transfer process and pattern of tourism ecosystem health in each province of China from 2000 to 2015 were analyzed using the spatial Markov chain analysis, which can visually reveal the heterogeneity of the "spatial spillover" effect of tourism ecosystem health and the influence of geospatial background. (2) In contrast to the idealistic treatment model of mean regression, the panel quantile regression model emphasized the heterogeneity of driving factors in the context of various tourism ecosystem health types. Its empirical findings could more accurately reflect the actual situation. Thus, the results can provide a research methodological reference for a more comprehensive, systematic, and dynamic exploration of the driving mechanisms of tourism ecosystem health in similar areas, especially in developing countries, in the future. (3) The research scale was reduced to the provincial level, and the heterogeneity and regularity of tourism ecosystem health at the regional scale could be better explained, providing empirical support for local governments to formulate appropriate tourism ecosystem health strategies for different provinces.

The findings of this paper have important policy implications: (1) The government and tourism authorities should give due consideration to regional synergy and integrated management in tourism cooperation and development and tourism environmental protection policies as a means of reducing the constraints and impacts of spatial effects on tourism ecosystem health, reducing spatial differences in tourism ecosystem health between provinces, and achieving the goal of regional coordination and sustainable development of the tourism industry. (2) More attention should be paid to the dynamic evolution of tourism ecosystem health in different provinces, especially in provinces with a "generally healthy" neighborhood type, to avoid the risk of downward transfer resulting from the crude growth of their tourism economies. (3) The provinces with high tourism ecosystem health must make efforts to accelerate the process of allocating tourism industry elements, continuously promote structural reform on the supply side of tourism, guide tourism development and transformation and upgrading with the concept of ecological priority and green development, and actively cultivate new low-carbon and green tourism industries. Meanwhile, actions must be taken to initiate the allocation of land resources in ways that are compatible with the direction that the tourism industry is going as well as through intensive utilization for sustainable development. For provinces with low tourism ecosystem health, the research and development of tourism pollution treatment and prevention technologies should be focused on further improving tourism ecosystem health. Additionally, regional tourism ecosystem health policies should be continuously improved. Tourism ecosystem health should be promoted through new media platforms to encourage green travel and low-carbon consumption among tourists.

Data availability statement

The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding author.

Author contributions

FL: conceptualization, software, data curation, and writing-original draft preparation. HR: methodology and writing-reviewing. XZ: editing and visualization. All authors contributed to the article and approved the submitted version.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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Mechanisms influencing the factors of urban built environments and coronavirus disease 2019 at macroscopic and microscopic scales: The role of cities

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In late 2019, the coronavirus disease 2019 (COVID-19) pandemic soundlessly slinked in and swept the world, exerting a tremendous impact on lifestyles. This study investigated changes in the infection rates of COVID-19 and the urban built environment in 45 areas in Manhattan, New York, and the relationship between the factors of the urban built environment and COVID-19. COVID-19 was used as the outcome variable, which represents the situation under normal conditions vs. non-pharmacological intervention (NPI), to analyze the macroscopic (macro) and microscopic (micro) factors of the urban built environment. Computer vision was introduced to quantify the material space of urban places from street-level panoramic images of the urban streetscape. The study then extracted the microscopic factors of the urban built environment. The micro factors were composed of two parts. The first was the urban level, which was composed of urban buildings, Panoramic View Green View Index, roads, the sky, and buildings (walls). The second was the streets' green structure, which consisted of macrophanerophyte, bush, and grass. The macro factors comprised population density, traffic, and points of interest. This study analyzed correlations from multiple levels using linear regression models. It also effectively explored the relationship between the urban built environment and COVID-19 transmission and the mechanism of its influence from multiple perspectives.

KEYWORDS

COVID-19, urban built environment, relevance, street view images, computer vision, deep learning

1. Introduction

Novel pneumonia caused by coronavirus 2019 (COVID-19), which leads to severe acute respiratory syndrome, has been raging worldwide for nearly 3 years since December 2019 (1). The speed of transmission of the virus, its infectiousness, and the number of mutations have been the most unprecedented in human medical history. Large cities and metropolitan areas have been the areas most affected by the spread of the virus, exacerbated by the areas' dense population distribution (2). To strictly control the rate of COVID-19 transmission and to reduce the rates of infection and deaths, countries have adopted non-pharmaceutical interventions (NPIs) including urban lockdown, home isolation, controlled social distancing, and travel restrictions (3, 4). Ever since it reared its ugly head, COVID-19 has attracted substantial attention from the global community, and various studies on COVID-19 have emerged accordingly. A majority of the studies have focused on the related factors of sociodemographics and the urban built environment. The results vary from two different research perspectives.

From the sociodemographic perspective, the risk of COVID-19 infection is much higher for the elderly and children than it is for young and middle-aged adults (5–7). In addition, the degree of economic development across regions may exert an impact on the transmission rate of COVID-19 (8, 9). For example, the availability of health insurance has been highly correlated with the spread of COVID-19 (10). Low-income areas, especially older communities with low levels of income, have been more susceptible to COVID-19 infection (11, 12), all of which have been related to regional economic development. Using logistic regression models, several studies have demonstrated that levels of regional literacy are also associated with the prevalence of COVID-19 (13). Other factors have also been correlated with COVID-19 transmission, such as blood type, respiratory disease, and chronic diseases. Additionally, personal habits have been associated with COVID-19 transmission (14, 15). The strict implementation of NPI against COVID-19 has proven effective in mitigating the spread of the virus (16, 17). In the post-pandemic era, the patterns of behavior in daily life have changed due to reliable NPIs implemented by governments (18). Under the influence of NPIs, the range of activities of urban residents has been significantly reduced, thereby rendering them increasingly dependent largely on the surroundings of their homes, the natural urban environment, and the built urban environment (19). The surroundings of urban homes and the built environment have exerted a direct effect on the physical and mental health of urban residents (20). Simultaneously, low-density neighborhoods, large homes, developed urban residential surroundings and infrastructure, rich urban greenery, and large urban green spaces can greatly enhance the life satisfaction and wellbeing of residents under COVID-19 NPIs (21).

From the perspective of the urban built environment, the impact of the urban built environment on COVID-19 is extremely important in addition to socio-demographic factors, which has been confirmed by many studies. The relationship between COVID-19 transmission and population density is relatively controversial. Previous studies demonstrate that the incidence and transmission of COVID-19 are higher in densely populated areas with high population contact (22). A comparison of the results of linear regression models from 182 countries points to a positive association between population density and COVID-19 transmission (23). In contrast, the results of structural equation modeling at the city level illustrate that population density is negatively associated with COVID-19 transmission in Tehran (24). This result is interesting, where a few studies argue that urban population density is non-significantly correlated with the spread of COVID-19 (25). The relationship between urban population density and the transmission rate of COVID-19 is complex. Thus, the various responses of governments and urban residents to the pandemic across nations may lead to different results, which are reasonably explained by the findings of Hamidi et al. (26) in the United States, Lin et al. (27) in China, and Boterman (28) in the Netherlands. Meanwhile, the relationship between urban building density and COVID-19 lacks elucidation and is subject to a certain degree of controversy (29). A few studies demonstrate that no correlation exists between building density and COVID-19 after omitting certain confounding factors (28). During the COVID-19 pandemic and under government NPIs, the wellbeing of residents living in high-density areas was negatively correlated with living density due to changes in the scope of life and lifestyle behaviors. However, this compact urban form leads to relatively easy access to urban healthcare resources, which could improve the health status of residents (18, 30).

From the perspective of the urban built environment alone, different factors in the urban built environment may have an impact on the spread and transmission of COVID-19 during an epidemic pandemic. For example, public transportation (31) and points of interest (POI) (32), among others, are generally considered to exhibit a positive association with COVID-19 transmission. When the outbreak was in its emergent stage, public transportation was considered the main method of COVID-19 transmission. Therefore, many governments advised urban residents to avoid public transportation as much as possible while introducing corresponding NPIs and limiting the range of activities of residents. In addition, they frequently urged urban residents to use multiple modes of transportation, such as self-driving, walking, and cycling (33). The results of analyses using multiscale geographically weighted regression suggested that the high availability of medical resources around a community could effectively inhibit the spread of COVID-19 (7). Through structural equation modeling and categorical regression modeling, other analyses demonstrated high-quality housing and high-quality green space as being negatively associated with the spread of COVID-19 (10, 34). Green spaces around large residential areas exerted an inhibitory effect on the deterioration of urban health and wellbeing due to COVID-19 (30). Notably, the risk of infection and transmission rates were high for neighborhoods with high levels of community convenience (35). Integrating all patients with COVID-19 into high-grade urban hospitals is unrealistic because hospital capacity is far from adequate for treating such a large number of patients at the burgeoning stage of a pandemic such as COVID-19. Moreover, the risk of collapse of urban public healthcare is prevalent as demonstrated by the collapse of public healthcare to varying degrees in various countries during the COVID-19 outbreak. Therefore, a community-level system for identifying and isolating individuals with infection is essential to the response to COVID-19 (36).

In summary, several questions can be elicited from the influence of the urban built environment on the spread of COVID-19: (I) how the macroscopic urban built environment and the microscopic urban built environment have an impact on the spread of COVID-19 in the urban built environment; and (II) what is the impact of the macroscopic urban built environment and the microscopic built environment on the incidence and lethality of COVID-19. However, most of the community-level studies at this stage have used administrative boundaries to delineate the selection of variables, and the disadvantage of this method of variable selection is that it does not reflect the actual activities of residents. In this regard, Li et al. used structural equation modeling to reveal the relationship between commercial vitality and transportation infrastructure on the increase in the number of confirmed cases, and innovatively used buffer zones to extract urban built environment factors around confirmed cases (37). Wang et al. used walking circles at different times to investigate the correlation between urban built environment and community level spatial distribution (38). By extracting the established environmental factors in both spatial dimensions and examining the correlation between these factors and the prevalence of COVID-19, the issue of the transmission mechanism of COVID-19 before and after the implementation of community-level NPI measures was then analyzed. Studies at this stage ignore the lack of multi-level studies on the mechanisms of the urban micro-built environment influencing the spread of COVID-19. Whether the urban street green environment and urban street spatial quality have an impact on the spread of COVID-19 has not been explored, and the impact of urban built environment on the long-term trend and overall trend of COVID-19 has not been considered comprehensively. In this study, based on the study of the influence mechanism between the macroscopic built environment and COVID-19, the influence mechanism between the microscopic built environment and COVID-19 was considered at multiple levels using Google Street View panoramic street view images. The impact of urban built environment on the long-term trend and overall trend of COVID-19 is investigated using multiple variables, and the influence mechanism of urban built environment on COVID-19 is examined at multiple levels (macro level and micro level) and multiple dimensions (time dimension). The results of the study can provide a basis and reference for governmental decision makers to formulate more reasonable NPI policies to slow down the spread of COVID-19 during pandemic periods. The results of the study may provide a reference solution to control the spread and spread of the virus, and the results may provide effective recommendations to contain potential respiratory disease outbreaks.

2. Data

2.1. Research region

New York City is considered the first epicenter of the COVID-19 outbreak in the United States. It has a population of ∼8.51 million (as of 2017) and an area of ∼1,214 km^2 (including the sea). With an average of 28 people per square mile, New York City is the main international maritime, airport, and financial metropolis of the United States and has five boroughs under its jurisdiction, namely, Brooklyn, Queens, Manhattan, the Bronx, and Staten Island.

Manhattan is the most densely populated and smallest of the five boroughs of New York City, which translates to a very high population and housing density when compared with those of other boroughs in New York City. Manhattan is described as the economic and cultural center of the United States and is home to New York's central business district, which houses the headquarters of most Fortune 500 companies and the headquarters of the United Nations. Thus, the nearly 50 million tourists who visit New York City each year significantly contribute to the risk of COVID-19 transmission and routes of transmission. Figure 1 describes the study area and its road network. As the center of the metropolitan area, a major outbreak of COVID-19 is likely to spread rapidly to other areas of the metropolis and continue to expand outward. Thus, understanding the relationship between the spread of COVID-19 and the factors of the urban built environment is an important aspect for urban decision-makers in mitigating the spread of the disease and in developing openness measures.

2.2. Google street view images and dataset

2.2.1. Google street view images

The study obtained urban street panorama images from Google Maps to reflect the physical characteristics of the urban environment. Factors related to the urban environment were extracted from these images as evaluation indexes of the urban environment. To improve the representativeness of the physical features and environmental factors of the urban environment, the study created a collection point for every 100 m on all urban roads in the study area. A total of 67,025 collection points were set up to collect images with each collection point having one image based on a 90° view. Moreover, the study collected four images for each collection point to synthesize the panoramic streetscape images, which reached 268,100 images. The images were cleaned according to the availability of data, and all images were collected from Google Street View (GSV) to analyze the physical characteristics of the city and extract the factors of the urban environment. By appropriately establishing the parameters for image retrieval, the images captured both sides and frontal images of the street. This image acquisition covered all roads in Manhattan. Figure 2 provides a demonstration of the acquisition of the GSV images.

2.2.2. Dataset for training the neural network model

The study used datasets from Cityscape, ADE20K, and S-S-G-S to train the neural network model, a dataset open to researchers at the Mercedes-Benz R&D Center and Darmstadt University of Technology and published in the 2016 Clean Vehicle Rebate Project. The dataset was collected from 50 cities in Germany and nearby countries, including street scenes in spring, summer, and autumn. Different annotators with 96 and 98% pixel consistencies repeatedly annotated the 30 selected data after omitting categories that could be annotated as unclear. The drawback was that the segmentation dataset contained 33 classes, whereas the validation dataset was composed of only 19 semantic segmentation classes because the data volume of a few classes was very sparse. The ADE20K dataset is intended for Scene Understanding, which was opened by the Massachusetts Institute of Technology (MIT) in 2016 and can be used, for instance, in semantics and part segmentation. Using image information for Scene Understanding and parsing, the dataset consists of 27,000 images from Scene Understanding (an open dataset released by Princeton University in 2010) and Places (an open dataset by MIT released in 2014). The ADE20K contains

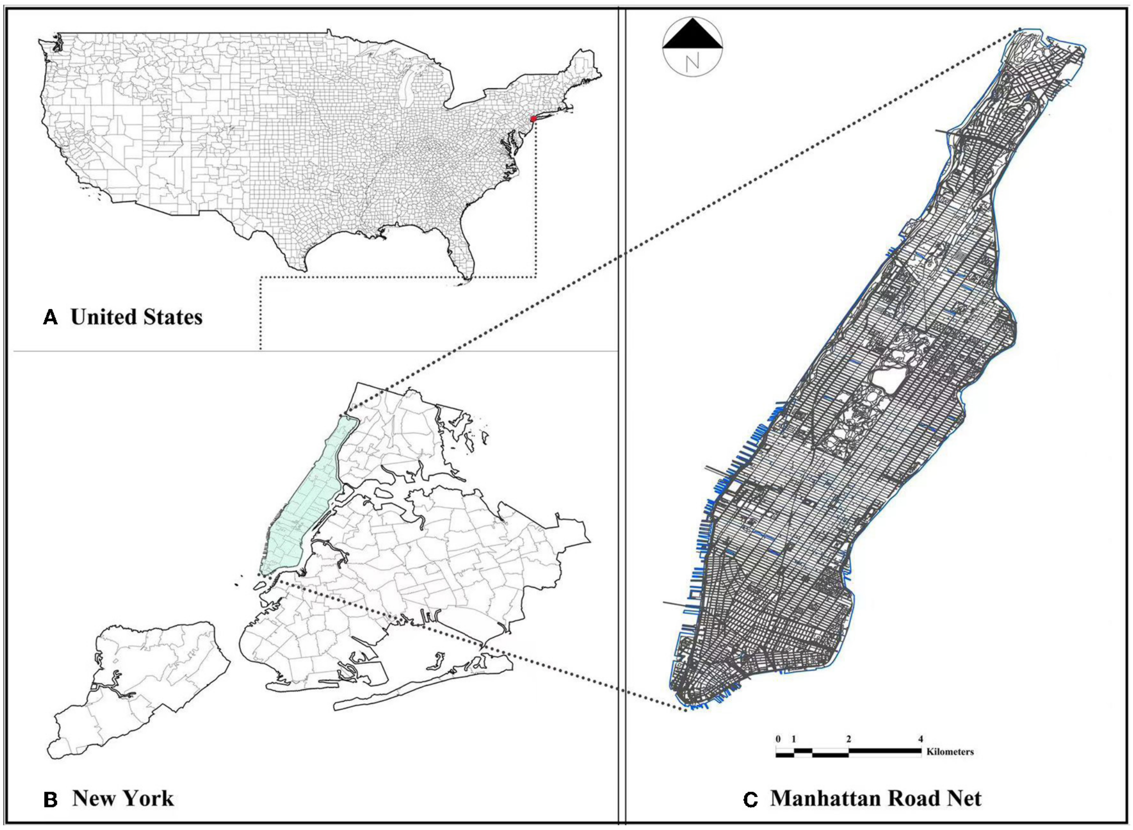


FIGURE 1
Study area: **(A)** Map of the United States; **(B)** New York County; and **(C)** Manhattan road network.

more than 3,000 object classes, which greatly compensates for the shortcomings of the Cityscape dataset. The S-S-G-S dataset was constructed by Zhang et al. (39) in 2022 and is mainly used for the analysis of urban vegetation communities. A neural network model trained using this dataset can classify and visualize the structure of urban street vegetation communities. S-S-G-S differs from the Cityscape and ADE20K datasets in that it is directed toward the analysis of urban greenery. The study mainly used the trained DeepLabV3+ neural network model to extract urban features at the micro level.

2.3. COVID-19 dataset

The first confirmed case of COVID-19 was reported in Manhattan on March 1, 2020. At the time, the number of confirmed cases of COVID-19 in the entire United States was only 76. However, as of March 25, 2020, the number of confirmed COVID-19 cases in the United States spiked to 69,008, and the number of deaths reached 1,045, such that COVID-19 rampaged through the country at a rate of 10,000 per day for three consecutive days. However, according to the Centers for Disease Control and Prevention, nearly 50% of all confirmed cases in the United States as of March 25, 2020, are in New York State, which establishes it as the epicenter of the outbreak. Out of the 33,006 cases diagnosed in New York State, 20,011 were derived from New York City. Over time and with the introduction of various restrictive policies and concerted national efforts to combat the outbreak, the spread of COVID-19 decelerated. Moreover, the outbreak appeared to be moving in a positive direction with the advent of COVID-19 vaccines.

Moving forward to late December 2021, a variant of COVID-19 (omicron) is once again ravaging New York State with a record-breaking 21,908 cases detected in New York State on December 18, 2021, alone. Moreover, an alarming spike in cases was noted in several highly vaccinated neighborhoods in Manhattan. With 7-day positivity rates exceeding 10% in more than 10 areas of New York City from December 10 to 16, 2021, Manhattan, once again, clearly became a hotbed of COVID-19 transmission. A total of 790.87 cases were identified per 100,000 people, and an extremely alarming rate was noted in specific Manhattan neighborhoods as of December 24, 2021. Greenwich Village and SoHo reported 2,850 confirmed cases per 100,000 people, and Chelsea reached 2,400 confirmed cases per 100,000 people. Nevertheless, no pandemic hotspot in the nation could compare to the dire outbreak in Greenwich Village.

The COVID-19 case data in the study were derived from the publication by NYC Health (https://www1.nyc.gov/site/doh/index.page), which included cumulative totals since the COVID-19 outbreak in New York City. The Department of Health (DOH) defined the first case of COVID-19 as the one confirmed on February 29, 2020. In addition, the DOH recommended the

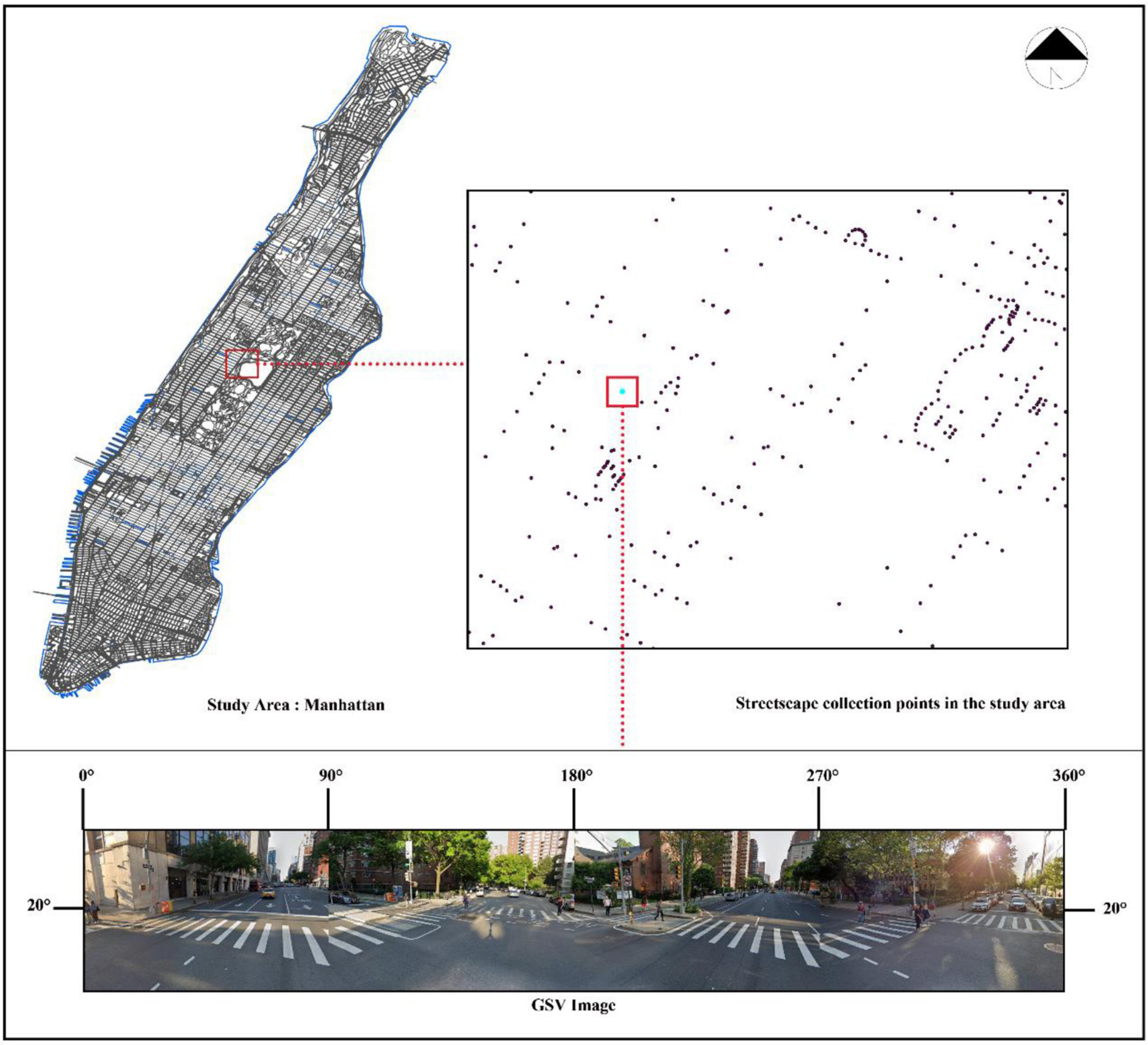


FIGURE 2
Demonstration of the acquisition of GSV images.

avoidance of interpreting the daily changes in these files as 1-day data due to the discrepancy between the date of the event and the date of reporting. The internal division of the study area was divided according to the Modified ZIP Code Tabulation Areas (MODZCTA).

NYC Health uses MODZCTA to report information according to geographic location. However, several issues emerge when mapping data reported based on ZIP codes because they do not designate a single area but a collection of points that compose the route of mail delivery. Moreover, a few buildings and non-residential areas were frequently assigned unique ZIP codes. To address these issues, the DOH uses ZIP Code Tabulation Areas (ZCTA) to convert ZIP codes into area units. The United States Census Bureau developed ZCTA geography to map data reported according to ZIP codes using ZCTA. MODZCTA geography combines census blocks with small populations to provide stable estimates of population size for rate calculations. The visualization is available on the website of NYC Health, which also open-sources the case data (https://github.com/nychealth/coronavirus-data#geography-zip-codes-and-zctas). In this manner, accessing appropriate data is easy for researchers.

This study used Manhattan, New York in the United States as the study area and created a fishing network according to the 68 zones of MODZCTA to compare the mechanisms between the factors of the urban built environment and COVID-19 transmission in different zones and to investigate the reason Manhattan became the center of the pandemic many times during the outbreak.

3. Methodology

3.1. Outcome variable: COVID-19

The outcome variables of the study were the number of confirmed and suspected cases of COVID-19 [COVID_CASE_COUNT (CCC)] and the incidence of confirmed and suspected cases of COVID-19 per 100,000 people [COVID_CASE_RATE (CCR)] in Manhattan, New York, United States. The difference between CCC and CCR is that CCR is a longer-term trend than CCC, and the relationship between the factors of urban built environment and COVID-19 under NPIs can be determined by comparing with CCC.

According to MODZCTA, the Manhattan area of New York City, United States, was divided into 68 areas. After data filtering, the study identified 45 valid areas, and a fishing net was generated within the study area for a total of 1,551 grids. These grids will be used for analysis and spatial cells. The study calculated the CCC and CCR of the 45 independent areas and averaged them according to the fishing nets to reflect the overall number of cases in Manhattan. In addition, by calculating and visualizing the average of the number of valid POIs and environmental factors of the urban streetscape within the grids, the study intends to better establish the relationship of the urban built environment at the macro- and micro-levels to COVID-19. Figure 3 presents the visualization results of CCC and CCR in the study area.

3.2. Macro-scale: Factors of urban built environment

The study selected only three aspects, namely, density, diversity, and traffic, from the 5D's model framework (40, 41) for the evaluation of the factors of the built urban environment and the physical characteristics of the city at the macro level. In terms of density, the study used urban population density as an evaluation indicator. In the evaluation index of diversity, the study selected the data on POIs to measure the diversity of the urban environment. A POI consists of fine-grained data that comprehensively reflect accurate information on urban land use. The POI data used in the study were downloaded from OpenStreetMap (OSM) and reclassified according to the basic functions of the city after the data were screened, which included the omission of irrelevant, duplicate, and empty data. The study obtained 16,003 valid entity POIs for Manhattan, which were classified using C·M·E·P·R (Table 1). The C·M·E·P·R classification, as a method of classifying urban POIs on the basis of built-up characteristics, categorizes urban POIs according to urban functions such as commerce, healthcare, education, public services, and entertainment. Moreover, the POIs were classified according to C·M·E·P·R. The valid POIs were mapped to the fishnet grid of the study area, and the entropy score of the POI data per grid was calculated to determine diversity (42), which is calculated as follows:

$$Mix\ Index = -\sum_{i=1}^{n} p_i ln p_i.$$

The formula pi is the proportion of the ith type of POI, and n is the total number of all POI types in the fishing grid. In turn, it better reflects the influence relationship between the urban built environment and COVID-19. Figure 4 provides the visualization results of macro factors of the urban built environment.

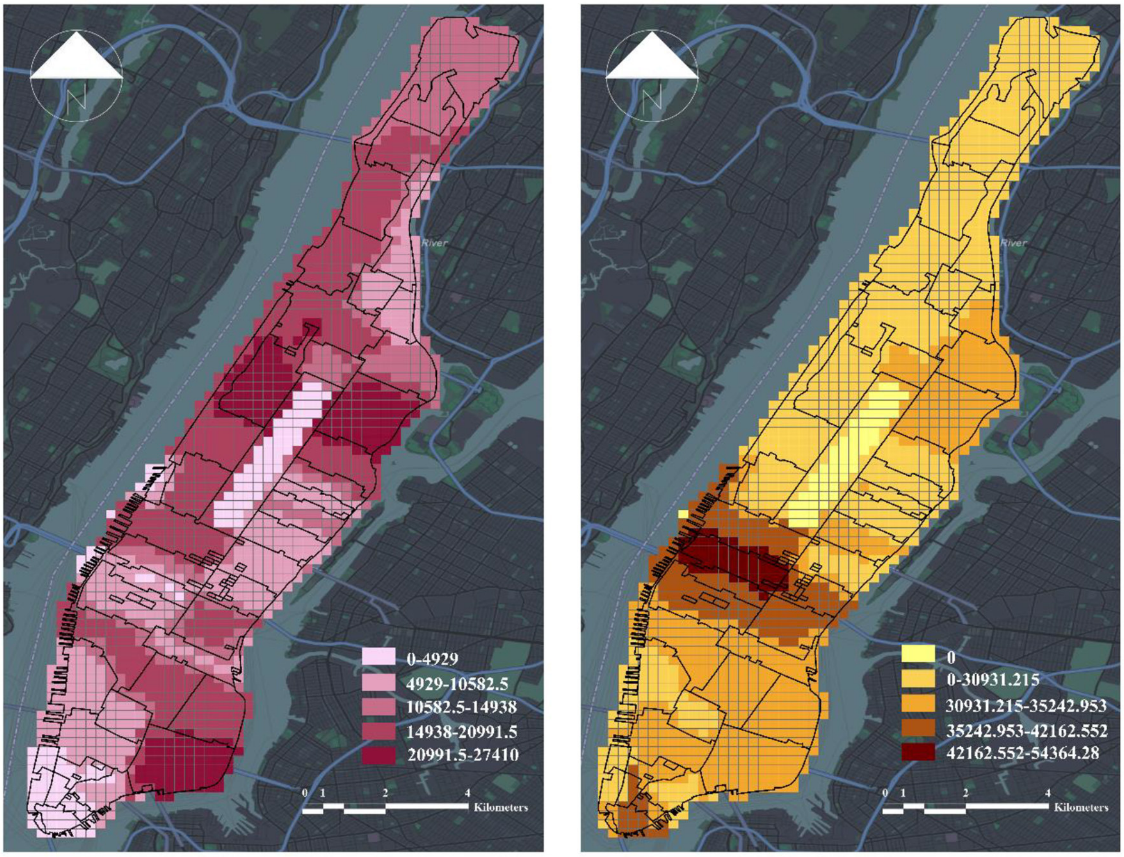
3.3. Micro-scale factors of urban built environment

In this study, micro-level urban built environment specifically refers to the direct perception of the features of the urban landscape by pedestrians. Many studies demonstrate that computer vision combined with panoramic urban streetscape images can extract the features of the urban built environment and evaluate the urban built environment at the street level. This tendency proves that computer vision has gradually entered the scope of urban research. The current study selects the network model open-sourced by Chen et al. (43) in 2018, which pertains to a semantic segmentation network based on the DeepLabV3+ neural network model. The study made this selection for two reasons. The first is that the DeepLabV3+ neural network model is the latest version in the DeepLab series, which modifies VGG16 to introduce null convolution in DeepLabV1. The Atrous Spatial Pyramid Pooling (ASPP) model is designed in DeepLabV2; DeepLabV3 combines. The model proved its accuracy by outperforming mainstream deep learning algorithms (such as SegNet and PSPNet) in performance evaluation competitions such as the PascalVOC and Cityscapes benchmark tests in 2012. The second is that DeepLabV3+ features a better recognition effect compared with other mainstream deep learning models in the interpretation of urban scenes. The reason is that the model is designed for analyzing urban scenes, such that it exhibits certain advantages compared with those of other models when recognizing green structures in urban streets. The third is that the model uses DeepLabV3 as an encoder to generate the features of arbitrary dimensions using Atrous Convolution and adopts the ASPP strategy to use multiple effective sites with upsampling to achieve multiscale feature extraction. Moreover, it uses a cascade decoder to recover boundary detail information. Depthwise Separable Convolution is also used to reduce the number of parameters to further improve the accuracy and speed of the segmentation algorithm. This study selects the panoramic green view rate, the green structure of urban streets, buildings, roads, walls, and sky visibility to represent the micro-scale features of the urban built environment (Figure 5).

3.4. Statistical analysis

The study conducted a four-step statistical analysis, namely:

(i) Pearson's correlation analysis of the CCC and CCR data using all data on the macro- and micro-level factors of the urban built environment, respectively.
(ii) Z standardization of two independent variables. The z-score can transform two or more sets of data into unitless z-scores, which renders data standards uniform and, thus, improves



A CCC Visualization in Manhattan, New York **B** CCR Visualization in Manhattan, New York

FIGURE 3
Visualization of CCC and CCR in the study area. **(A)** CCC Visualization in Manhattan, New York. **(B)** CCR Visualization in Manhattan, New York.

TABLE 1 Classification of POI types according to C·M·E·P·R and corresponding categories in the original OpenStreetMap (OSM) dataset.

POI types	Categories in the OSM dataset	Count	Percentage
C	Restaurants, beverages, malls, markets, stores, various shops, greengrocers, hairdressers, vendors, cinemas, car dealerships, car rentals, etc.	8,997	56.22%
M	Chemist, clinic, dentist, doctor, hospital, optician, pharmacy, veterinary, etc.	630	3.94%
E	College, kindergarten, library, playground, school, university, etc.	357	2.23%
P	Governmental organization, social group, communal facilities, financial facilities, convenience, camera surveillance, etc.	5,331	33.31%
R	Scenic spot, park, open square, tourist attraction, theater, viewpoint, etc.	688	4.30%

C, commercial; M, medical; E, education; P, public service; R, recreation.

data comparability and weakens data interpretation. The z-standardization formula is as follows:

$$Z = \frac{X - \mu}{\sigma},$$

Where μ is the mean and σ is the standard deviation.

(iii) The existence of a degree of correlation (approximate covariance) between the explanatory variables can also be called multicollinearity. In this case, the results of parameter estimation are no longer valid; thus, the current study uses variance inflation factor (VIF) to test for potential multicollinearity between the macro- and micro-level independent variables (Table 2). VIF is calculated as follows:

$$VIF = \frac{1}{1 - R^2},$$

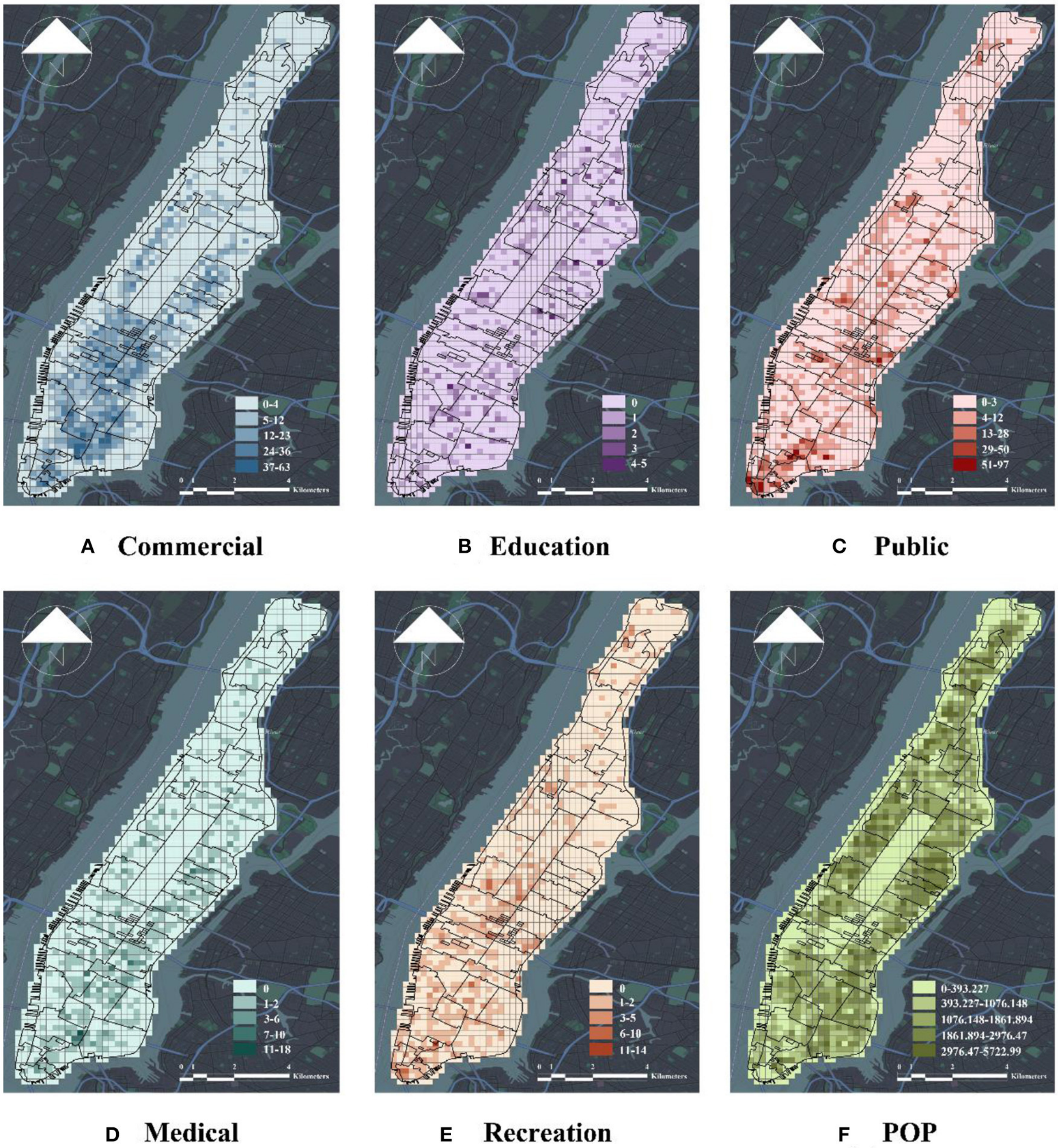


FIGURE 4
Visualization of macro-scale factors of urban built environment. **(A)** Commercial, **(B)** education, **(C)** public, **(D)** medical, **(E)** recreation, and **(F)** POP.

Where R^2 denotes goodness-of-fit or the determination coefficient of linear regression and describes the percentage of explanatory variables in the regression equation. The results indicate the absence of covariance for all independent variables, VIF values are <5, and all factors can be included in the linear regression model.

Lastly, data at different levels with various dependent variables were included in the ordinary least squares (OLS) model. Furthermore, the study employed the White and BP tests to verify whether or not heteroscedasticity exists in the data, to test the original hypothesis that there was no heteroscedasticity in the model, to confirm whether or not the results rejected the original hypothesis, and to determine if there was a rejection of the original hypothesis that there was heteroscedasticity. To address these concerns, the study employed the robust regression method.

4. Results

4.1. Pearson's correlation analysis

This study used Pearson correlation analysis to examine the correlations between CCC and CCR and 12 macro-level urban built environment (Public, Education, Commercial, Medical, Recreation, Airports, Bus Station, Bus Stop, Ferry, Railway, Taxi, and POP) and 8 micro-level urban built environment (i.e.,

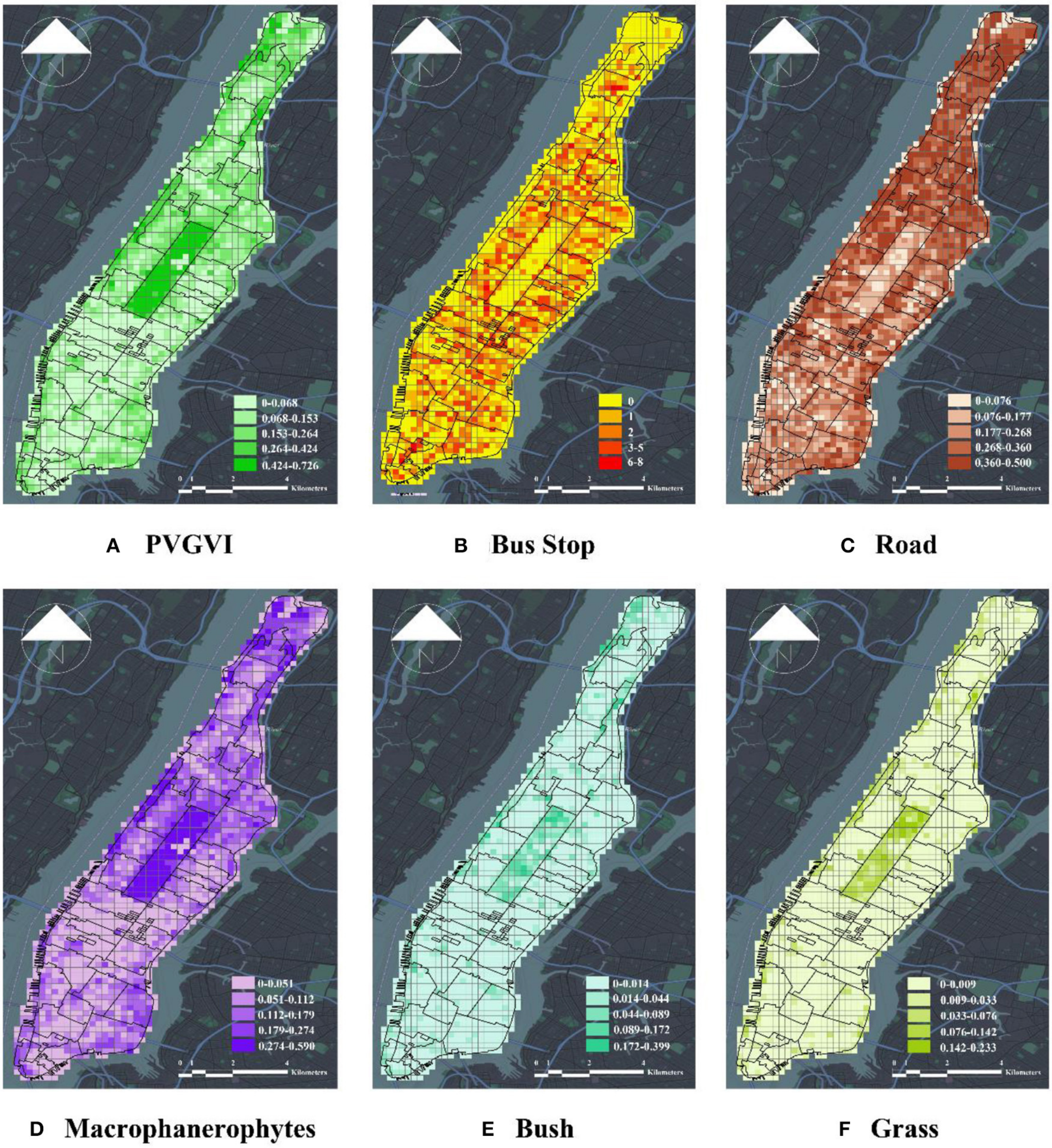


FIGURE 5
Visualization of micro-scale factors of urban built environment. **(A)** PVGVI, **(B)** bus stop, **(C)** road, **(D)** macrophanerophytes, **(E)** bush, and **(F)** grass.

Sky, Building, Road, Wall, Macrophanerophyte, Grass, Bush, and PVGVI) in Manhattan, New York, USA, respectively, using Pearson's correlation coefficient (PCC) to indicate the strength of the correlations.

Figures 6A, 7A depict the relationship between CCC and CCR and macro-level factors, where CCC presents a significant negative correlation with Public (PCC $= -0.12$, $p < 0.001$), Recreation (PCC $= -0.16$, $p < 0.001$), and Ferry (PCC $= -0.077$, $p < 0.01$). Moreover, the study observes a significant negative correlation between Public and Recreation. Both correlations indicate significance at the 0.001 level. Education (PCC $= 0.11$, $p < 0.001$), Bus Stop (PCC $= 0.13$, $p < 0.001$), and POP (PCC $= 0.30$, $p < 0.001$) displayed significant positive correlations with CCC at the 0.001 level of significance. Although the study noted no correlation among Commercial, Medical, Airports, Bus Station, Railway, Tax, and CCC, their PCC values are close to 0, and all p-values are >0.05. Figure 4C illustrates that Public, Education, Commercial, Medical, Bus Stop, Railway, Taxi, and POP have significant positive correlations with CCR, where Commercial (PCC $= 0.26$, $p < 0.001$), Medical (PCC $= 0.11$, $p < 0.001$), Bus Stop (PCC $= 0.16$, $p < 0.001$), Railway (PCC $= 0.10$, $p < 0.001$), and POP (PCC $= 0.092$, $p < 0.001$) demonstrated showed significance at the 0.001 level, which indicate a significant positive correlation with CCC. Lastly, the study found no correlation among Recreation, Airports, Ferry, and CCR.

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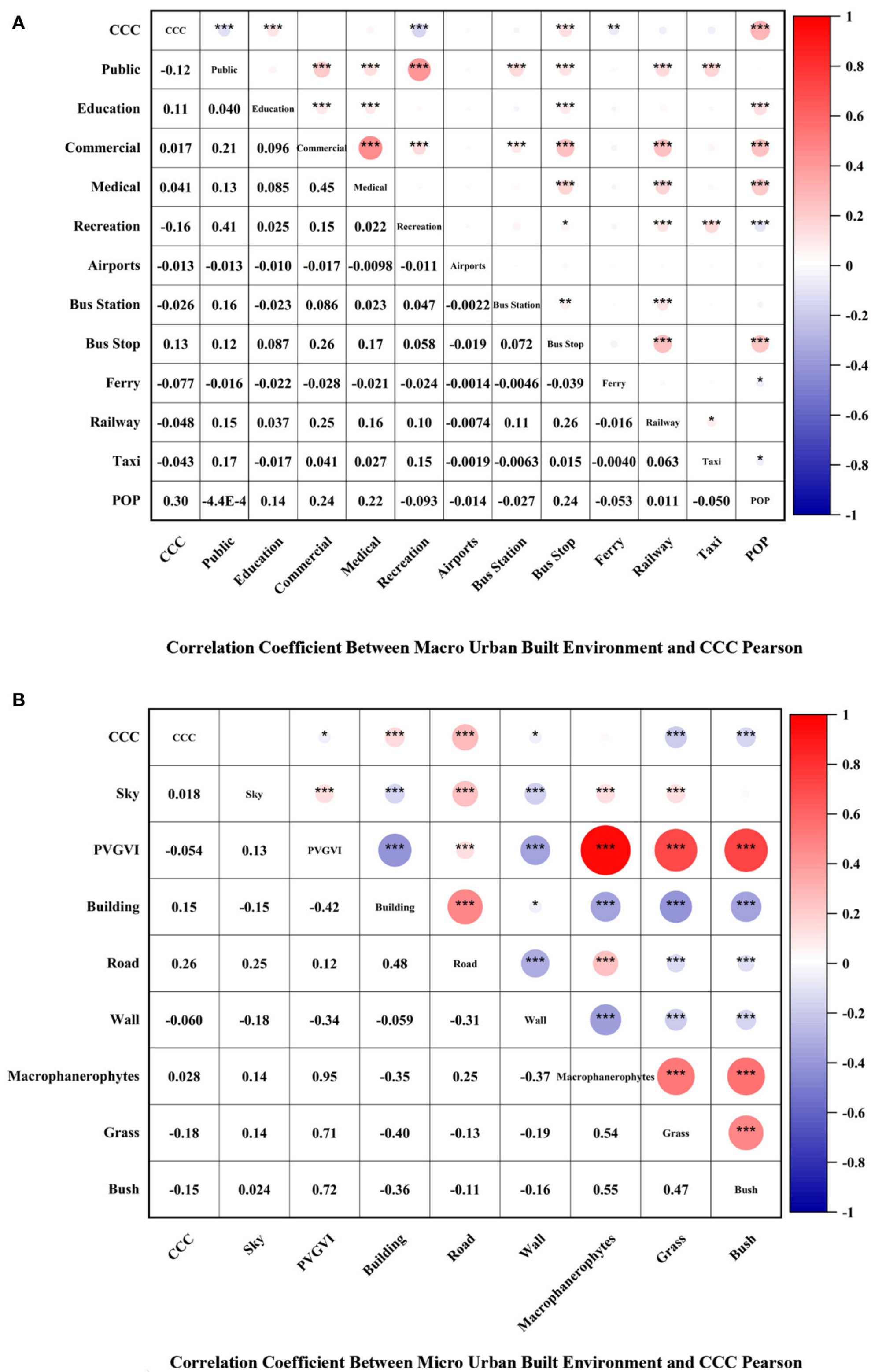

FIGURE 6
Correlation coefficient between urban built environment and CCC Pearson. **(A)** Correlation coefficient between macro urban built environment and CCC Pearson. **(B)** Correlation coefficient between micro urban built environment and CCC Pearson. *$p < 0.05$, **$p < 0.01$, ***$p < 0.001$.

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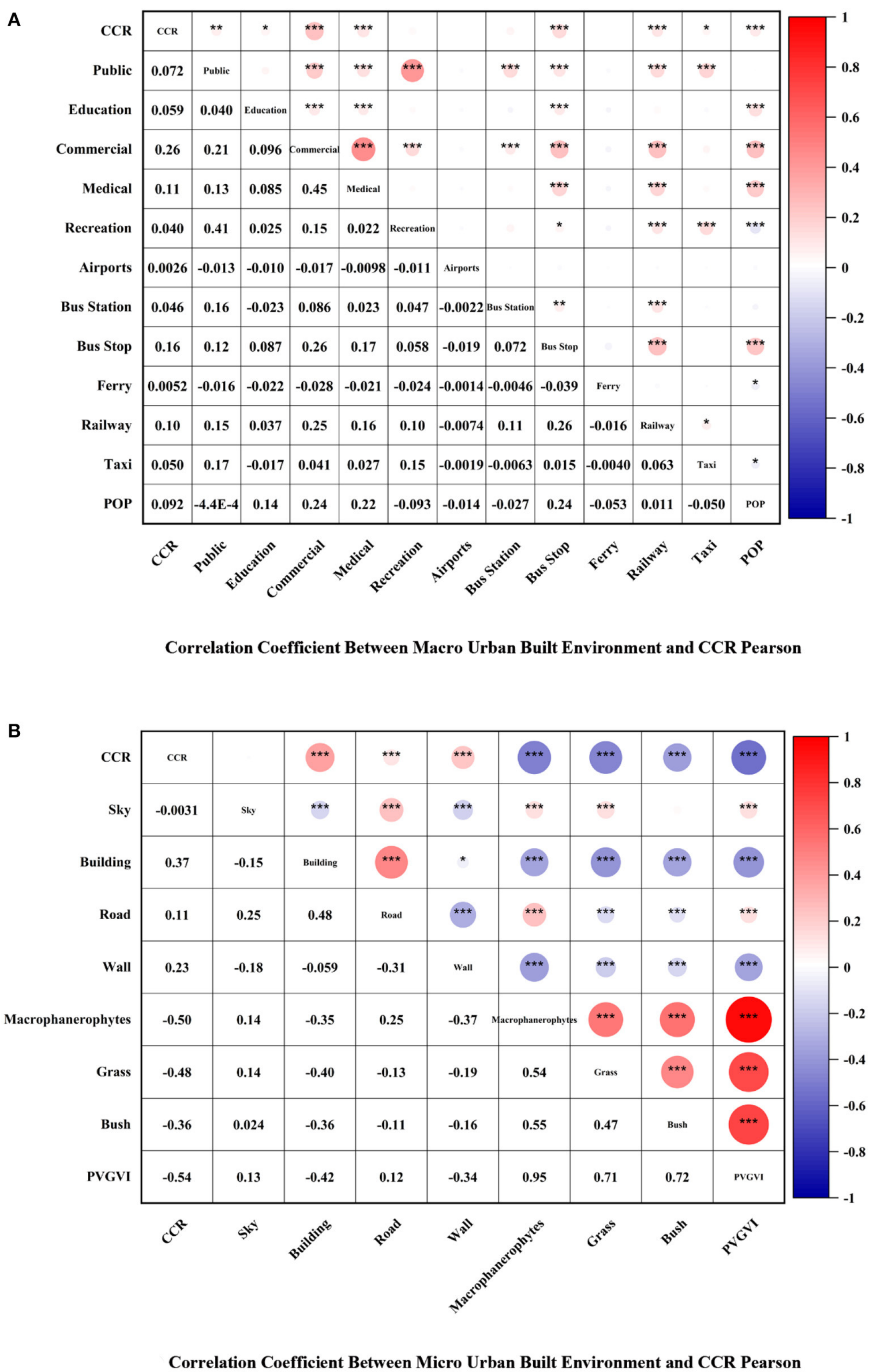

FIGURE 7
Correlation coefficient between urban built environment and CCR Pearson. **(A)** Correlation coefficient between macro urban built environment and CCR Pearson. **(B)** Correlation coefficient between micro urban built environment and CCR Pearson. *$p < 0.05$, **$p < 0.01$, ***$p < 0.001$.

TABLE 2 Summary statistics of all variables in Manhattan, New York, United States ($n = 1,551$).

Variables (unit)	Min	Max	Mean	SD	VIF (Z-score)
Dependent variable					
COVID Case Count (CCC) (N)	0	27,410	13814.951	6340.799	
COVID Case Rate (CCR) (N)	0	54364.28	30825.563	7509.91	
Independent variables					
Macro-scale built environment					
Public service (N)	0	97	3.437	6.911	1.296
Education (N)	0	5	0.23	0.576	1.029
Commercial (N)	0	63	5.801	8.736	1.417
Medical (N)	0	18	0.406	1.055	1.287
Recreation (N)	0	14	0.444	1.016	1.244
Airports (N)	0	1	0.001	0.025	1.001
Bus station (N)	0	2	0.008	0.098	1.041
Bus stop (N)	0	8	0.932	1.275	1.175
Ferry (N)	0	2	0.004	0.072	1.005
Railway (N)	0	3	0.102	0.348	1.144
Taxi (N)	0	2	0.006	0.088	1.043
POP (N)	0	5722.99	1042.108	1033.205	1.167
Micro-scale built environment					
Sky View Factors (SVF) (%)	0	0.279	0.038	0.042	1.224
Building (%)	0	0.45	0.186	0.109	2.245
Road (%)	0	0.504	0.253	0.131	1.999
PVGVI (%)	0	0.529	0.111	0.104	1.791
Wall (%)	0	0.459	0.058	0.077	1.256
Street greening structure					
Macrophanerophytes (%)	0	0.59	0.114	0.098	1.667
Bush (%)	0	0.399	0.016	0.032	1.518
Grass (%)	0	0.234	0.012	0.029	1.496

(i). All VIF values were standardized using z-score; (ii). Min., minimum; Max., maximum; SD, standard deviation; N, number; %, Percentage; (iii). Concerning the problem that the minimum value of the micro-scale factors of the built environment is 0, the reason is that during panoramic streetscape crawling, certain indoor images will be crawled, which leads to the minimum value of certain micro-scale factors at 0. At the same time, model recognition errors were noted, but the sample size is very small, which will not influence the results.

Figures 6B, 7B present the relationship of CCC and CCR to micro-level factors, where positive correlations were noted among Building (PCC $= 0.15$, $p < 0.001$), Road (PCC $= 0.26$, $p < 0.001$), and CCC, and all of them show. The study found negative correlations among Wall, Grass, Bush, PVGVI, and CCC, where Grass (PCC $= -0.18$, $p < 0.001$) and Bush (PCC $= -0.15$, $p < 0.001$) at the 0.001 level of significance, which indicates a significant negative correlation with CCC, whereas no correlation was found between Sky and Macrophanerophytes to CCC. Figure 4D points to a positive correlation among Building, Road, Wall, and CCR at the 0.001 level of significance, which indicates a significant negative correlation with CCR. The correlation between Macrophanerophytes, Grass, Bush, PVGVI, and CCR was all negative at the 0.001 level of significance, among which the PCC value of Macrophanerophytes was −0.5, which extremely exceeded the other variables and indicates a significant negative correlation with CCR.

4.2. Robust regression model

The OLS linear regression of CCC and CCR as outcome variables resulted in four models. Macro- and micro-level factors of the urban built environment were separately included as variables in the models to determine the relationship of CCC and CCR to

TABLE 3 Results of the white and BP tests.

White heteroscedasticity test		BP heteroscedasticity test	
X^2	P	X^2	P
White test and BP test results of CCC and macro urban built environment			
91.844	0.034	24.380	0.018
White test and BP test results of CCC and micro-level urban built environment			
182.923	0.000	120.011	0.000
Results of white test and BP test of CCR and macro urban built environment			
182.923	0.034	120.011	0.000
Results of white test and BP test of CCR and micro-level urban built environment			
435.371	0.000	273.668	0.000

the independent variables at different levels. The equation for OLS linear regression is as follows:

$$Y = X\beta + \varepsilon,$$

Where Y is the dependent variable, X denotes the matrix of explanatory variables, β represents the vector of coefficients, and ε is the vector of random error terms.

The variables were included in the OLS model for the White and BP tests. Table 3 presents the results. In the case of heteroscedasticity, the study conducted the White and BP tests to verify the original hypothesis, that is, no heteroscedasticity exists in the model. Table 3 illustrates that both tests reject the original hypothesis at $p < 0.05$, which indicates that heteroscedasticity exists in the model.

Table 3 suggests that heteroscedasticity exists in the regression data, and the conclusions obtained by the commonly used OLS regression estimation method may be biased because it considers the minimized residual sum of squares as a criterion. Therefore, it also considers anomalous data. In this case in the model regression considered for robust regression analysis (M-estimation), the study uses the Huber robust method with the following formula:

$$\sum_{i=1}^{n} \rho \left(P_i^{\frac{1}{2}} \left(a_i^T X - L \right) \right) = \min \sum_{i=1}^{n} \rho \left(P_I^{\frac{1}{2}} \left(a_i^T X - L \right) \right),$$

where a real function ρ defined in a one-dimensional Euclidean space R is selected for the independent identically distributed equal precision model, such that a_i^T denotes the row vector of the design matrix; X is the extreme value solution; and P represents the weight of the corresponding observation or observation error.

Tables 4, 5 depict Models 1 and 2, respectively. The difference between the models is the use of CCC and CCR as the dependent variables, respectively. CCR can be used to illustrate the long-term trend of COVID-19, which could help in analyzing the impact of NPIs on the relationship between the urban built environment and COVID-19. Alternatively, CCC can be used for analyzing the relationship between the impact of a pure urban built environment and COVID-19.

Table 4 depicts the correlation between Model 1 with CCC as the dependent variable and 20 factors of the urban built environment as the independent variables. It uses robust regression analysis (M-estimation) to construct the correlation between the variables of urban built environment and COVID-19. The study finds that the macro-level factors, Education, Commercial, POP, and Bus Stop, exert a significant positive influence on the relationship between the urban built environment and COVID-19. The correlation coefficient of POP was 0.297, which exceeded all other variables. In particular, Commercial is the only factor that exerts a significant positive effect on CCC and CCR as the dependent variables for both regression models. The regression coefficient of Public is −0.255 with a p-value of 0.004, which is more significant than the other variables.

The micro-level factors that displayed significant negative effects in the micro-urban built environment were significantly higher; Building, Wall, Grass, Bush, and PVGVI exerted significant negative effects on CCC, where Grass obtained a regression coefficient of −0.357 and a p-value of 0.000, which were higher than those of the other variables in the same model in terms of significance and regression coefficient. PVGVI and Grass exhibited a significant negative effect relationship for Models 1 and 2. The regression coefficient for Grass was higher in Model 1 than that in Model 2; however, the significance of both Models is the same (p-values = 0.000). Road and Macrophanerophytes exerted a significant positive effect on CCC; both p-values were 0.000, which is higher than the other variables in terms of significance, except for Grass, which is equal.

Table 5 presents the results of the robust regression analysis for Model 2 with CCR as the dependent variable and the 20 urban built environment factors as the independent variables. The finding indicates that Public and Commercial show a significant positive relationship with CCR at the macro level, whereas POP indicates a significant negative relationship with CCR. Public and POP produced the opposite results for both models (Model 1: Public: regression coefficient = −0.255, POP: regression coefficient = 0.297; Model 2: Public: regression coefficient = 0.07, POP: regression coefficient = −0.088).

The micro-level factors Sky, Building, and Wall presented a significant positive relationship with CCR, whereas Macrophanerophytes, Grass, and PVGVI pointed to a significant negative relationship with CCR. PVGVI is more significant in Model 2 than it was in Model 1 (Model 1: PVGVIp = 0.023; Model 2: PVGVIp = 0.000). Macrophanerophytes present opposite results in Models 1 and 2 (Model 1: regression coefficient = 0.213; Model 2: regression coefficient = −0.047).

5. Discussion

This study investigated the relationship between the factors of the urban built environment and COVID-19 using robust regression analysis (M-estimation) based on solving the heteroscedasticity of the OLS regression model. The study categorized urban built environment into two dimensions, namely, macro and micro, in two urban spatial dimensions, where

TABLE 4 Model 1: Robust regression results of CCC and urban built environment ($n = 1,551$).

	Regression coefficient	SD	t	p	95% CI	R^2	Adjusted R^2	F
Constant	0.423	0.02	21.266	0.000**	0.384 to 0.462	0.193	0.183	$F_{(20, 1,530)} = 18.302$, $p = 0.000$
Macro urban built environment								
Public	−0.255	0.088	−2.884	0.004**	−0.428 to −0.082			
Education	0.141	0.049	2.885	0.004**	0.045 to 0.236			
Commercial	0.116	0.055	2.107	0.035*	0.008 to 0.224			
Medical	−0.013	0.107	−0.122	0.903	−0.222 to 0.196			
Recreation	−0.235	0.085	−2.747	0.006**	−0.402 to −0.067			
POP	0.297	0.037	8.001	0.000**	0.224 to 0.369			
Traffic factors								
Airports	−0.06	0.217	−0.278	0.781	−0.485 to 0.365			
Bus station	0.026	0.115	0.228	0.82	−0.199 to 0.251			
Bus stop	0.138	0.038	3.612	0.000**	0.063 to 0.212			
Ferry	−0.363	0.155	−2.351	0.019*	−0.666 to −0.060			
Railway	−0.09	0.051	−1.765	0.078	−0.189 to 0.010			
Taxi	0.029	0.128	0.225	0.822	−0.222 to 0.280			
Micro-level urban built environment								
Sky	0.053	0.043	1.237	0.216	0.384 to 0.462			
PVGVI	−0.05	0.022	−2.276	0.023*	−0.094 to −0.007			
Building	−0.145	0.037	−3.891	0.000**	−0.218 to −0.072			
Road	0.141	0.032	4.374	0.000**	0.078 to 0.204			
Wall	−0.115	0.041	−2.8	0.005**	−0.196 to −0.035			
Macrophanerophytes	0.213	0.05	4.259	0.000**	0.115 to 0.311			
Grass	−0.357	0.058	−6.136	0.000**	−0.470 to −0.243			
Bush	−0.198	0.08	−2.481	0.013*	−0.355 to −0.042			

Dependent variable: CCC; $^*p < 0.05$, $^{**}p < 0.01$.

macro-level factors include variables related to urban traffic, and micro-level factors pertain to urban green structures.

5.1. COVID-19 and urban built environment

The study used the relationship between the number (CCC) and incidence (CCR) of confirmed and suspected cases of COVID-19 per 100,000 people in Manhattan, United States, as an entry point for the factors of the urban built environment. However, in the regression analysis with CCR as the dependent variable, POP exhibited a significant negative effect on CCR. In analyzing this entirely contradictory result, the study considered the effect of Commercial, which exerted a significant positive effect on CCC and CCR but with different factors at 0.116 and 0.041, respectively. In other words, residents can obtain necessities in a small area after the outbreak of a potential pandemic, and NPIs are better compared with those in areas with low population density. Residents in these areas must travel long distances to obtain essential resources, where long-distance travel implies increased chances of contact with strangers and COVID-19 infection. In summary: (i) high population density increases the likelihood of human contact, which facilitates the spread of the virus. However, with the implementation of NPIs, residents could only move within a small area; thus, the virus could not spread among areas. (ii) Areas with high-density populations typically have relatively well-developed infrastructure to provide convenient and timely treatment for residents, which, thereby, inhibits the spread of NPI (26, 29). In particular, under strict NPIs, the outdoor activities of residents are restricted, which effectively inhibits the spread of the virus in high-density areas (24). However, at the CCC level, the government for areas with high population density and high commercial activities performs better in terms of pandemic control and detection than did areas with low population density with a higher detection rate than that of areas with low population density. This finding results in a higher number of confirmed and suspected cases compared with those of areas with low population density.

TABLE 5 Model 2: Robust regression results of CCR and urban built environment ($n = 1,551$).

	Regression coefficient	SD	t	p	95% CI	R^2	Adjust R^2	F
Constant	0.557	0.006	93.445	0.000**	0.545 to 0.568	0.283	0.273	$F_{(20,\ 1,530)} = 30.130$, $p = 0.000$
Macro urban built environment								
Public	0.07	0.026	2.63	0.009**	0.018 to 0.122			
Education	−0.006	0.015	−0.416	0.677	−0.035 to 0.023			
Commercial	0.041	0.017	2.473	0.013*	0.008 to 0.073			
Medical	0.006	0.032	0.198	0.843	−0.056 to 0.069			
Recreation	0.044	0.026	1.706	0.088	−0.007 to 0.094			
POP	−0.088	0.011	−7.893	0.000**	−0.110 to −0.066			
Traffic factors								
Airports	−0.031	0.065	−0.47	0.639	−0.158 to 0.097			
Bus station	0.028	0.034	0.819	0.413	−0.039 to 0.095			
bus stop	0.012	0.011	1.066	0.287	−0.010 to 0.035			
Ferry	−0.032	0.046	−0.688	0.492	−0.123 to 0.059			
Railway	−0.01	0.015	−0.65	0.516	−0.040 to 0.020			
Taxi	0.049	0.038	1.263	0.207	−0.027 to 0.124			
Micro-level urban built environment								
Sky	0.029	0.013	2.27	0.023*	0.004 to 0.055			
PVGVI	−0.063	0.007	−9.421	0.000**	−0.076 to −0.050			
Building	0.079	0.011	7.074	0.000**	0.057 to 0.101			
Road	0.009	0.01	0.882	0.378	−0.010 to 0.027			
Wall	0.069	0.012	5.574	0.005**	0.045 to 0.093			
Macrophanerophytes	−0.047	0.015	−3.123	0.002**	−0.076 to −0.017			
Grass	−0.115	0.017	−6.594	0.000**	−0.149 to −0.081			
Bush	0.023	0.024	0.952	0.341	−0.024 to 0.070			

Dependent variable: CCR; $^*p < 0.05$, $^{**}p < 0.01$.

At the same time, control and control efforts are correspondingly lower due to the lower population density, which results in an increased number of cases without data. The situation of no data collection. The number of bus stops tends to be proportional to population density; the higher the population density, the higher the number of bus stops. Essentially, bus stops are places where urban residents are most likely to come into contact with strangers. A high frequency of contact with strangers implies an increased chance of infection. In general, public transportation infrastructure that increases population contact is considered a key factor in the spread of infectious diseases (25). Thus, a range of effective measures should be taken to limit the spread of disease in public transport, including limiting passenger density, increasing the frequency of services, and reserving tickets. Other low-carbon and environmentally friendly active transportation modes, such as walking and bicycling, should also be encouraged.

Similarly, at the public level, the results of CCC and CCR indicate a clear contradiction. From the CCR level, the higher the use of public facilities, the higher the probability of exposure to unfamiliar environments. Thus, the virus is likely to spread through public facilities before the introduction of corresponding NPIs. The number of public facilities in areas with high population density far exceeds that in areas with low population density, such that corresponding transmission rates and probability of transmission are also higher. On the contrary, at the CCC level, the frequency of the use of public facilities is suppressed due to NPIs, and residents will voluntarily reduce their frequency of use of public facilities when they are aware of a potential pandemic. This scenario indirectly leads to a negative correlation between CCC and the Public with a regression index of −0.235 over other factors. Schools tend to be places where pedestrian traffic is high, no less than in commercial areas, and the interaction between students and teachers may accelerate the spread of the virus. When students are infected with the virus at school, NCPI can easily infect family members through parent–child interaction, and the spread of the virus within colleges and universities is typically difficult to reasonably control. As the implementation of NPIs led to school closure, the correlation between schools and CCR became negligible; instead, many schools were requisitioned for the isolation of patients, which exerted a positive effect on the control of the outbreak after lockdowns. Alfano et al. (44) demonstrated that the premature opening of schools increased the number of COVID-19 cases in Italy. This result suggests that during an outbreak, the government should implement strict NPIs in schools while ensuring equity in education.

The higher the PVGVI, the farther away from the city center, the lower the population density, and the less space and medium for virus transmission and corresponding inhibitory effects on virus transmission.

Macrophanerophytes exerted a significant positive effect on CCC, whereas Bush and Grass exerted a significant negative effect on CCC when analyzed from the perspective of the green structure of urban streets. The reason for this phenomenon may be that in densely populated areas with developed commercial activities, the green structure is relatively homogeneous and shows a single-tree state. Conversely, areas with a rich green structure have correspondingly low population density and more homogeneous commercial activities, which can be analyzed in combination with macro-level POP and Commercial.

5.2. Research values

A series of recommendations for the results of the study have the following applications: (i) they can be applied at the level of prevention of widespread spread of COVID-19 in cities to minimize the risk of infection and the rate of virus transmission among urban residents by exploring the mechanisms of influence of the built environment and COVID-19. Effective control of virus transmission was achieved at the early stage of the outbreak. (ii) Based on the results of the study, government officials and policy makers can better formulate more reasonable NPI policies to prevent widespread infection and cross-infection and reduce the risk of infection among urban residents, while ensuring the wellbeing, health and comfort of urban residents. (iii) The study uses Google Street View panoramic street view images to extract and quantify urban micro built environment factors from the macro built environment and the micro built environment, respectively, to explore the impact of COVID-19 at the urban street level, and the results provide a data base for future urban renewal. This enables cities to play a more important role in facing the trend of COVID-19 epidemic normalization.

5.3. Research limitations

This study has its limitations. First, the data published by NYC Health are divided according to the MODZCTA, where individual buildings are designated unique zip codes in several instances. This tendency can exert a confounding effect on the data, and although the study screened a few of the confounding factors at certain levels, this data-level confounding continues to exist. Moreover, although the study sample was expanded according to fishnet divisions, the original sample only comprises 45 areas, which is not representative of all areas in the United States. Second, other demographic data for Manhattan were not available or could not be specifically mapped within each study area, such as household income structure, demographics, gender, underlying disease status, occupation, and ethnic composition, which have been noted in previous studies to be associated with 2019 coronavirus disease transmission. At the same time, within the time point of the COVID-19 pandemic, the lives of residents were frequently restricted by various NPIs, which resulted in extremely complex and confusing life activities and social relationships. Thus, the study selected only 20 variables, which indicates the exclusion of other potential variables such as the density of foot traffic in the region. Previous studies demonstrated that individual behaviors exerted an effect on the spread of COVID-19; however, such variables are statistically unavailable, relatively difficult to obtain, and more difficult to collect in the field due to various policy restrictions imposed by NPIs. The absence of such variables may have led to certain anomalies in the results of the study. Moreover, the effect of spatial autocorrelation cannot be avoided despite the multilevel and multidimensional considerations. Thus, future studies should consider additional aspects and potential variables to explore the relationship between the factors of the urban built environment and COVID-19. This, data on COVID-19 published by NYC Health provided substantial support to various urban studies on COVID-19. However, the published information on the number of cases is, in fact, incomplete due to the lack of statistical data on the number of cases due to the current pandemic policy implemented in the United States. Thus, certain individuals contracted COVID-19 but displayed no symptoms (asymptomatic) due to the lack of assurance of the detection rates of COVID-19 in the population. Moreover, individuals with the infection were not sampled for nucleic acids; thus, they remained unaware of their COVID-19 infection, which rendered their network and range of activities and transmission of the virus virtually uncontrollable and unavoidable. Possible non-linear effects of the variables in this study. The starting point of the robust regression is still based on the processing method of linear data, but the principle of adopting the method should be considered when processing the experimental data, and if the data have non-linear effects, the experimental data can be made permutation substitution so that they are transformed into a linear functional relationship for the test. In future studies, we will apply multiscale geographically weighted regression models with added potential factors to calibrate the existing models for further accuracy in the analysis given that more data are available at the city level.

6. Conclusion

The study draws preliminary conclusions on the relationship between the urban built environment and COVID-19 transmission, which focused on the relationship between CCC and CCR as the independent variables and the influence of the urban built environment. The correlation between the urban built environment and COVID-19 transmission was determined using Robust regression analysis (M-estimation). The major findings are summarized as follows:

(i) Education, Commercial, POP, and Bus Stop exerted a significant positive relationship with CCC at the macro level. Public and Commercial displayed a significant positive relationship with CCR. Public and Recreation have a significant negative relationship with CCC. POP has a significant negative relationship with CCR.

(ii) Macrophanerophytes, Grass, and PVGVI have a significant negative effect on CCR. Road and Macrophanerophytes have a significant positive effect on CCC. Sky, Building, and Wall have a significant positive effect on CCR.

(iii) Medical, Airports, Bus Station, Railway, and Taxi do not exert any influence on the relationship between CCC and CCR at the macro- and micro-levels of the urban built environment.

The current COVID-19 situation remains severe, and predicting the direction of the pandemic is difficult. To cope with more severe pandemic situations, this study provides several recommendations for urban built environments in the context of its results. First, the government should provide easy access to essential resources for urban residents within a controlled range, reduce the frequency of long-distance travel, save travel costs, reduce unnecessary human contact, and control the medium of transmission to reduce the speed and efficiency of the virus transmission. Second, for areas with high population density and commercial activities, strict NPIs should be implemented, such that if a potential outbreak occurs, then the area can quickly and adequately mobilize favorable resources to effectively control the outbreak. Third, the frequency of use of public facilities should be controlled. Although urban public transportation is an important part of the future low-carbon city, it continues to play an important role in the spread of the virus at this stage. In addition, the number of passengers should be controlled, their health status should be strictly tested, and safe social distancing should be observed to effectively control the spread of the virus. The government can promote and introduce incentives to encourage residents to use other modes of travel. Fourth, schools or educational settings were found to be at risk during outbreaks of COVID-19 due to their dense population and foot traffic; thus, a series of strong measures should be taken such as distance teaching or a limited number of people in schools.

The recommendations may serve as a reference for solutions for other cities at the level of controlling the transmission and spread of the virus. Meanwhile, the findings may provide valid suggestions for curbing potential outbreaks of respiratory diseases. However, the applicability of the variables is limited and does not reflect the regional economic level, demographic, and other sociodemographic characteristics of the city due to the limitations of this study and the data sources. Therefore, the generalizability of the results should be carefully considered.

Author's note

The S-G-S-S datasets used in this study can be downloaded and used from our GitHub site (https://github.com/muteisdope/S-G-S-S-Dataset.git), allowing users to modify, upload, and optimize the datasets. We will continue to upload new datasets and optimize the datasets in the future. Our research team based on Python language, Pytorch deep learning framework, DeepLabV3+ neural network used in our research, the code can be downloaded from our GitHub website (https://github.com/muteisdope/Model.git).

Data availability statement

The datasets presented in this study can be found in online repositories. The names of the repository/repositories and accession number(s) can be found in the article/supplementary material.

Author contributions

LZ and XH: conceptualization and writing—original draft. LZ and JW: resources. LW and JW: supervision. LW: validation. All authors contributed to the article and approved the submitted version.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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Supply-demand balance and spatial distribution optimization of primary care facilities in highland cities from a resilience perspective: A study of Lhasa, China

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Introduction: The development of urban resilience, which is fundamentally a balance between the supply capacity of primary care resources and the demand from urban residents, includes an appropriate architecture of primary care facilities. Resilient city construction in highland areas is hampered by the physical environment and transportation constraints and frequently encounters issues like poor accessibility and unequal distribution of primary care facilities.

Methods: To optimize the supply and demand of primary care resources in highland cities and effectively improve the resilience of urban public health, this paper assesses the distribution of primary care facilities within the built-up area of Lhasa (China) through a spatial network analysis method based on GIS, combined with population distribution data, and employs a location-allocation model to optimize the distribution.

Results: Firstly, the overall supply of primary care exceeds the overall demand, but the facilities' service area can only accommodate 59% of the residences. Secondly, there is a clear spatial variation in the accessibility of primary care facilities, and the time cost of healthcare is too high in some residences. Thirdly, the supply-demand relationship of primary care facilities is unbalanced, with both over-saturated and over-deficient areas.

Discussion: After distribution optimization, the coverage and accessibility of primary care facilities have increased significantly, and the spatial imbalance of supply and demand has been alleviated. This paper proposes a research method to evaluate and optimize the spatial distribution of primary care facilities from multiple perspectives based on the resilience theory. The results of the study and visualization analysis methods can be used as an invaluable reference for planning the distribution of urban healthcare facilities and urban resilience construction in highland areas and other underdeveloped areas.

KEYWORDS

resilient city, public health, spatial analysis, urban planning, highland area

Introduction

Widely employed in economic (1, 2), social (3), ecological (4, 5), and urban safety (6, 7) disciplines, the idea of resilience refers to the capacity of a system, community, or city to resist, absorb, adapt, and recover from hazard consequences in a timely and effective manner (8–10). Introducing the notion of resilience into urban planning can help cities effectively withstand the effects of risks such as climate change, natural disasters, and resource depletion and improve the stability of urban operations and capacity for comprehensive catastrophe prevention (11–13). Since 2019, as a result of the COVID-19 pandemic, the level of urban public health construction and services has now become an essential criterion for gauging the resilience of cities (14–18). Improving urban public health systems and reducing vulnerability and increasing the resilience of health systems have become major goals of national health policies (19–21). In this context, how to optimize the healthcare service system and increase public health resilience is one of the most important directions for advancing urban resilience theory (22).

The majority of the healthcare service system consists of hospitals, primary care facilities, and specialized public health facilities. Among them, primary care facilities serve as the primary providers of community medicine, infectious disease prevention, and healthcare. The Declaration of Astana proclaims, "We will benefit from sustainable public healthcare that enhances health systems resilience to prevent, detect and respond to infectious diseases and outbreaks" (23). Other previous studies have also linked primary care to public health resilience, demonstrating the positive effect of the primary care level on public health and the efficiency of the healthcare system (24–26). Areas with well-equipped primary care facilities also have healthier populations (27). Therefore, the rationality of the spatial distribution of primary care facilities is not only significant to the construction of urban public health resilience but also directly related to social equity (28–30). Compared to plain areas, cities in highland areas are confined by a severe natural environment and transportation limitations, making the cross-regional deployment of medical resources more challenging. As a result, primary healthcare facilities must shoulder more pressure to provide medical services. Moreover, most of these cities are situated in high-altitude and alpine regions, as well as underdeveloped areas, and the overall level of urbanization is low. Consequently, it is difficult to match the supply level of primary medical resources with the health needs of urban residents, and the spatial distribution has issues such as low accessibility and uneven distribution. However, previous studies on the distribution of healthcare facilities rarely address highland areas or focus on the supply-demand balance for primary care. Therefore, a comprehensive assessment of the supply and demand of primary healthcare resources in highland cities and optimization of the spatial distribution of primary care facilities are essential to improve the epidemic prevention and control capacity and the health level of residents in highland cities.

This paper uses the urban built-up area of Lhasa, China, as the study area. We use the resident population based on cell phone signaling data and the seventh national census data to calculate the resident medical demand and combine the network analysis method of the GIS platform to calculate the supply capacity of primary care facilities. On this basis, the rationality of the supply-demand relationship and spatial distribution of primary care facilities in Lhasa are evaluated in terms of redundancy, accessibility, and balance. An optimal distribution plan is then proposed using the locational allocation model, and the optimization results are validated. This paper's contributions can be summarized as follows. Firstly, it considers the distribution of population and the balance of supply and demand, since previous distribution evaluation studies are mostly from the perspective of facility accessibility. Secondly, previous studies on the optimal distribution of care facilities focus primarily on megacities or urban clusters with high economic development levels as the objects but less on cities in the underdeveloped areas of the highlands, which are complemented by this study. Thirdly, based on an evaluation of the supply-demand relationship and spatial distribution of primary care facilities, this study proposes an optimization scheme coupled with a locational allocation model that can not only be used as a guide for public health resilience construction and urban public service facilities planning but also be widely applied to the study and planning of primary care facilities in other highland areas and cities in underdeveloped regions.

The following sections comprise the remainder of this study. The "Literature Review" examines previous studies on urban resilience and the evaluation of primary care facilities. "Data" provides an overview of the research subject and data sources. "Methodology" outlines the geographic analytic techniques employed in this study. "Results" presents the results of the evaluation of the supply and demand relationship and spatial distribution of primary care facilities in Lhasa. "Discussion" discusses the "Results" section and proposes distribution optimization solutions. "Conclusion" highlights the study's key results, consequences, and limitations.

Literature review

The concept of resilience has evolved from engineering resilience (31, 32) to ecological resilience (33) and then to evolutionary resilience (34, 35). After its introduction into the field of urban studies, urban resilience is defined as "the capacity to achieve normal functioning of public safety, social order, and economic construction by adequately preparing, buffering, and responding to uncertainty perturbations" (11, 36–40). Jha et al. (41) proposed four components of urban resilience based on this finding: infrastructure resilience, institutional resilience, economic resilience, and social resilience. Currently, urban resilience research focuses more on the maintenance and coordination capability of the social-ecological system (42–44). Public health resilience, as part of social resilience, is generally understood to be the ability of healthcare systems and facilities to maintain function and recover from public health crises, both sudden (e.g., natural disasters and COVID-19) and slow (e.g., chronic diseases, etc.) (45–47). Previous research on public health resilience can be split into two main categories. Some studies examine the benefits of individual healthcare facilities, taking into account factors like staff management, built environment, intelligent systems, and medical equipment (21, 48–51). The others broaden the focus to include urban healthcare networks, taking into account the quantity, distribution, and interactions of healthcare facilities (52–55). According to Kruk et al. (52) a resilient healthcare system should cover multiple levels of facilities with wide coverage, while Hassan and Mahmoud (54) argue that a resilient healthcare network should consider not only the quantity and quality of facilities but also the demand and accessibility of healthcare services to the population.

In urban resilience construction, community resilience plays a fundamental and crucial role (56). As the fundamental urban unit, the level of community resilience can influence a city's capacity to resist and recover from calamities. Therefore, primary care facilities serving the community are important components in terms of their large quantity and wide distribution. A reasonable distribution of primary care facilities can enhance the robustness of the healthcare system, the redundancy of healthcare resources, and the rapidity of residents' access to healthcare services (57, 58), thereby enhancing the resilience of urban public health (24, 26, 27, 59–61). Existing studies generally agree that the resilience of primary care facilities, which are the first point of contact between the population and the healthcare system (59), will be most severely tested in a pandemic such as COVID-19 (26). These facilities not only perform medical functions but also include prevention, immunization, rehabilitation, healthcare, and education throughout each period of the pandemic (60), which is consistent with the principles of the resilience concept: resistance, adaptation, and recovery. On this basis, Akman et al. (61) suggest that the capacity of primary care services can hardly develop spontaneously but needs to be well-organized and planned, which demands the optimization of the distribution of primary care facilities.

Existing studies on the location and arrangement of public facilities can be divided into two categories: distribution evaluation and distribution optimization (62–64). Among them, most distribution evaluation studies are conducted from the perspective of spatial accessibility to calculate the transportation convenience from residences to facilities to accurately identify the areas lacking public services due to poor accessibility and to provide distribution optimization recommendations (65–72). For instance, some scholars analyzed the accessibility of public playgrounds from the standpoint of spatial justice while taking numerous social potential aspects into account (67).

The study of optimization models is another crucial aspect of the distribution of public facilities research. According to the different considerations and optimization objectives, scholars in the disciplines of operations research, geography, and computational science have proposed numerous facility distribution optimization models, such as the P-median model that minimizes facility distance (73) and the coverage model that maximizes coverage area (74) in the traditional location model, the equity maximization model that pursues the minimum distance difference (75), the multi-objective model that minimizes the sum of all distance differences (76), and expanded models such as the dynamic locality model (77), stochastic locality model (78), and multi-level locality model (79), among others. Gu et al. (76) constructed a dual-objective planning model that takes into account the efficiency of distribution facilities and the maximum coverage area to explore the optimal distribution of preventive care facilities. Other scholars introduced the concept of service radius in the coverage model and combined it with a gravity model to identify areas lacking care facilities (80), etc. These models have been increasingly utilized in care facility distribution studies. These studies focused on the accessibility and service coverage of care facilities, with the accessibility studies seeking to minimize the access distance and improve the convenience of healthcare, and the service coverage studies seeking to maximize the coverage area to increase the supply capacity of medical services.

Most existing studies concentrate on Nanjing, Wuhan, Zhengzhou, and other large cities with favorable economic and social conditions, where the primary medical system is relatively complete, and the medical supply is sufficient. However, these cities have high population density and service pressure on primary care facilities. Consequently, spatial accessibility and convenience of facilities are regarded as important evaluation indices, while coverage capacity is considered less frequently. Studies on distribution optimization models concentrate on maximizing the service supply capacity of care facilities, with little attention paid to the effect of the geographical variation in the medical demand levels of residents. In contrast, the urban primary care system in highland areas is underdeveloped, and the ability to distribute resources among multi-level care facilities is limited. Simultaneously, the urbanization rate in these areas is lower. The topography restricts the geographical development of the city, and the spatial diversity of population density is more pronounced. Fully based on the characteristics of highland cities, this study combines the supply level of primary care facilities and the demand level of residents to evaluate the primary care services in Lhasa, China and optimizes the spatial arrangement of primary care facilities aiming for the supply-demand balance to make the results more objective and credible.

Data

Study area

As the capital of the Tibet Autonomous Region (China), Lhasa is the political, economic, cultural, and religious hub of Tibet. The city is in the midst of the Tibetan Plateau, in the valley plain of the Lhasa River (a tributary of the Yarlung Tsangpo River), at an elevation of 3,650 m above sea level. According to the seventh national census and Tibetan Statistical Yearbook, as of 2021, Lhasa has a population of 867,800 and a GDP of 67.8 billion yuan, ranking it last among China's provincial capitals in terms of economic volume.

This study identifies the urban built-up area under the jurisdiction of Lhasa by combining Landsat remote sensing imagery in 2021 (Figure 1), which covers portions of Chengguan, Dulongdeqing, and Dazi districts with a total size of 268.5 km^2.

Population distribution data

Existing statistics on urban populations typically use administrative districts or streets as the statistical unit, making it more challenging to capture the spatial distribution of the population to evaluate the amount of healthcare demand. With the advancement of information and communication technology, cell

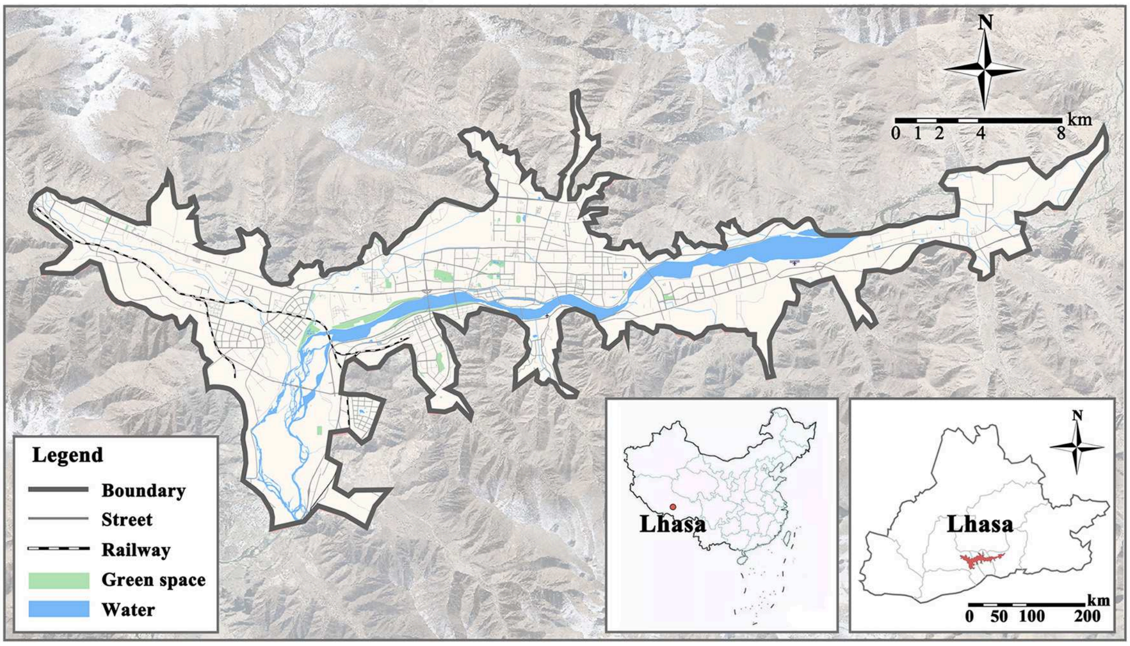

FIGURE 1
Map of the Lhasa study area.

phone signaling, as a new type of data, can more accurately reflect the spatial distribution characteristics and spatiotemporal variation characteristics of the population and is thus widely used to study population distribution and activity characteristics (81, 82). In this study, we gathered the cell phone signaling data of Lhasa in September 2021 and coupled it with the city's seventh census data in the study area (Chengguan, Dulongdeqing, and Dartse districts) to acquire the final population distribution statistics. On this basis, this research splits the study area into 300 × 300 m grids using the network processing tool in GIS and then determines the population density in each grid. The formula is as follows.

$$\mathbf{P_i}=\frac{\mathbf{P_T}}{\mathbf{M_T}}\times\mathbf{M_i} \tag{1}$$

Where $\mathbf{P_i}$ and $\mathbf{M_i}$ are the number of resident population and cell phone signaling in grid $\boldsymbol{i}$. $\mathbf{P_T}$ and $\mathbf{M_T}$ are the total number of the resident population and cell phone signaling in three urban districts, respectively. This conversion method can transform macro demographic data into geographic distribution data, thus clearly reflecting the amount of primary care demand.

Facilities and residences distribution data

As an emerging data source, POI (Point of Interest) can depict the spatial distribution characteristics of residential areas and diverse service facilities (83, 84). In this paper, we used Python to crawl the POI data of Lhasa within the study area from Gaode Map (https://www.amap.com). We then selected the residential areas and villages as the residence data required for the study and the healthcare service category as the primary care facility data. Large general hospitals in the healthcare service category are also the main providers of medical services for residents. However, on the one hand, Lhasa is the capital city of the Tibet Autonomous Region. The 3-tier healthcare system in China consists of primary care facilities, secondary hospitals, and tertiary hospitals. The primary care system can be further divided into two categories: community clinics and health centers, with the former referring to community-based care facilities and the latter to subdistrict-based care facilities (85–87). The secondary and tertiary hospitals in the city must provide medical services to residents from other cities in the region at the same time, so it is difficult to accurately calculate the coverage area and healthcare supply of their service areas. On the other hand, the breadth of healthcare services provided by general hospitals and primary care facilities are not identical, and their positions in the development of public health resilience cannot be interchanged. As a result, these hospitals are only used as a reference for the research outcomes and not as the primary target of the investigation.

Road network data

This study uses GIS spatial network analysis to investigate the relationship between the primary care facility supply-demand relationship and its spatial structure. A vector road network is required for precisely calculating the real geographic distance between care facilities and residences. Therefore, the vector road network in the Lhasa study area was downloaded from the OpenStreetMap platform (https://www.openstreetmap.org), and the road centerline data was extracted from it.

Methodology

Combining the characteristics of urban resilience, this study evaluates the spatial distribution of primary care facilities in terms of redundancy, accessibility, and balance. These three aspects correspond to the redundancy, rapidity, and robustness of the famous resilience "4R" for physical and social systems (88), and play different roles in the three phases of urban resilience consisting of resisting, adapting, and recovering (89) (Figure 2). In addition, the resourcefulness in the "4Rs" requires a combination of redundancy, accessibility, and balance of primary care facilities to enhance the healthcare efficiency and the learning capacity of the system by enhancing the organizational capacity of the urban health system.

Firstly, the service area analysis method in GIS spatial network analysis is used to calculate the service coverage of primary care facilities and determine the overall supply and demand relationship. Secondly, the accessibility of residents to primary care facilities and their spatial differentiation characteristics are analyzed by constructing an Origin-Destination matrix and combining it with the space syntax method. Thirdly, the level of primary care demand is computed based on the study area's population. Finally, the level of primary care demand was computed using population distribution data and geographically overlapped with the level of medical supply to analyze the supply and demand balance of primary care facilities in Lhasa. Based on the assessment results, this paper combines the location-allocation model to optimize the spatial distribution of primary care facilities.

Spatial analysis

This study's spatial analysis method is based on the GIS platform and consists of kernel density analysis, service area analysis, and Origin-Destination matrix analysis. Among them, kernel density analysis is used to calculate the spatial density of points in the surrounding search radius, which can reflect the distribution characteristics of primary care facilities and residences within the study area. Service area analysis and Origin-Destination matrix analysis are based on the network data set constructed by the GIS network analysis tool and can assess the service scope and accessibility of primary care facilities. In the examination of the service area, according to the requirements of the "15-min living circle" for service facilities, the service distance of community clinics and health centers are set at 5 and 15 min walking distance, i.e., 400 and 1,200 m, respectively (the walking speed is set at 80 m/min), which is used to calculate the service area coverage of care facilities. While the Origin-Destination matrix can be constructed, and the distance from the residential point to the closest care facility can be calculated. In addition, the service density within the service area of each facility level can be determined based on the number of people served and the size of the service area using the method shown below.

$$\mathbf{D}=\frac{\mathbf{P}}{\pi\mathbf{R}^2} \tag{2}$$

Where ***D*** is the service density (this study assumes that the service density is the same for each raster within a facility's service area). ***P*** is the number of people served by the facility, which is 5,000 for community clinics and 30,000 for the health center. ***R*** is the service distance.

Space syntax

As an effective theory and method for spatial quantification, the computation of integration degree by space syntax may describe the spatial potential of the reached sites and is frequently used to reflect road accessibility, which is separated into global integration and local integration. The global integration represents the degree of connection between a node and all nodes in the region and can be used to reflect the overall accessibility of the distribution of care facilities in Lhasa. On the other hand, the local integration represents the degree of connection between a node and nodes within a few steps of the topology and can be used to reflect the degree of connection between each care facility location and its surrounding residential points. In this study, we use the axis analysis method in the Depthmap platform to transform the vector road network into at least the longest road axis, and we calculate and display the global integration and the local integration of the road axis to visually represent the spatial accessibility of each care facility.

Location-allocation model

The location-allocation model is a system that picks the facility site with the optimal service capacity from a large number of candidate facility locations based on the defined service demand and a specific optimization model to optimize facility architecture. The minimization facility point model, maximization coverage model, minimization impediment model, and maximization pedestrian flow model are the most prevalent location-allocation models today. Highland cities have limited medical resources and facility construction capacity, and it is difficult to optimize the spatial layout of facilities by simply increasing the healthcare supply. Therefore, the total quantity of primary care facilities before and after optimization is proposed to be unchanged in this study. The maximizing coverage model is used to calculate the optimal architecture of primary care facilities that maximize coverage of current residential sites by considering existing primary care facility sites and residential sites as candidate facility sites, as illustrated in Figure 3.

Results

We compiled 1,040 residences (containing 746 residential communities and 294 villages) and 253 primary care facilities (including 212 community clinics and 41 health centers) in the study area using the POI data. In addition, we gathered data from ten general hospitals as a point of comparison. According to population-based calculations, the total healthcare service supply of community clinics and health centers was 1.06 and 1.23 million, respectively, which could fulfill approximately three times the demand for primary medical services (the total population in the study area was only 0.34 million). Using the GIS kernel density

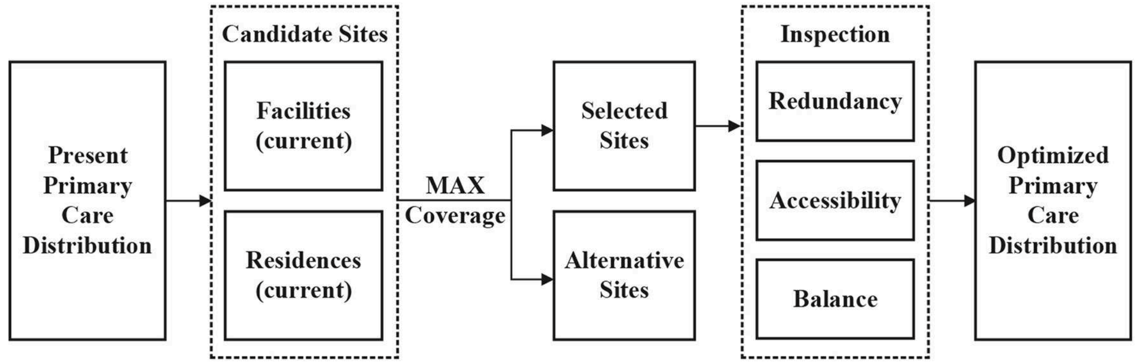

FIGURE 2
The framework for the impact of primary care facility distribution on urban public health resilience.

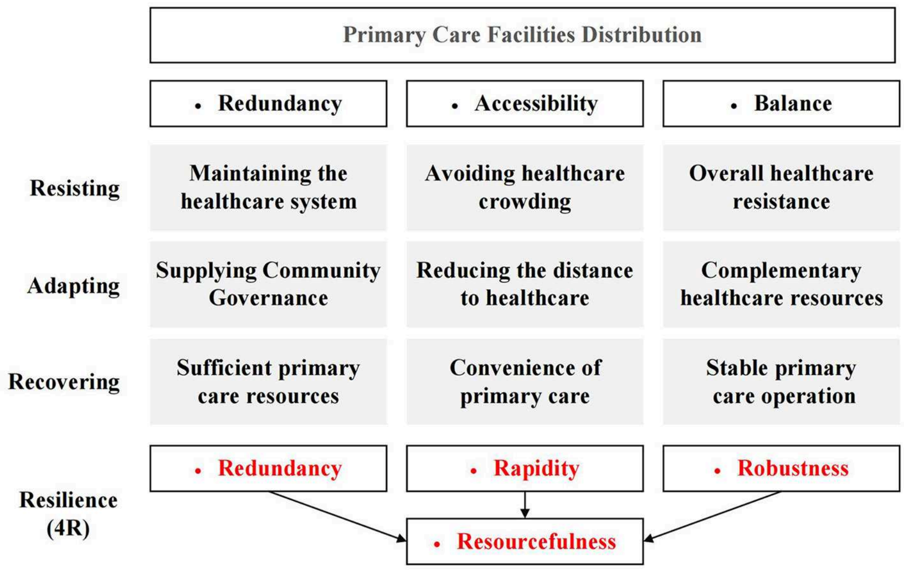

FIGURE 3
Maximized coverage model operation process.

analysis tool, we assessed the current primary care facility locations and residences in the study area. As depicted in Figure 4, the distribution of primary care facilities in Lhasa is comparable with the distribution of residences, with large concentrations in the center and low concentrations in the east and west.

By creating the service areas of primary care facilities in the GIS platform, the scope and coverage of all facility service areas may be obtained (Figure 5). Overall, only 59.23% of the residences in the study area (616 out of 1,040 places) are covered by the service areas of primary care facilities. And this percentage rises to 77.31% (804) when the service areas of general hospitals are considered. We can see that these unserved communities are primarily located on the eastern, western, and northern land borders of the research area, with primary care facility services being especially scarce in the eastern region.

The Origin-Destination matrix in GIS network analysis was utilized to calculate the actual distance between each residence and the nearest primary care facility and to build their connection. The results of the calculations (Table 1) indicated that the average distance between residences and the nearest care facility exceeded their service radius, and the number of residences within the service area of either community clinics or health centers was less than half of the total. Since the healthcare service duties of community clinics and health centers are not interchangeable, this information is a more accurate indicator of the paucity of primary care facilities than the coverage rate. The community clinic with the highest service pressure would provide medical services to 19 residences (nine of which are inside the service area), compared to 112 for health centers (28 of which are within the service area).

After visualizing the spatial distribution of the Origin-Destination matrix between the residence and primary care facility (Figure 6), it was discovered that most residences, including those in the east and west areas, have access to a community clinic within half the service radius (400–800 m), whereas health centers

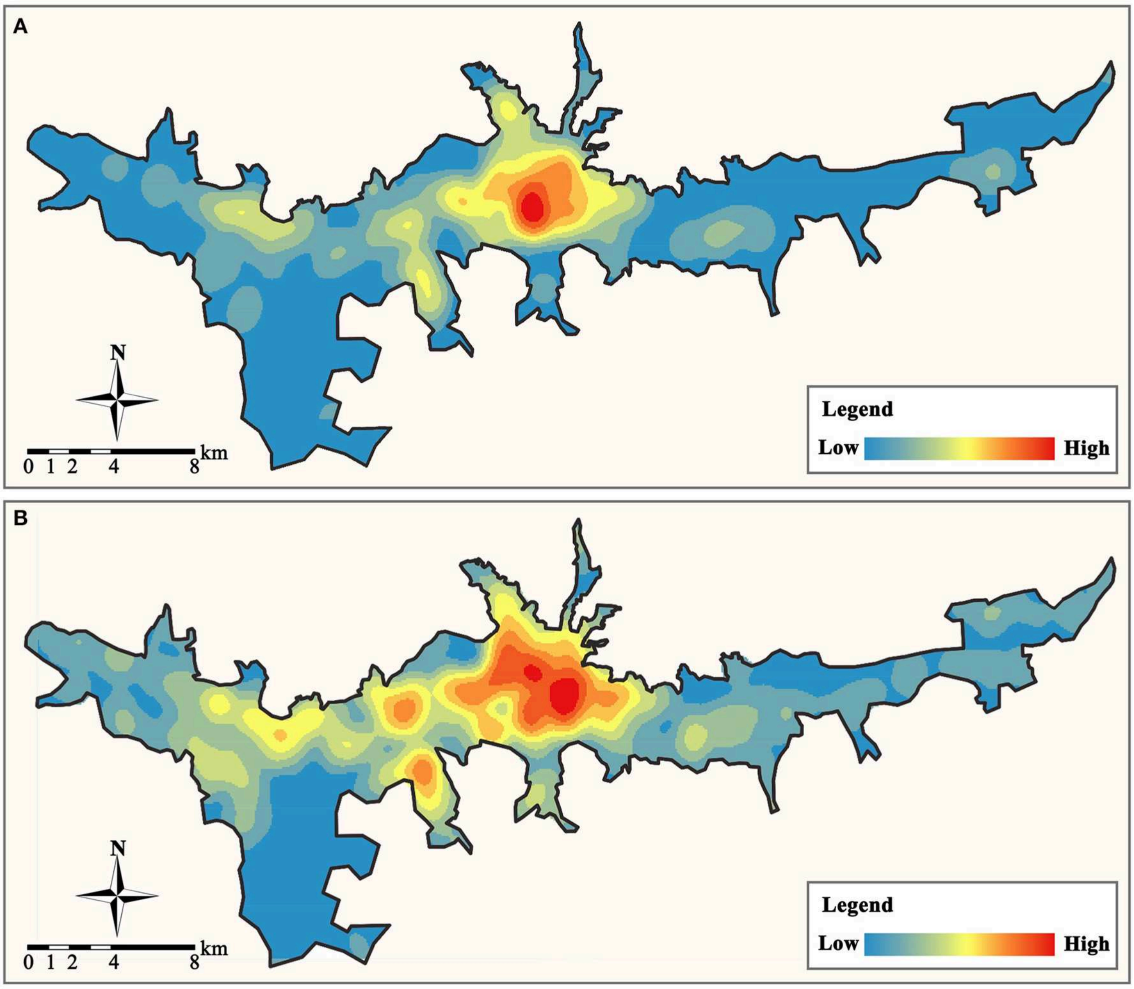

FIGURE 4
The distribution of primary care facilities and residential locations. **(A)** Primary care facilities. **(B)** Residences.

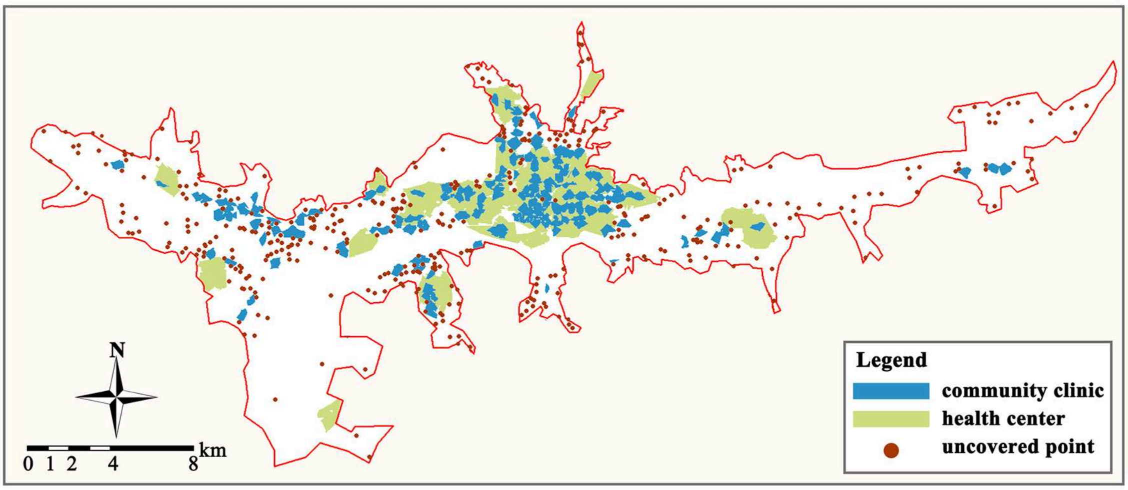

FIGURE 5
Service area of primary care facilities and uncovered residences.

TABLE 1 Results of the Origin-Destination matrix calculation.

Facilities	O-D Distance (m)			Sites in the service area	Max served	Max served (In service area)
	Max	Min	Average			
Community clinics	4186.2	4.4	636.8	366	19	9
Health centers	7732.7	2.1	1797.4	486	112	28

are not easily accessible. Most residences at the perimeter of the city's built-up area are more than 3,000 m away from the nearest health center. As a result, residents may not be able to walk to the health center. Therefore, they are required to drive to the general hospital. This can also be independently confirmed by integrating the Depthmap platform integration analysis (Figure 7). Most residences that are not within the service area of primary care facilities are in areas with low global integration, and the local integration with the surrounding three-step topological distance nodes is also significantly insufficient, making it extremely difficult to walk to the care facilities.

Finally, we established a 300 × 300 m grid to determine the demand density and supply density of primary care facilities in the study area, where the demand density is the resident population density, and the supply density is the service density of all primary care facilities. We can determine the supply and demand relationship of primary care services in the study area by comparing the disparity between the two to the average demand density in the study area (3,000 people/km^2 is calculated to be the average demand density in the study region). When the disparity between supply and demand is less than zero, it indicates that regional primary care facilities are inadequately supplied and that residents' demand for medical services is unmet. When the disparity is between (0, 1), it indicates that regional medical service facilities have a balanced supply and demand relationship. When between (1, 3), it indicates that there is an excess of regional primary care facilities. When the disparity exceeds three, primary care services in a region have reached saturation. Our analysis results are depicted in Figure 8. Overall, the distribution of primary care supply and demand in the study area is extremely unbalanced, with community clinics in the central area being severely saturated with supply and health centers supplying at a level that can meet demand. But the level of primary care supply in most areas to the east and west of the study area is insufficient to meet the demand for healthcare services, and there is a severe shortage of primary care facilities.

Discussion

Redundancy

In the context of the idea of resilience, redundancy refers to the diversity of functional components and the replicability of functions in a city. It guarantees that if the capacity of a component or a level is compromised, the city system can still rely on other levels to function normally (90, 91). Kharrazi et al. (92) argue that systems can be made more fault-tolerant by replicating and creating new paths, functions, or components, and demonstrate the importance of diversity and redundancy by showing the relationship between modules, nodes, and paths. When the urban healthcare system is confronted with a public health event shock, a large number of seriously ill patients tend to quickly deplete the medical resources of the urban general hospital. Consequently, it is necessary to ensure that the urban primary care facilities have sufficient resources and capacity to meet the requirements for the admission and treatment of mildly ill patients, community governance, and other daily medical services to ensure that the urban healthcare system can withstand the public health event shock.

The total supply of primary healthcare services in the built-up area of Lhasa exceeds the total demand, but the service area of the facility can only cover <60% of the population. And the primary medical system is still in an imperfect and unbalanced state. In general, people can satisfy their healthcare needs by going to facilities or general hospitals in neighboring communities to avoid "difficulty in seeing a doctor. In general, individuals can avoid "difficult access" by visiting nearby community centers or general hospitals. However, several studies have demonstrated that when a pandemic exacerbates the problem of resource shortages and poor transportation, the healthcare system is overwhelmed (93, 94). When a major public health event such as COVID-19 occurs, nearly half of the communities in the built-up area will have trouble obtaining healthcare services from nearby primary care facilities and will need to deploy personnel and resources from other communities or general hospitals. This will undoubtedly pose a significant challenge to the operational capacity of the urban healthcare system and will indirectly increase the pressure on community governance. When there are no primary care facilities nearby to provide treatment and healthcare services, residents will be forced to travel to health centers or general hospitals further away, which will result in staggering movement within the city, thereby increasing the risk of illness among residents. In contrast, the lack of primary care facilities makes it difficult for community governors to detect and comprehend the health status of inhabitants, hence increasing the likelihood of mass infection. Therefore, it is necessary to increase the redundancy of urban primary care by optimizing the spatial distribution, expanding the service coverage area of primary care facilities, and closing the gap in medical services. This is the fundamental objective for reducing the risk of primary care and bolstering the resilience of urban healthcare in mountainous regions.

Accessibility

The notion of accessibility is derived from the field of transportation, where it refers to the capacity of individuals to

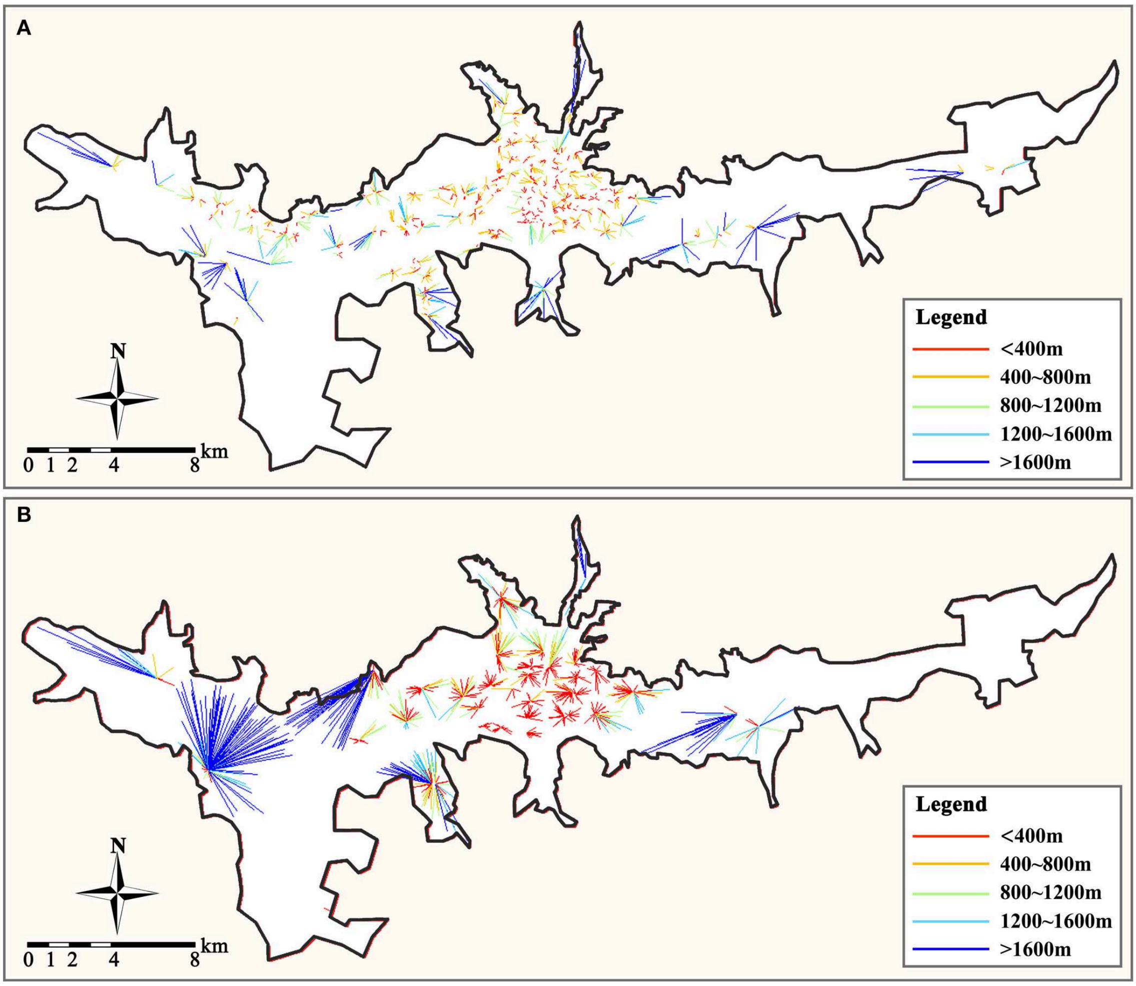

FIGURE 6
Spatial distribution of Origin-Destination links. **(A)** From residences to community clinic. **(B)** From residences to health center.

reach a certain place, which is typically expressed by the journey time, cost, number of destinations, and attractiveness between the origin and destination (68, 70–72). Accessibility corresponds to the rapidity in urban resilience characteristics, and a healthcare service system with better overall accessibility can help people access healthcare resources in a timely manner, thereby avoiding or reducing urban risks from public health events (70). And in the recovery phase following a public health event shock, a healthcare facility with high accessibility can also provide more convenient services. Depending on the variation in the function of primary care facilities, national studies have evaluated their accessibility in different ways. As Luo and Wang (66) define the physician's service area by threshold travel time and consider physician availability based on the demand around them in Chicago, while accessibility studies for cities such as Shanghai and Wuhan in China mostly used healthcare facilities as destinations (95, 96). Accessibility encompasses some transportation modes, with pedestrian transportation having the strongest association with primary care facility accessibility.

There is a substantial disparity between the walkability of community clinics and health centers in the primary care facility system in the Lhasa built-up area. Comparatively, only about one-third of the residences have Origin-Destination distances smaller than the service range of community clinics, but the majority do not exceed the service range by too much. This means that when there is no community health station in the community, residents can reach other community care facilities by walking 500 to 1,500 m. However, the accessibility distribution of health centers has some hidden problems. While the Origin-Destination distance to health centers in the middle of the city is within the service area, it is difficult for residents of urban fringe areas to walk to the nearest community health center. And most health centers in urban fringe areas must serve the healthcare needs of 10 to 15 residences, which makes it challenging to match their supply.

Balance

The equilibrium of public service facilities is manifested on the one hand by the equilibrium between the supply capacity and demand level of healthcare services in a particular area, and on the other hand by the spatial distribution of the supply-demand

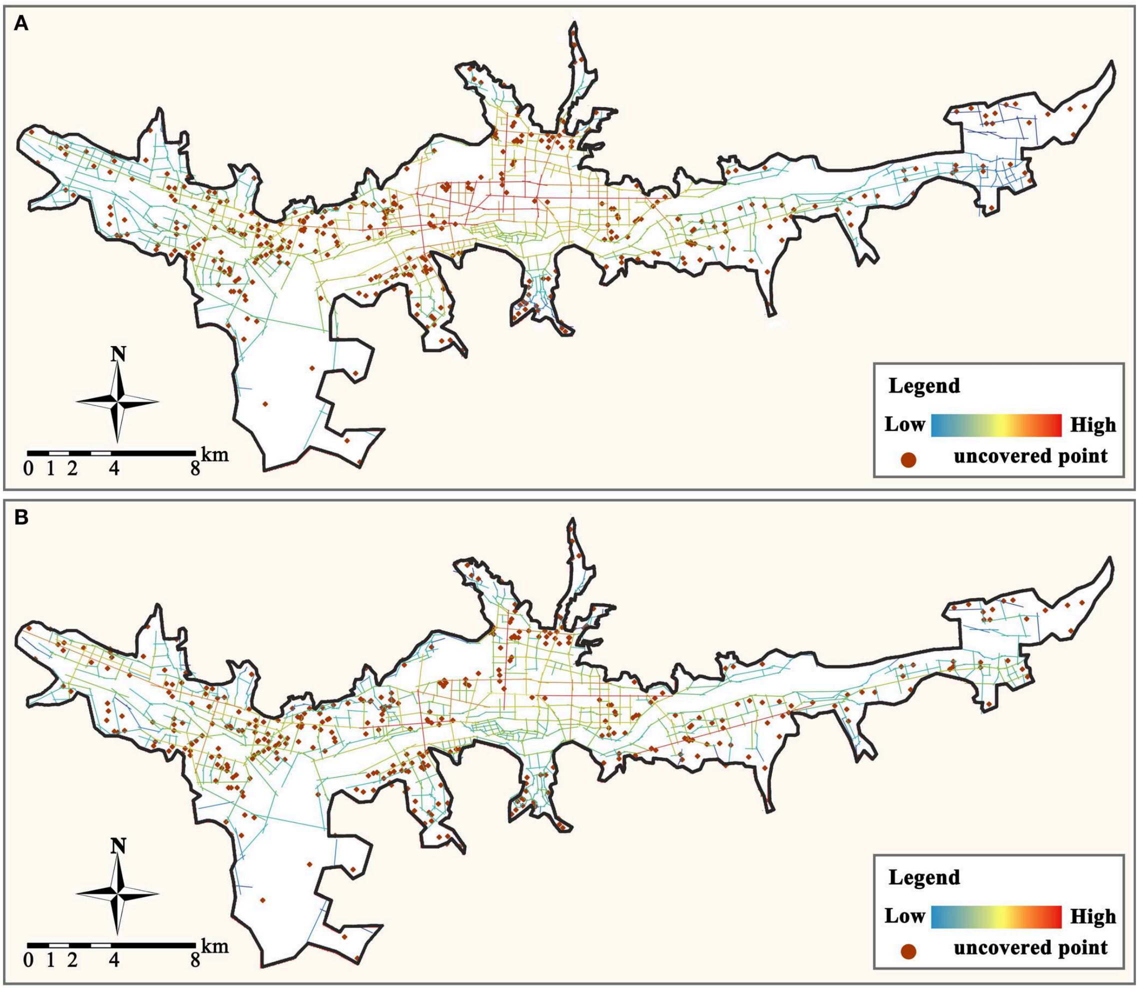

FIGURE 7
Analysis of urban road axis integration. **(A)** Global integration. **(B)** Local integration.

relationship between different areas within the study's scope (71, 97, 98). The balance of supply and demand is intended to be the equilibrium between all products and services provided by society and social requirements in each period, as evidenced by the changes in product supply and social demands in response to product price changes, and at a certain price point (99, 100). Healthcare services are public services under government regulation and do not fully follow the price-driven market law, but primary care facilities (especially community clinics) are not all publicly owned. Some of them are operated by communities or private contractors, leading to an unbalanced distribution of primary care facilities. This has resulted in an imbalanced urban geographic distribution of primary care services.

The distribution of primary care facilities is crucial for sustaining community resilience. A balanced link between supply-demand and spatial distribution is favorable to macroeconomic regulation of the distribution and use of medical supplies, as well as to the maintenance of community stability and the decrease of crowds during public health events. In densely populated areas with permanent residents, to avoid medical congestion, the supply of primary medical services can be made greater than the residents' medical demand, and multiple points can be dispersed. In urban fringe areas with scattered residential points, consideration must be given to maximizing the service area coverage of primary care facilities to maintain the efficiency of primary care access when there are fewer facilities, and the latent demand is greater. However, the current distribution of primary care facilities at both levels in Lhasa cannot meet the needs of services in densely populated and dispersed areas, and the supply of primary care services in the central area is oversaturated, whereas the majority of areas on the city's periphery have an excess of healthcare services.

Optimization based on the location-allocation model

As revealed above, the supply-demand relationship and the spatial distribution of primary care facilities in the built-up area of Lhasa are flawed in terms of redundancy, accessibility, and lack of balance. In this study, we optimize the spatial distribution of primary care facilities from a macroscopic perspective to

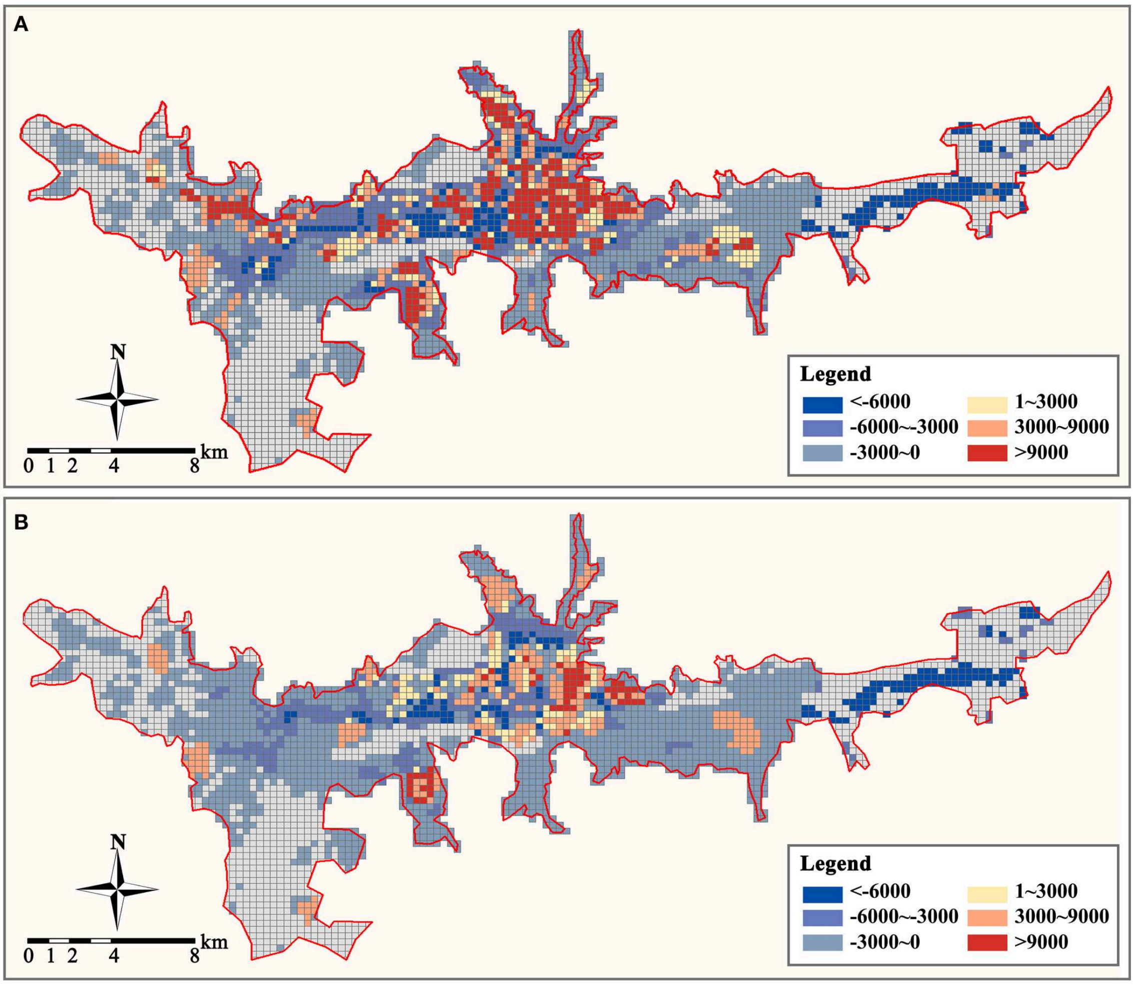

FIGURE 8
Supply and demand disparity of primary care facilities (person/km2). **(A)** Community clinic. **(B)** Health center.

improve the supply-demand relationship of primary medical services while keeping the total supply of primary medical services constant. The maximized coverage model intuitively extends the coverage area of primary care services, reduces the average time for residents to reach primary care facilities, and decreases the difficulty of access to care in areas lacking primary care services. The optimized distribution scheme improves the overall efficiency of the healthcare system and effectively reduces the risks associated with healthcare crowding and resource imbalance, thereby enhancing urban public health resilience.

The optimized primary care facility system consists of 177 added facility sites (including 152 community clinics and 24 health centers) and 176 retained facility sites (including 60 community clinics and 17 health centers). We reevaluated the supply and demand of optimized primary care facilities based on three indicators: redundancy, accessibility, and balance, to confirm the rationality of the optimized structure of the facilities. Through distribution optimization, the residential point coverage rate of primary care facilities grew from 59.23 to 83.27%, and the capacity of primary care services increased significantly, but there were still some marginal locations that were not covered by the service area (Figure 9). This finding indicates that even with the maximum service area, the current number of primary care facilities cannot cover all residential points in the study area. Therefore, the government needs to appropriately increase the number of primary care facilities according to the fluctuation of healthcare demand or open mobile healthcare service stations in residences that are far from primary care service areas.

After distribution optimization, the average distance between residences and the community clinics is reduced from 636.8 to 364.3 m, and it is reduced from 1977.4 to 912.3 m between residences and health centers. It indicates that the accessibility of primary care facilities is significantly improved. Simultaneously, the maximum number of residences served by community clinics and health centers was reduced from 19 to 11 and 112 to 57, and the demand for primary care services was balanced. Analyzed from the spatial distribution perspective (Figure 10), after distribution optimization, the accessibility of residences to primary care facilities is significantly enhanced, and most residences can quickly reach the nearest facility site. However, there are still some urban fringe areas where residents' accessibility is poor.

To determine the effect of distribution optimization on the spatial distribution of the primary care supply-demand relationship in the study area, we evaluated the supply-demand density disparity

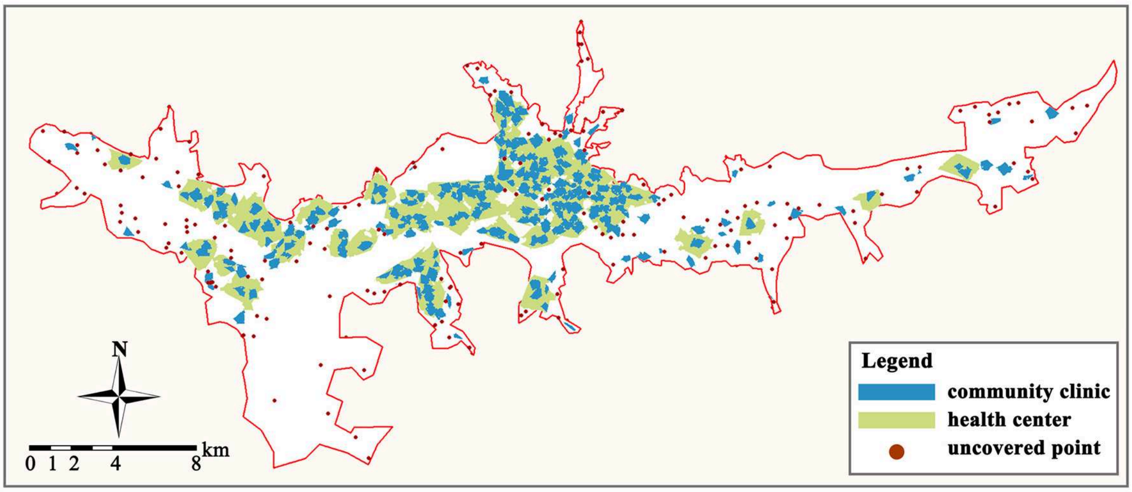

FIGURE 9
Optimized primary care facility service area and uncovered residences.

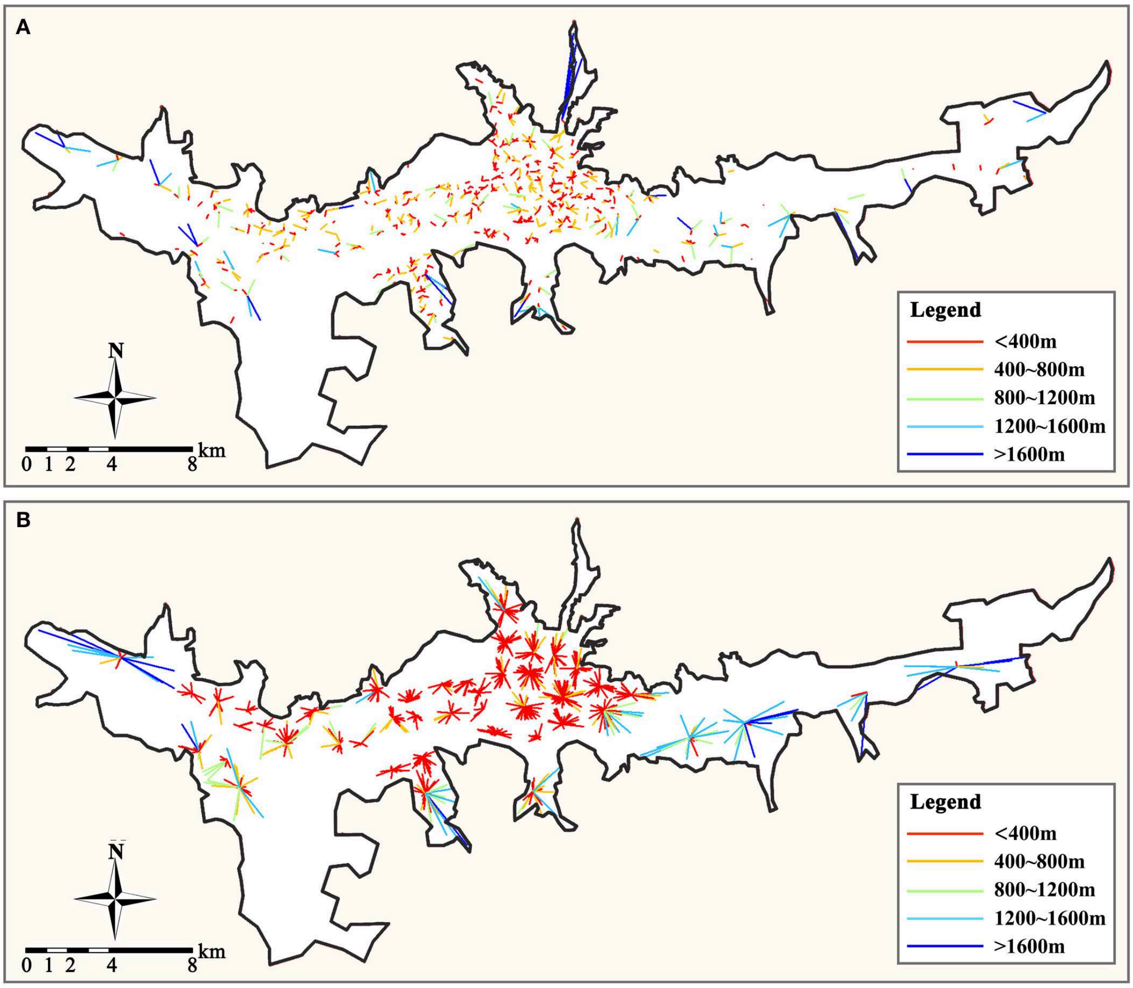

FIGURE 10
Optimized spatial distribution of Origin-Destination links. **(A)** From residences to community clinic. **(B)** From residences to health center.

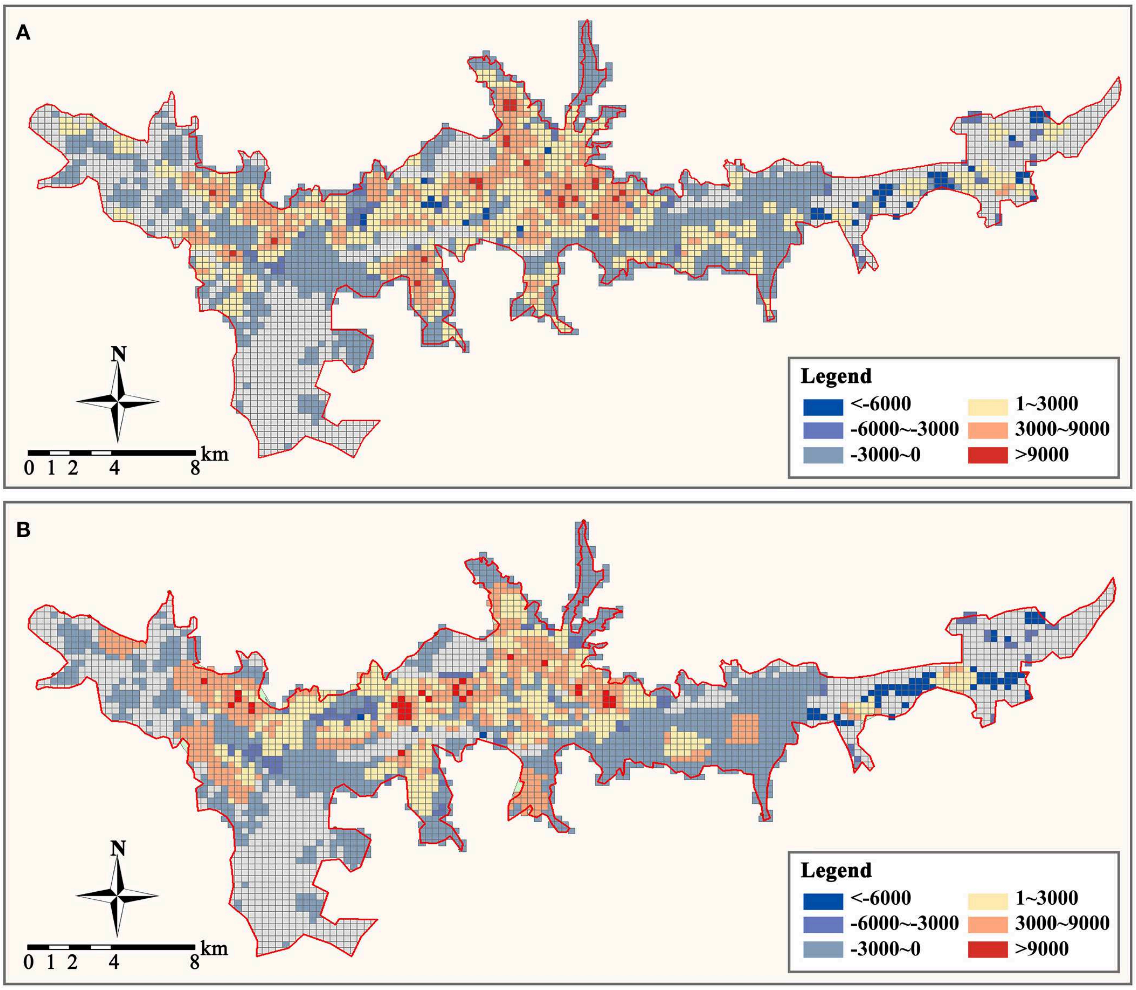

FIGURE 11
Optimized supply and demand disparity of primary care facilities (person/km^2). **(A)** Community clinic. **(B)** Health center.

of primary care services within each raster after distribution optimization (Figure 11). After optimization, the overabundance of medical supply in the central area and the severe deficiency of medical supply in the urban periphery can be eased. In the majority of Lhasa's central area, the disparity between primary medical supply and demand is kept between 0 and 3 times the average demand density, which is sufficient to cover both daily and emergency medical demands. Compared to the current arrangement of primary care facilities, the optimal architecture has partially reversed the primary care deficit in most locations on the west and east sides of the research area, although there are still certain areas where primary care services are few. In conducting the residence coverage analysis and constructing the zone distribution model, we use POI points to represent the spatial distribution of each residence. However, the areas of the residences represented by these points vary in size, making it challenging for some communities and villages with large areas and dispersed populations to be covered by primary care services. For these residences, access to the nearest primary care facilities (even if they are slightly outside the service area) via internal roads is still the most logical option.

Conclusion

This paper employs a GIS-based method to evaluate the supply-demand relationship and spatial distribution rationality of urban primary care facilities in the built-up area of Lhasa, China, as the study area to conduct an empirical study and proposes an optimization scheme for the spatial distribution of primary care facilities in conjunction with a location-allocation model. The program may effectively alleviate the oversupply and uneven distribution of primary care facilities in the study area, allowing them to satisfy the development needs of public health resilience and withstand the effects of disasters.

This paper's findings, methodology, and technique have practical consequences for the site development of urban healthcare facilities in mountainous cities. Firstly, this paper integrates the concept of urban resilience to comprehensively assess and optimize the spatial distribution of urban primary care facilities, so that primary medical services can not only meet the daily needs of residents but also withstand the impact of public health events on the urban medical system. Secondly, existing studies are less involved in the underdeveloped regions of the highland area, which have lagging economic development. This paper integrates healthcare demand into the study of the spatial distribution of primary care facilities and establishes an assessment system combining redundancy, accessibility, and balance from the perspective of supply-demand balance, providing a new idea for the existing care facility distribution assessment research. At last, this paper presents a maximum coverage model that maintains the total amount of amenities, which can result in a more acceptable distribution optimization strategy for highland cities. This paper presents the importance of the distribution of primary care facilities. The results of the study can optimize and complement the existing hierarchical healthcare system to help build a more rational primary care network in highland areas and other underdeveloped regions, thereby reducing urban healthcare risks and enhancing urban public health resilience.

Nonetheless, the study does have certain drawbacks. Through analysis and evaluation, it is evident that the spatial distribution of primary care facilities in the study area is unbalanced. This imbalance is reflected in the number and supply of facilities as well as spatial accessibility. There are differences in the spatial distribution characteristics of facilities at various levels, and these problems are the result of a combination of factors. Not only is the distribution of healthcare services and function of supply and demand, but also the placement and distribution of geographic places. The optimization scheme based just on population, facility distribution, and road traffic is insufficient. It must also consider the influence of regional economics, policies, external transportation, ecological environment, geography, and other public service facilities siting. In addition, the demand for primary care services may be different for each population group, and the redundancy and accessibility of facilities are correlated with the population characteristics of the surrounding residences, thus affecting the study results. Therefore, we believe that it is possible to evaluate the distribution of urban care facilities from more perspectives and to superimpose the evaluation results from different perspectives, which will make the evaluation and optimization results of the spatial distribution of care facilities more scientific and guiding. It will be widely applicable to other site selection and distribution studies.

Data availability statement

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

Author contributions

YY: conceptualization, funding acquisition, and supervision. RZ: formal analysis, methodology, and writing. LQ, XY, LD, and GZ: review and editing. All authors contributed to the article and approved the submitted version.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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Restorative perception of urban streets: Interpretation using deep learning and MGWR models

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Restorative environments help people recover from mental fatigue and negative emotional and physical reactions to stress. Excellent restorative environments in urban streets help people focus and improve their daily behavioral performance, allowing them to regain efficient information processing skills and cognitive levels. High-density urban spaces create obstacles in resident interactions with the natural environment. For urban residents, the restorative function of the urban space is more important than that of the natural environment in the suburbs. An urban street is a spatial carrier used by residents on a daily basis; thus, the urban street has considerable practical value in terms of improving the urban environment to have effective restorative function. Thus, in this study, we explored a method to determine the perceived restorability of urban streets using street view data, deep learning models, and the Ordinary Least Squares (OLS), the multiscale geographically weighted regression (MGWR) model. We performed an empirical study in the Nanshan District of Shenzhen, China. Nanshan District is a typical high-density city area in China with a large population and limited urban resources. Using the street view images of the study area, a deep learning scoring model was developed, the SegNet algorithm was introduced to segment and classify the visual street elements, and a random forest algorithm based on the restorative factor scale was employed to evaluate the restorative perception of urban streets. In this study, spatial heterogeneity could be observed in the restorative perception data, and the MGWR models yielded higher R^2 interpretation strength in terms of processing the urban street restorative data compared to the ordinary least squares and geographically weighted regression (GWR) models. The MGWR model is a regression model that uses different bandwidths for different visual street elements, thereby allowing additional detailed observation of the extent and relevance of the impact of different elements on restorative perception. Our research also supports the exploration of the size of areas where heterogeneity exists in space for each visual street element. We believe that our results can help develop informed design guidelines to enhance street restorative and help professionals develop targeted design improvement concepts based on the restorative nature of the urban street.

KEYWORDS

deep learning, street view, semantic segmentation, multiscale geographically weighted regression, urban street environment, restorative quality

1. Introduction

Streets are used as passageways to a city; however, streets can be considered symbols of civilization, from which we derive multiple social functions, e.g., culture, politics, democracy, economy, and health (1). Compared to other urban spaces, e.g., squares and green spaces, city parks, and community parks, urban streets are functionally more diverse and complex, and they are important places for urban residents to walk, communicate, shop, exercise, and participate in multiple social activities (2). As the urbanization process continues, multiple negative impacts occur, e.g., urban sprawl, environmental damage in the central city, and the decline of street vitality. When people stay in a low-quality urban environment for a long time period, they will feel stress, and prolonged serious stress can to lead to mental illness and even physical illness (3). People born in urban areas possibly suffer from mental illness than those born in rural areas; as people become more urbanized and live longer, their risk of illness increases (4). However, high-quality urban streets are restorative and invigorating, and they can reduce psychological stress, clear negative emotions, and effectively reduce the incidence of many chronic diseases (5). The restorative nature of urban streets indicates that they can help people reduce stress and various negative emotions, relieve mental fatigue, and achieve improved mental and physical health (6). Hartig stated that "restoration" refers to regaining physical, psychological, and social abilities lost in the process adapting to the external environment (7). The restorative nature of high-quality urban streets and the reduction of psychological stress have led researchers and urban planners to focus on the creation of high-quality restorative urban streets (8).

Early restorative environmental research focused on natural environments or urban environments dominated by natural elements (9). For example, Nordh examined restorative perception by selecting 74 images of a park and identified the restorative characteristics of a park environment (10). With the expansion of scientific perspectives in recent years, the restorative potential of urban streets is being gradually explored. As one of the most important public spaces in cities, the restorative nature of urban streets should be carefully considered. Researchers in many fields have attempted to understand the restorative effects of urban streets. For example, Linda et al. studied the restorative nature of urban streets and reported that tall buildings around urban streets hinder the perception of restorative nature. Furthermore, Lindal and Hartig reported that plants along streets have a positive effect on the perception of restorative nature (11). Zhang et al. used virtual reality technology to simulate an urban street environment and reported that plants along the street demonstrated positive correlation with restorative perception (12). Although such methods can help us understand the restorative perception of urban streets, they are limited in terms of the restorative perception measurement of large-scale complex streets. Time-consuming, small sample size, high cost, and low efficiency can only be studied for restorative perception of small-scale sites, and not for large-scale street perception. Recently, because of the development of multi-source big data services, e.g., Baidu Street View (BSVI), Tencent Street View (TSVI), and Google Street View (GSVI), high-quality and reliable research data are available to examine the restorative perception of urban streets on a large scale. Furthermore, with the rapid development of computer technology, the application of deep learning is becoming increasingly widespread, and more researchers are employing deep learning technologies to solve urban problems (13). The use of multiple linear regression models to explore the relationship between the perceptions of cities and multiple explanatory variables is well established (14); However, many studies have been conducted to model and analyze the cause and effect for the global space. Street view images with geographic coordinates are standard spatial data, research on the restorative perceptions of street views may be heterogeneous in space, and global spatial regression interpretation analysis of spatial data may have errors, which can lead to biased results that are not accurately representative of reality. The GWR and MGWR models are more accurate for spatial data because they take into account geospatial heterogeneity and make use of local regression. Thus, the choice of a suitable spatial processing model is important for the accurate representation of the results (15, 16).

The study area considered in this study is the Nanshan District of Shenzhen City, Guangdong Province, China, which is covered by Baidu Maps compared to other map systems (17). Using Baidu Maps enables a more detailed study of urban streets in the Nanshan District; thus, Baidu Street View was used as a data source for the restorative perception of urban streets. This study has two primary objectives. (1) Prediction of restorative perception of urban streets using a random forest algorithm based on a restorative scale to identify the characteristics of visual element combinations in urban streets under different restorative perception scores. (2) The effect of visual street elements on restorative effects is identified using OLS, GWR, and MGWR to select the model having the most explanatory power. Compared with a single global regression model, a comprehensive study using OLS, GWR, and MGWR models can determine whether the restorative perception data are smooth in space and whether a spatial regression model needs to be selected for the study, and secondly, comparing different spatial regression models, the model with the highest accuracy can be selected for the phenomenological interpretation, which can more accurately reflect different regions of different visual elements in space for impact on restorative perception. This has an important practical significance for rational regional planning. The joint analysis method of street view big data, deep learning, and the spatial regression model can help urban planners and urban humanities researchers to have more targeted and deeper understanding and knowledge of the restorative perception of urban streets.

2. Workflow, study area, and data collection

Figure 1 shows the conceptual framework of urban street restorative perception exploration from a holistic perspective. Firstly, the road network of the study area is downloaded from the OSM website based on the administrative area, a street spot is taken every 50 m of the road network, and the street view image acquisition parameters are adjusted by simulating the pedestrian's viewpoint, and the Baidu Map API is called to collect the urban

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street view big data, and four street view images of the same street spot are stitched together to finally obtain all the street view images of the study area. The semantic segmentation of the training images is used to obtain the data of urban street view visual elements, while volunteers are invited to score some street views for restorative perception according to the restorative perception scale, and the scoring results and the street view visual elements are made into a machine learning training dataset and imported into a random forest model to predict the restorative perception of all the street view images in the study area. The restorative perception scores were subjected to OLS regression analysis with the visual elements of urban streets, and the results were judged to be spatially heterogeneous, and then GWR and MGWR regression analyses were conducted to select models with high explanatory strength for the restorative perception phenomenon, and finally to discuss and provide urban planners' opinions on improving the effect of restorative perception.

2.1. Study area

In this study, we focused on one of the most economically developed regions in China, i.e., the Nanshan District, Shenzhen, Guangdong Province (Figure 2). The population of Nanshan District is ∼1.79 million, accounting for 10.23% of the resident population of Shenzhen. The Nanshan District has several hills, the highest of which is 587 meters above sea level, several bays (including Shenzhen Bay), five islands, and numerous rivers and reservoirs. Nanshan District is bordered by the ocean and has a coastline of 43.7 km. The geographical and environmental conditions are very rich compared to other regions; thus, the potential perceptual spatial heterogeneity caused by the geographical environment can be fully considered. In addition, Nanshan District is the center of scientific research, education, and sports in Shenzhen, and is the location of Shenzhen University, Southern University of Science and Technology, Shenzhen High-Tech Industrial Park, and the Shenzhen Bay Sports Center. As one of the faster-growing economic regions in Shenzhen, Nanshan District is likely more advanced in terms of urban construction and renovation. Empirical research on restorative perceptions in Nanshan District can serve as a test for other developing regions and provide suggestions to guide how other regions can improve restorative perceptions on the path to urbanization. Thus, Nanshan District was selected in this study to investigate the perceived restorative nature of urban streets.

2.2. Collecting Baidu street view image data

Street view images were collected along roads in the Nanshan District to mimic human perspective in order to assess the restorative perception of the area. Urban environment analysis studies that use streetscape image big data to evaluate urban street quality are becoming increasingly common (18). Street view data can be used to perceive and observe an urban environment from a human perspective (19). The street view data platform provides street view browsing services to web users and publishes an application programming interface (API) that allows users to download massive amounts of street view data. Thus, street view data are used to represent the environment of city streets as a basis to measure restorative perception. To collect street view images, street view collection georeferenced points were generated at 50-m intervals using the roadway network provided by OpenStreetMap. Then, the Baidu Map API interface was used to download the latest street view image data in 0°, 90°, 180°, and 270° views at each point location. Specifically, each coordinate point is collected the 360° image of the street view, and each point consists of 4 images (0–90°, 90–180°, 180–270°, 270–360°). The following URL was used to obtain the image ID for a specific location: http://api.map.baidu.com/panorama/v2?ak=API_Key&width=600&height=400&location=LAT,LON&pitch=20&fov=90&heading=0/90/180/270. Here, LAT and LON are latitude and longitude, respectively, FOV determines the horizontal field of view of the image, HEADING indicates the compass heading of the camera, PITCH indicates the upward or downward angle of the camera relative to the street view vehicle, and API key is the credential required to validate the request. Each coordinate point was downloaded from four angles to obtain the street view image data, and a total of 442,252 street view images were collected from the Nanshan District.

2.3. Restorative perception label data

To generate the restorative perception label data, we arranged the street view image scoring program in a Tencent cloud server such that the experimenter could easily access the server from any computer during the street view restorative perception scoring experiment. In this study, a human-centered perspective was used as an entry point for the evaluation of restorative perceptions. To measure the perception of urban street restoration in the Nanshan District, a total of 25 university students and staff were recruited as volunteers in this study, with a male to female ratio of ∼1:1, ranging in age from 21 to 55 years old. Volunteers scored the city street recovery perception of Nanshan District Street view data through a Tencent cloud server. Laumann's Restorative Perception Factor Scale (RCS) (20) was used to guide the volunteers to engage in restorative perception thinking. Among them, the restorative perception questionnaire used in this study was based on the restorative perception factor scale, which is used to investigate people's experience of restorative perception when they observe a street view image, and the final score was the volunteers' true subjective restorative perceptions of the street view. The questionnaire included 50 random street view images and 15 questions corresponding to each street view image (Table 1) to evaluate the perception of street restorability in terms of four aspects, i.e., escape, extent, fascination, and compatibility. We studied the time criteria for scoring single images in other experiments, and we informed the volunteers to observe each image for no <10 s (21, 22). During this period the volunteers will feel the restorability of the street view images and score their responses on a seven-point Likert scale, with a score of 0–6, where 0 means the description of the question did not match the volunteer's feelings when they observed street view image,

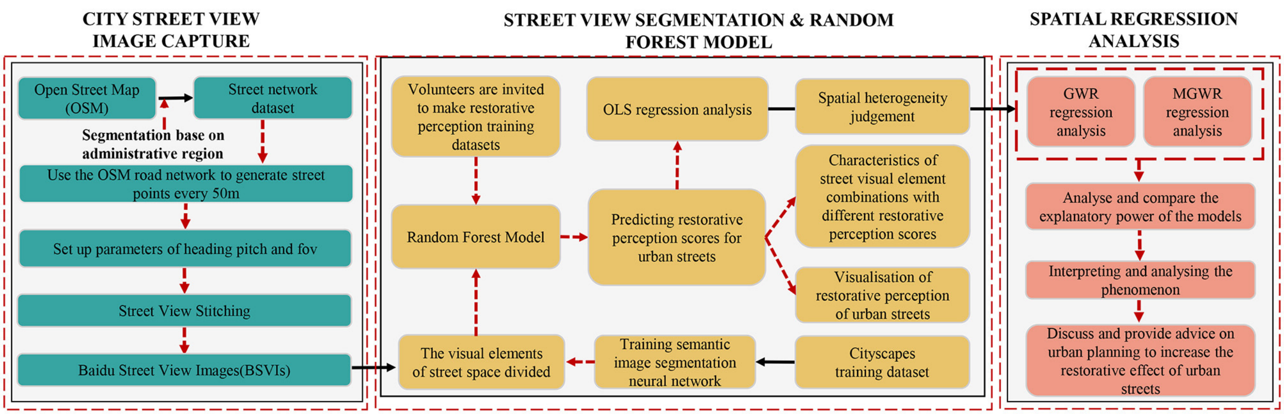

FIGURE 1
Overview of our workflow.

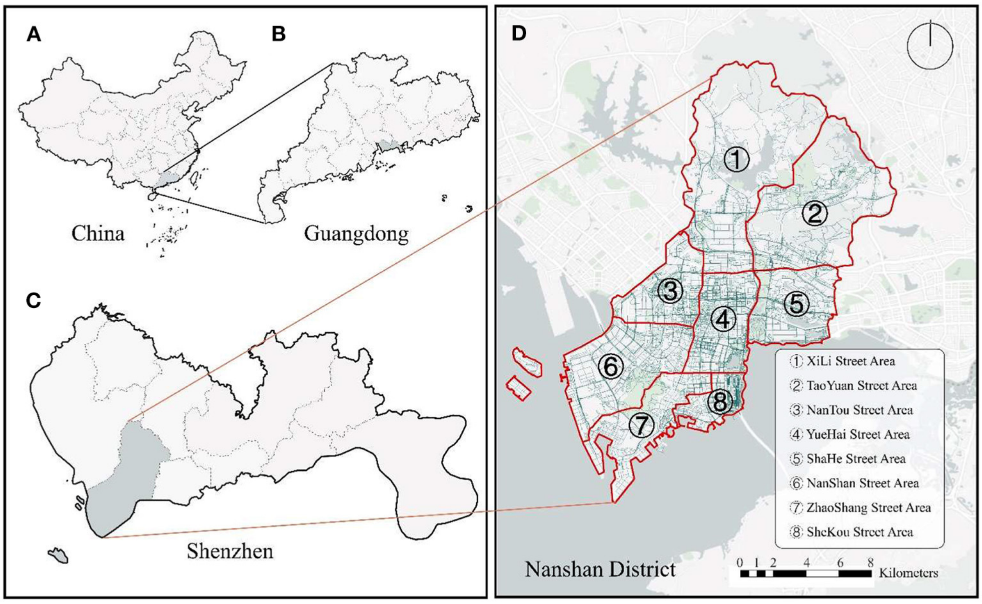

FIGURE 2
Study area (Nanshan District, Shenzhen, China): **(A)** China; **(B)** Guangdong Province; **(C)** Shenzhen; **(D)** Nanshan District.

and 6 means the description matched the volunteer's feelings. The scores for the 15 questions were then averaged as the final score. Rather than selecting the street view images perceived by volunteers according to the sequential location of adjacent street viewpoints, we used incomplete randomization for street view image extraction such that the distribution of restorative perceived street view locations covered the entire study area comprehensively (17). Finally, the scoring data for all volunteers' perceptions of street view restorability were aggregated as a labeled dataset to train the random forest model. As a result, we were able to create restorative perception labels. This data labeling method is more convenient, efficient, and cost effective than traditional survey methods because it is conducted entirely over the Internet.

2.4. Data of visual elements of urban streets

To explain the mechanisms that may lead to a location being perceived with high or low restorative perception, we introduced visual element data to determine the association of a place with a high degree of human restorative perception. To interpret restorative perception through visual element data, we used semantic image segmentation techniques to calculate the percentage of semantic object elements in each street view image. Semantic scene parsing is an important technique used to understand the perceptions of a given scene. Here, the goal is to segment and recognize object instances in a street view image. Given an input street image, the trained model is used to predict the type of visual elements for each category. We trained a classical

SegNet model that has demonstrated good scene segmentation performance, and the training results exhibited an accuracy of 90.83% on the training set and 89.95% on the validation set. This high level of accuracy can facilitate better explanatory work for restorative perception.

The Cityscapes dataset, which contains 34 types of objects in daily life scenes (e.g., sky, roads, cars, and plants), provides rich explanatory variables to explain restorative perception (23); thus, this dataset was selected as the training dataset for the semantic image segmentation model in this study. The Cityscapes dataset is a semantic understanding dataset of urban street scene image. This dataset primarily contains street scene images captured in 50 different German cities (of which 2,975 for train, 500 for val, 1,525 for test, and 19 classes are turned on by default for training in the dataset used for the research).

TABLE 1 Restorative perception scale.

ART factor	RCS questions
Escape	Here you can temporarily forget the worries of work and daily life
	Here you can temporarily forget the pressure of other people's demands and expectations
	Here you can forget about your responsibilities and obligations for a while
Extent	Here everything is interconnected
	Here everything is well integrated into the environment
	The surroundings as a whole are coherent
Fascination	Here are many things you want to explore
	Here are many things you feel curiosity
	Here are many things that attract you
	Here's where you want to spend a long time
	You feel immersed in your surroundings
Compatibility	Here you have the opportunity to do things you like
	Here you will be able to solve some of the problems that arise
	You can quickly adapt to the environment
	Here you can satisfy your travel needs

To implement and train the deep learning method used in this study and unify the computer training variables, all training processes were executed on the same Windows computer with an NVDIA GeForce GTX 1070 graphics processing unit, an AMD Ryzen5 2600X Six-Core Processor (3.60 GHz), and 16 GB RAM. An overview of the semantic segmentation of the street view images is shown in Figure 3. Here, we applied SegNet to achieve accurate pixel-level segmentation of objects in the target images. SegNet is open-source project for image segmentation developed and published by a team at the University of Cambridge in 2015. The network has two main components, i.e., an encoder and a decoder. The encoder compresses and extracts the object information, the decoder reduces the extracted semantic information to the size of the input image, and each pixel can be classified as its corresponding object information to be represented by its color.

We constructed the SegNet neural network based on the Python language, the Keras deep learning framework, migration learning techniques, and the Tensorboard module to document the training process. For the neural network settings, the input image remapping window was set to 416 × 416 pixels, and the learning rate was set to decrease by 50% when no decrease in loss was observed for three rounds. In addition, early stopping training was set to terminate and finish network training when there no drop in loss was observed for 10 rounds. In the migration learning training phase, the Adam optimizer (24) was used and the learning rate was set to 0.001. In the global learning training phase, the Adam optimizer was used with a learning rate of 0.0001. We used the Keras Tensorboard module to record the training data. Here, the migration learning training phase took 113 min, and the global learning training took 281 min; thus, the total training time was 394 min (6 h and 34 min). The code used to repeat the experiment can be downloaded from our GitHub site (https://github.com/landscapewl/Segnet-Transfer-Learning).

3. Methodology

As shown in Figure 1, this study was conducted according to three main processes. Here, we focus on the random forest-based machine learning algorithm used to score the restorative perception of urban streets in the second process to obtain an

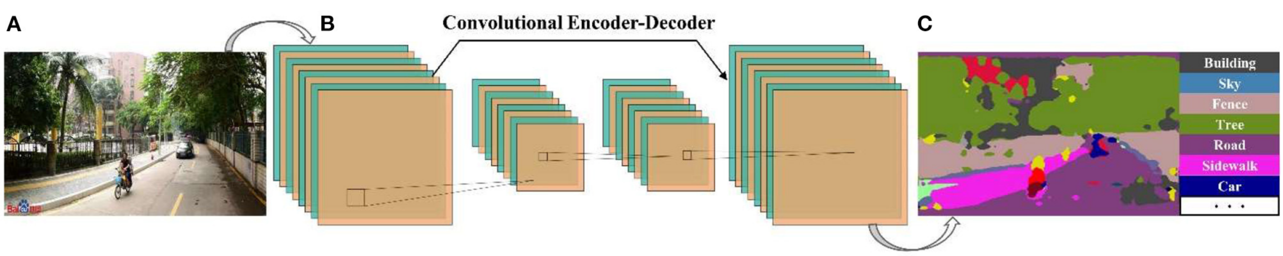

FIGURE 3
Overview of semantic image segmentation using SegNet trained on Cityscapes dataset: **(A)** input urban natural image; **(B)** SegNet architecture; **(C)** output image with segmentation mask.

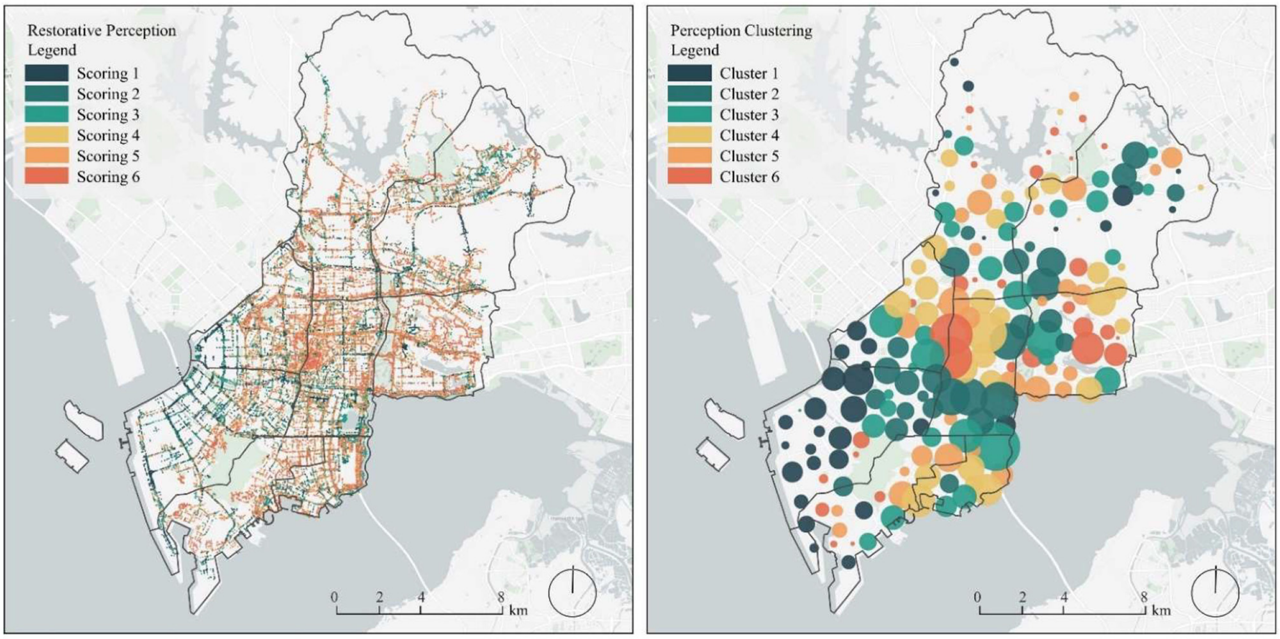

FIGURE 4
Distribution of restorative perception scores on street **(left)** and restorative perception clustering with different scores **(right)**.

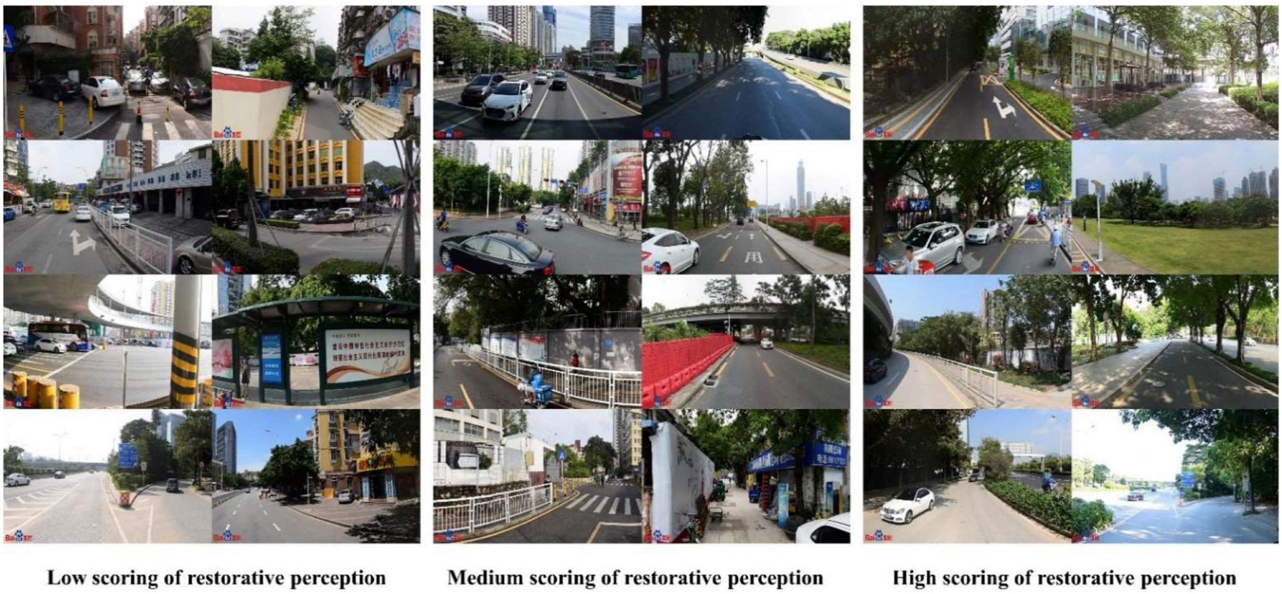

FIGURE 5
Samples of labeled street view images classified by the machine learning model. Street view images that represent low scoring of restorative perception **(left)**; street view images that represent medium scoring of restorative perception **(middle)**; and street view images that represent low scoring of restorative perception **(right)**.

overall description of the restorative perception of urban streets. In the third process, we used the OLS, GWR, and MGWR models to perform practical exploration of restorative perception and analyze the spatial heterogeneity phenomenon of visual elements and the relationship between visual elements and the restorative perception of urban streets.

3.1. Random forests based prediction of urban street restorability perception

To explore urban residents' perceptions of restorative urban streets, we employed a random forest-based machine learning model. This machine learning model has demonstrated good fitness in previous research studies (2, 14, 17). Here, we used it to perform a convenient and effective evaluation of the restorative perception of urban streets in the Nanshan District. Each volunteer scored 50 street images in terms of restorative perception, and the scoring results of all volunteers were used to generate a dataset to train the random forest model. During training, the bootstrap randomly selected two-thirds of the samples for data fitting or classification, and the remaining one-third of the model was defined as out-of-bag (OOB) data, which were used to evaluate the overall model error and the importance of variables. If X_j is input the input variables to the equation, then to calculate the importance of the input variable X_j in the Nth tree VI_n, it is necessary to use the sample data extracted by bootstrap to create the regression tree model Tn and calculate the prediction error of OOB again, and finally replace the observations in the variable X_j randomly. Re-establish the model Tn' and calculate the prediction error of OOB'. After processing the prediction error of the two OOB data, the average of all regression tree results is the importance of variable X_j in the Nth random tree, $VI_n\ (X_j)$, by the formula.

$$VI_n\left(X_j\right) = \left\{ \sum_{i=1}^{N_{OOB}} I\left[f\left(X_i\right) = f_n\left(X_i\right)\right] - \sum_{i=1}^{N_{OOB}} I\left[f\left(X_i\right) = f_n\left(X_i^{'}\right)\right] \right\} / N_{OOB}$$

TABLE 2 Top eight visual elements identified after segmentation of BSVIs.

Number	Visual elements	Mean	Max	Min	S.D.
1	Others	0.112	0.558	0.001	0.075
2	Building	0.053	0.527	0.001	0.066
3	Sky	0.300	0.714	0.001	0.112
4	Road	0.176	0.441	0.001	0.084
5	Sidewalk	0.029	0.343	0.001	0.035
6	Car	0.083	0.331	0.001	0.045
7	Fence	0.005	0.106	0.001	0.009
8	Vegetation	0.156	0.691	0.001	0.119

3.2. Explanatory model for restorative perception of urban streets

After calculating the restorative perception scores of the urban street environments, we examined the association between restorative perception and the visual element features of the urban streets. To understand where and how urban street visual element features affect the perceptions of resilience in space, we used three different regression models, i.e., the OLS, GWR, and MGWR models. Many studies have used OLS as a linear regression method for parameter estimation to explore the association between dependent and independent variables (25, 26). OLS linear regression is a global model that estimates the parameters of the explanatory variables in a linear model by minimizing the sum of the squared differences between the predicted and observed values in the dataset (a_k). The formula is as follows.

$$Y_i = \alpha_0 + \sum_{k=1}^{m} a_k X_k + \varepsilon_i$$

TABLE 4 OLS diagnostics.

Indicator	
Number of observations	110,563
Multiple R^2	0.553
Joint F-Statistic	7,116.729
Joint Wald Statistic	60,169.649
Koenker (BP)	2,887.57
AICc	115,384
Adjusted R^2	0.552
Joint F-Statistic's Prob	0.000***
Joint Wald Statistic's Prob	0.000***
Koenker(BP)'s Prob	0.000***

R^2 and adjusted R^2 were nearly identical; thus, only R^2 is reported.
***Denotes significance at the 0.1% level, **at the 1% level, and *at the 5% level.

TABLE 3 Summary of OLS results (model variables).

Variable	StdError	t-Statistic	Probability	Robust_SE	Robust_t	Robust_Pr	VIF
Intercept	0.043	64.774	0.000***	0.043	65.721	0.000***	–
Others	0.076	−6.450	0.000***	0.074	−6.607	0.000***	2.083
Building	0.079	−4.318	0.000***	0.079	−4.325	0.000***	1.813
Sky	0.065	12.450	0.000***	0.064	12.574	0.000***	3.445
Road	0.074	31.112	0.000***	0.075	30.679	0.000***	2.550
Sidewalk	0.128	22.033	0.000***	0.121	23.352	0.000***	1.311
Car	0.077	−4.233	0.000***	0.068	−5.656	0.000***	3.323
Fence	0.223	−31.612	0.000***	0.245	−28.760	0.000***	1.560
Vegetation	0.0690	118.287	0.000***	0.069	118.639	0.000***	3.664

***Denotes significance at the 0.1% level, **at the 1% level, and *at the 5% level.

TABLE 5 Model regression results.

Variables	OLS coefficients	GWR coefficients		MGWR coefficients	
	Mean	Mean	Min, Max	Mean	Min, Max
Intercept	0.000	0.214	(−4.534, 9.189)	0.230	(−1.943, 4.885)
Others	−0.029**	−0.069	(−1.293, 1.587)	−0.067	(−0.927, 1.032)
Building	−0.018**	−0.106	(−10.847, 10.717)	−0.114	(−2.315, 1.778)
Sky	0.072**	0.092	(−6.787, 3.817)	0.179	(−2.941, 2.198)
Road	0.155**	0.049	(−1.968, 1.814)	0.056	(−0.925, 0.851)
Sidewalk	0.079**	0.031	(−5.572, 3.939)	0.030	(−1.968, 1.285)
Car	0.001**	0.201	(−1.346, 0.924)	−0.012	(−0.948, 0.647)
Fence	−0.123**	−0.228	(−4.566, 6.597)	−0.218	(−1.273, 1.228)
Vegetation	0.705**	0.652	(−3.439, 6.360)	0.651	(−2.451, 3.805)
R^2	0.552	0.740		0.756	
AICc	115,384.147	78,025.554		73,858.933	

R^2 and adjusted R^2 were nearly identical; thus, only R^2 is reported.
**at the 1% level, and *at the 5% level.

TABLE 6 Summary of model bandwidth results.

Indicator	OLS	GWR	MGWR
Bandwidth	—	135 (intercept)	62 (intercept)
	—	135 (others)	91 (others)
	—	135 (building)	65 (building)
	—	135 (sky)	55 (sky)
	—	135 (fence)	110 (fence)
	—	135 (vegetation)	75 (vegetation)
	—	135 (road)	116 (road)
	—	135 (sidewalk)	151 (sidewalk)
	—	135 (car)	136 (car)

The assumption underlying the use of OLS regression models is that the explanatory variables for restorative perceptions are smooth in space, which suggests that the spatial distance and location between the data will not otherwise affect the final regression results. However, many explanatory variables are in fact non-stationary in space, and the explanatory strength of the data varies across locations in space; thus, the effect of different spatial locations may differ. If Koenker (BP) is statistically significant ($p < 0.05$), which indicates that the study data are spatially non-smooth, then the data should be modeled using a spatial regression model (27). GWR is a spatial regression model first proposed by Fotheringham et al. in 1996. The GWR model can handle the spatial non-stationarity problem in regression analysis effectively (28). Many studies have utilized the GWR model in spatial modeling. For example, Zhou used the GWR model to explore the causes of haze pollution in China, and Robinson used GWR models and geostatistics to improve the accuracy of nitrogen dioxide pollution mapping. In addition, Liu explored spatial variability, temporal variability, and spatial differentiation of confirmed COVID-19 cases in the Hubei Province using a GWR model. If the restorative perceptual data are non-stationary in space, the GWR model can be used as a spatial analysis tool. The GWR is expressed as follows.

$$Y_i = \alpha_{0(u_i,v_i)} + \sum_{k=1}^{m} a_{k(u_i,v_i)} X_{k(u_i,v_i)} + \varepsilon_i$$

Here, Y_i is the recovery perception score and its coordinates (u_i, v_i), $\alpha_{0(ui,vi)}$ is the intercept of the model, $a_{k(ui,vi)}$ is the regression coefficient of the k^{th} independent variable data at (u_i, v_i), $X_{k(ui,vi)}$ is to the k^{th} attribute at position i, and ε_i is the random error of the model. The regression coefficients of the restorative perceptions obtained using this model can vary in space at different locations, and we can understand how the explanatory variables affect restorative perceptions of urban streets in space according to the variation of the regression coefficients of the explanatory variables in space. To use the GWR model, a neighborhood range must be determined, meaning the data points included in this range. The GWR model uses a single fixed bandwidth to define the neighborhood, which means that all regression coefficients of the explanatory variables are assumed to vary in the same spatial scale. The bandwidth is in distance-based metric units. Using Here, using the bi-square kernel, all data points within the bandwidth range are weighted inversely by the distance to the center of the local region, and the data points outside the bandwidth range are weighted as 0. In this study, we used golden section search optimization with the routine Akaike information criterion (AICc) as the criterion for the model. Both local R^2 and global AICc can be used as parameters to evaluate the model. GWR is performed using the same bandwidth when evaluating the regression coefficients of the explanatory variables.

In fact, the explanatory variables may have different scales of influence in space. The MGWR model allows each explanatory variable to have separate bandwidth, and the size of the bandwidth is scaled according to the scale of the space, which has the potential to reduce errors in parameter estimation (29) using the following equation.

$$Y_i = \alpha_{0(u_i,v_i)} + \sum_{k=1}^{m} a_{bwk(u_i,v_i)} X_{k(u_i,v_i)} + \varepsilon_i$$

This model is a modification of the GWR model. Here, a_{bwk} is the k^{th} explanatory variable with an added bandwidth term *bw*, and each explanatory variable has a separate spatial scale. MGWR differs from GWR in that it uses an adaptive nearest neighbor bandwidth kernel, which specifies the number of data points that must be included in each local regression model to handle edge effects and non-uniform spatial distributions. As with GWR, a bi-square distance weighting function is used. For parameter optimization, we used the golden mean search optimization procedure using AICc as the model fit criterion. Here, R^2 and AICc were used to evaluate model fitness, and the parameter estimates were mapped out as in GWR.

4. Experiments and results

4.1. Detection accuracy of random forest algorithms based on restorative factor scales

From the labeled data scored by the volunteers for restorative perception, two-thirds of the data were used to train the random forest model, and the remaining one-third was used to test the accuracy of the model. The fitting results are as follows, with average error of 2.01%, RMSE of 2.91, OOB Error of 5.96%, and OOB RMSE of 8.47 for the city street restorative perception results. The accuracy of estimation of restorative perception of urban streets based on random forest was >90% on average; thus, this model has strong practical application in predicting human perception.

4.2. Spatial distribution of restorative perception of urban streets

We divided the restorative perception scores for the urban streets in Nanshan District according to the natural breakpoint method, which is divided into six categories. In the legend of Figure 4, left, the restorative perception scores are shown as Scoring 1, Scoring 2, Scoring 3, Scoring 4, Scoring 5, and Scoring 6 in descending order. To observe the distribution of restorative perceptions in the Nanshan District, we also performed cluster analysis of the restorative perceptions. As shown in the legend of Figure 4, right, the clusters of restorative perception scores from low to high are Cluster 1, Cluster 2, Cluster 3, Cluster 4, Cluster 5, and Cluster 6. As can be seen, the restorative perception varies considerably in different regions of the study area. The higher recovery perceptions are more concentrated and primarily distributed in the Yuehai street, Shahe street and Shekou street areas of the Nanshan District, while lower recovery perceptions are more dispersed and primarily distributed in the Nanshan street areas of the Nanshan District. Shenzhen University is located in that area of Nanshan District, with good greenery in the school and a better environment compared to other areas in Nanshan District. This area is more open; thus, there is a higher restorative perception. Other areas in the Yuehai street area of Nanshan District have large urban parks with good plant configurations, garden vignettes, and water features, which helps create a natural and vivid urban landscape. This is an important reason for the high restorative perception of the that area. In contrast, the Nanshan street area region has a low level of greenery, freight terminals, and logistics factories. In addition, a monotonous construction method was used for the main roads in this region, and the skyline is monotonous. Finally, this region offers only a single urban function. These factors likely contribute to the low restorative perception of this region.

We classified the street views identified by the machine learning model into three categories according to their scores. Here, street views with restorative perception scores <2 were defined as low restorative perception street views, those with scores between 2 and 4 were defined as medium restorative perception street views, and those with scores >4 were defined as high restorative perception street views. Figure 5 shows representative street views for low, medium, and high restorative perception scores.

Table 2 shows the eight visual elements of the street view with the highest average share in the image segmentation process. These visual elements are the most likely to have a positive impact on the perception of restorative urban streets. The visual elements of the streetscape with low, medium and high restorative perception scores were averaged as the visual element percentage characteristics of each street under this perception (Figure 6). We found that the proportion of high restorative perception is low for others and low for building relative to low to medium perception. In addition, the proportion of vegetation is significantly higher than that of low to medium restorative perception. We assume that others may have increased the level of chaos in the street space, resulting in a poor restorative perception. A high proportion of buildings block part of the visual landscape and sunlight, which may lead to a depressed mood in residents and reduce the restorative perception. Plants release oxygen and negative ions through respiration, which regulate the function of the human cerebral cortex and balance the excitatory and inhibitory mechanisms, thereby reducing fatigue, improving mood, and increasing the restorative perception.

4.3. Regression results

To understand the causes of reasons in restorative perception, we conducted experiments using the OLS, GWR, and MGWR models. To explore the association between restorative perception of urban streets and different visual elements. First, OLS regression of urban street restorative perception with each visual element of the street was performed. OLS regression can determine whether the study data are smooth in space and is the prior judgment for spatial regression. Table 3 shows that the VIF of each visual element is <7.5, which indicates that there is no covariance problem. Table 4 shows that the Koenker (BP) is significant, and it is necessary to

	Others	Building	Sky	Fence	Vegetation	Road	Sidewalk	Car
Low scoring of restorative perception	0.139	0.077	0.331	0.033	0.027	0.162	0.015	0.078
Medium scoring of restorative perception	0.132	0.066	0.355	0.015	0.077	0.170	0.023	0.081
High scoring of restorative perception	0.096	0.042	0.266	0.015	0.204	0.182	0.035	0.085

FIGURE 6
Percentage of visual elements with low, medium, and high perception of urban street restorability.

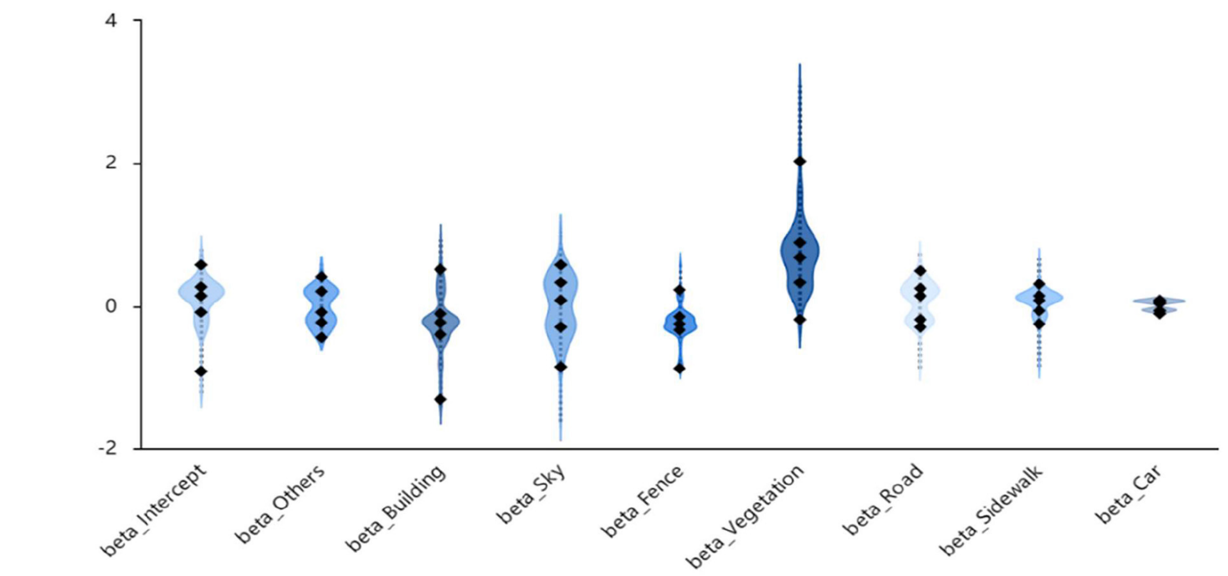

FIGURE 7
Violin plot of MGWR model regression coefficient distribution.

judge the significance of each visual element by Robust_Pr. The significance P are <0.05, which means that each visual element is statistically significant. However, Koenker (BP) is significant, which proves that each visual element is non-stationary in space, and this indicates that the same variables are fitted differently in different regions of space and that there is heterogeneity; thus, the next step of spatial regression analysis of the GWR and MGWR models can be performed. To explore the most suitable spatial regression model to explain the relationship between restorative perception and each street visual element, we compared the performance of the three models. The results are shown in Table 5. As can be seen, regardless of the model, others, buildings, and fences are negatively correlated with restorative perceptions; thus, these elements are obstacles to enhancing restorative perceptions. Roads, sidewalks, vegetation, and the sky are all positively correlated with restorative perceptions; thus, these elements have a positive impact on enhancing restorative perceptions. GWR and MGWR have significantly improved the model goodness-of-fit (R^2) compared to OLS models. Modeling with spatial heterogeneity in mind can obtain more details of street visual elements and restorative perceptual interpretation. Meanwhile, we can find that MGWR has the lowest AICc among the three models, which is a measure of a model's performance, and a smaller AICc value means a better performance of the model (30). Therefore, we will use MGWR to conduct a study on the relationship between restorative perception and street visual elements of urban streets.

4.4. Analysis of perception heterogeneity of restorative urban streets

Spatial heterogeneity was observed in the relationship between each visual element and the perception of street restorative, GWR and MGWR regression analyses were conducted to explore the association and patterns between them in more detail. The bandwidth of the variable measures the spatial scale of the action of each process, which can reflect the differences in the perception of urban street restorative according to the different visual street elements. Note that larger action scales indicate weaker spatial heterogeneity in the effect of the influencing factor and stronger spatial heterogeneity. Here, GWR is fixed bandwidth, and MGWR does not have fixed bandwidth. As shown in Table 6, the spatial heterogeneity of the intercept, sky, buildings, and vegetation is high. The differences in the style diversity among buildings, plant species, and growth status in space explain the high heterogeneity of these visual elements in space. In contrast, the spatial heterogeneity of others, fences, roads, sidewalks, and cars is weak. Among these visual elements, cars and sidewalks are near to the global scale, and cars and sidewalks are more consistent in style and have no characteristic distribution in space, which may help explain the low heterogeneity.

To obtain a clearer view of the model regression coefficients of the MGWR model, violin plots of the restorative perception

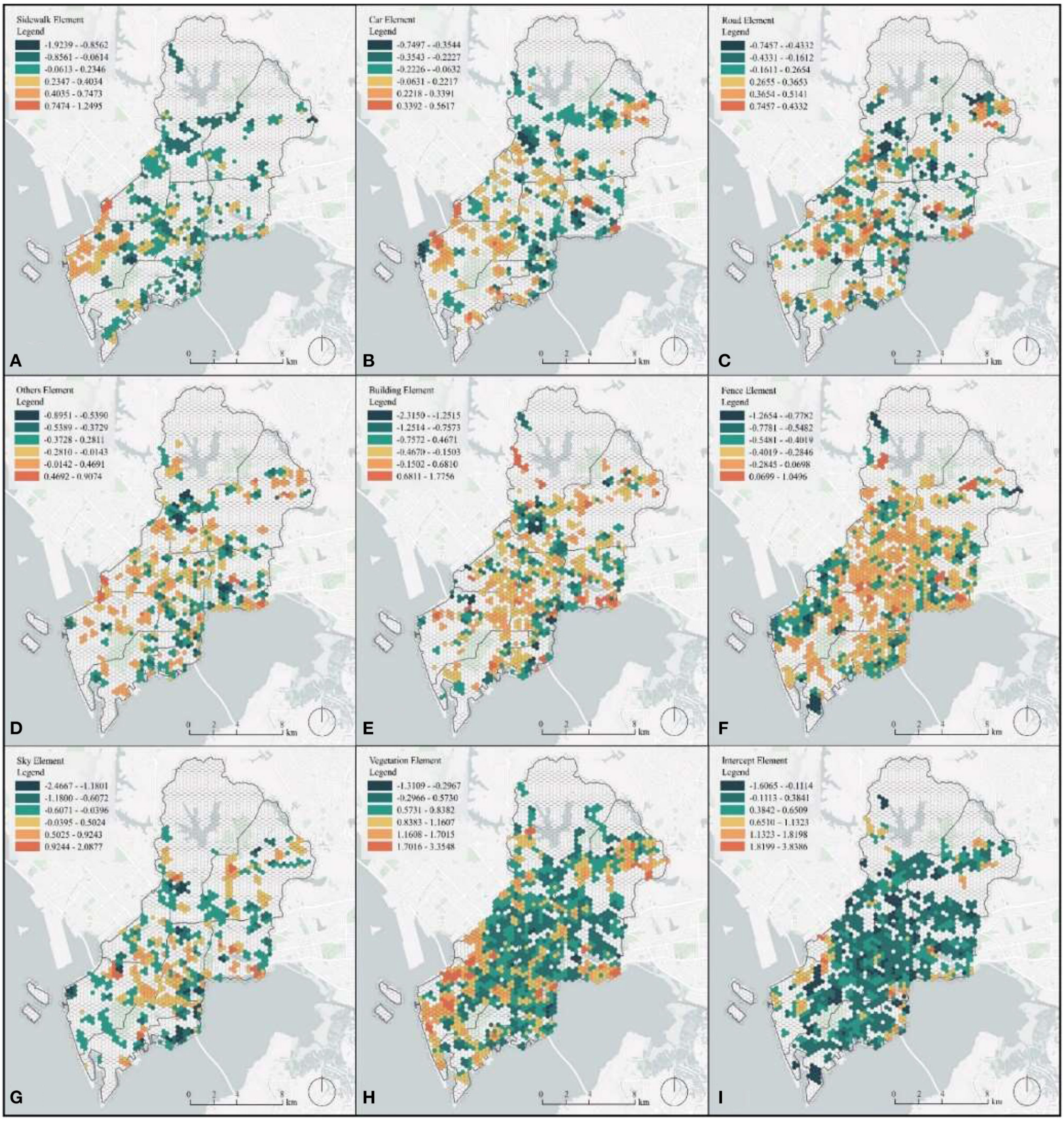

FIGURE 8
Multiple count MGWR coefficients for Nanshan District: **(A)** sidewalk, **(B)** car, **(C)** road, **(D)** others, **(E)** building, **(F)** fence, **(G)** sky, **(H)** vegetation, and **(I)** intercept.

regression coefficients were produced by retaining the data with significant ($p < 0.05$) data for each visual element, as shown in Figure 7. Violin plots can be used to show the distribution and density of the data by combining the advantages of box line and kernel density plots (31). The curved line in the violin plot is a symmetric display of the kernel density distribution, the middle part shows the 2.5, 25, 50, 75, and 97.5% quartiles, and the straight line in the middle of the violin plot connects the minimum and maximum values.

The distribution density of coefficients >0 in the Intercept term is much higher than that of the coefficients that are <0. This indicates that the impact of the constant term on the perception of restorability is more positive, and in a very few areas it has a negative impact. In addition, the impact of different locations on the perception of restorative of the street is more different. The distribution densities of coefficients >0 and <0 for the others and road terms are approximately equal. This indicates that the positive and negative effects of others on restorative perceptions are

FIGURE 9
(A–D) Example map of a representative area street views.

approximately the same, and there is little difference in the effects of others on restorative perceptions in different zones. The highest density of the coefficient distribution for the building term is in that are areas <0, which indicates that buildings have a negative effect on the restorative perception in most areas. In a very few regions, buildings had a higher positive impact and a higher negative impact, showing a more obvious polarization; thus, the role of building varies greatly between regions. The positive and negative effects of sky on the restorative perception were approximately equal, exhibiting quite strong negative effects in a very few areas. For fences, the region with the highest density of the coefficient distribution was ∼0, which indicates that the effect of fences on restorative perception is not prominent and has both positive and negative effects on perception in a very small area. The higher density of distribution of the vegetation coefficients in regions >0 indicates more positive effects on restorative perception, and in a few regions the positive effect is quite strong. The region with the highest density of the sidewalk and car coefficient distribution was ∼0, which indicates that the effect of sidewalks on restorative perception was not prominent.

The regression results of MGWR for each street point were averaged and projected onto a square hexagon with a side length of 120 m. The hexagonal cell grid shares more adjacent edges and the distance between the centers of mass of adjacent cells is equal, which makes the hexagonal grid more flexible in setting its radius and other parameters to represent the distribution of restorative perception systems with a smoother transition. Moreover, the hexagon can represent the overall situation of each small area, which can effectively avoid the errors caused by individual street points and can guide the planning and renovation of different areas.

Figure 8 not only shows the regression coefficients of each visual element, but also the percentage of heterogeneous areas with statistically significant visual elements in the space, and the more areas with colors indicate more areas with significant heterogeneous effects. As shown, the intercept, vegetation, and fence elements are more widespread in the area where heterogeneous effects are evident in Nanshan District. Note that there are obvious regional differences in topography and terrain in the Nanshan District mountainous region. The terrain is roughly high in the north and low in the south. In addition, from north to south, it can be divided into the northern hill basin area, the central low hill terrace area, and the southern low hill flat area, and the terrain decreases from north to south. Differences in topography are possible reasons for the wide distribution of intercept heterogeneity. In most areas, intercept has a positive effect on restorative perception; however, in a few areas, intercept may have a negative effect on restorative perception due to the monotony of the urban built environment. There is a wide variety of vegetation in the Nanshan District, including southern subtropical monsoonal evergreen broad-leaved forests and southern subtropical ravine monsoonal rain forests. The complex structure of vegetation communities, with southern subtropical evergreen high scrub, southern subtropical evergreen low scrub, etc., and the differences in restorative perception brought

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about by different vegetations may be one reason for the wide range of heterogeneous effects of vegetation in the Nanshan District. Specifically, the coefficient of vegetation is generally high in the Nanshan street area part of Nanshan District, which indicates that vegetation in this region has a high positive correlation with restorative perception, and the increase in vegetation can result in better restorative perception than other regions (Figure 9B). The Nanshan street and Zhaoshang street area part of Nanshan District has a single industrial structure, with more companies in logistics and customs, a single construction approach for urban main roads, and less plant greening compared to other areas of Nanshan District. Thus, the restorative effect of vegetation in that part is higher than in other areas (Figure 9C). Areas where the effect of vegetation heterogeneity is not significant Include Mountain parks with more plant coverage and large areas of homogenized plants without forming distinctive areas; thus, there is no perceived restorative heterogeneity (Figure 9D). Due to the differences in the properties of urban streets, the role played by fences is not exactly the same, which leads to a wider area of significant heterogeneity of fences. In the Yuehai street area, fences showed a positive correlation with restorative perception, and an increase in fences led to increased restorative perception. The Yuehai street and Nantou Street area of Nanshan District is more well developed and has more developed transportation than other areas, and the use of fences may provide a subjective feeling of safety to the urban residents, thereby causing an increase in the perception of restorative (Figure 9A). We also found that the sidewalk, car, road, others, building, and sky elements do not differ due to their distribution characteristics in the urban space, which results in significant regional underrepresentation of heterogeneity. The sidewalk element is positively correlated with restoration perception in the Nanshan Street area part of Nanshan District (a coastal park), and the increase of sidewalks.

5. Discussion

5.1. Measuring urban restorative perceptions to improve residents' quality of life

The development of global urbanization will cause different degrees of human psychological impacts, and restorative is proposed as a perceptual indicator of city friendliness. Shenzhen is one of the most developed regions in China. Urban commercial land use and boundary expansion are inevitable processes of urban GDP growth in developing countries. However, this is contrary to the subconscious expectations of urban residents for friendly and restorative cities. Thus, it is important to consider the preferences and needs of urban resilience in both current and future development stages. It is also important to consider the perceived measurement and enhancement of urban restorative as an implementable focus of future research. In this study, we attempted to explain the influence of spatial association between urban restorative perception and the visual elements in an urban environment in order to improve the overall urban restorative perception to satisfy the psychological requirements of residents and promote harmonious relationships between residents and the urban. An urban restorative perception measurement framework was developed based on large-scale urban street view data and random forest machine learning algorithms. The MGWR model was used to determine how the urban environment affects residents' perceptions of restorative and the spatial heterogeneity of their impacts. This work has led to relationships between urban planning and development decision makers and mental health researchers. Collaborative research to enhance the perception of urban restorative. Researchers can collect large volumes of data, measure perceptions of urban restorative, and map the perceived restorative clustering of urban residents. This can help urban planners identify areas with high restorative perception clusters. In addition, it will enable researchers to provide solutions to enhance the perceived restorative capacity of urban residents and build more humble urban areas from the perspective of different disciplines and industries.

5.2. Measuring perceptions of urban restoration to provide advice to urban planners

Most previous studies have explored the relationship between urban street restorative perception and explanatory variables from the perspective of the entire study area, but the relationship between the two at different spatial locations is unknown, and therefore the information provided to urban planners is limited. In this study, a spatial regression model was used to explore the relationship between restorative perceptions and visual elements on urban streets, not only to understand the role of each visual element at the macro level, but also to grasp the relationship between each visual element and restorative perceptions at the micro level in specific locations. Specifically, visual elements with high heterogeneity should be given priority attention by urban planners, and the effects of these visual elements on restorative perception may vary greatly in different locations. In places with high regression coefficients, the increase of visual elements may bring higher restorative perception effects. Where the regression coefficient is low, the configuration of visual elements is not sensitive to fluctuations in restorative perception and can be planned uniformly. Places with regression coefficients <0, where visual elements have a negative relationship with restorative perception, should be appropriately reduced in the allocation of visual elements. The scheme of this study can provide urban planners with more detailed advice on the configuration of visual elements in urban streets in urban physical examination or urban micro-renewal.

5.3. Exploring spatial heterogeneity in urban restorative perception using MGWR model

We constructed a complete methodological framework using GSV data and machine learning techniques to measure the level of restorative perception in urban spaces. The superior performance and reliability of the MGWR model compared to the OLS and GWR models were verified in our analysis of the spatial heterogeneity of restorative perception. The proposed framework in this study is more streamlined and effective compared to the traditional approach. This was followed by an empirical case study of restorative perception mapping in the Nanshan District of Shenzhen, China. We found that residents' perception of restorative was positively correlated with the percentage of visual road, sidewalk, vegetation, and sky elements, and was negatively correlated with the percentage of visual elements of others, building, and fence elements. In a comparative analysis of the collected data, the AICc values of the GWR and MGWR models were much less than that of the OLS model, and the performance of the GWR and MGWR models was much better than that of the OLS model. We found that the MGWR model outperformed the GWR model in terms of goodness of fit and performance, and the spatial heterogeneity results analyzed using the MGWR model were more scientific and reasonable. We found that the spatial heterogeneity of the intercept, sky, building, and vehicle elements is stronger, and the spatial heterogeneity of the others, fence, road, sidewalk, and car elements is weaker, among which cars and sidewalks are close to the global scale, cars and sidewalks are more consistent in style, and their distribution in space is not characteristic. Thus, we believe that our findings provide practical and innovative contributions. These demonstrate that the visual attributes of an environment have spatially heterogeneous effects on restorative perception, and that big data can be used to improve understanding of the relationship between restorative perception and urban environments.

5.4. The novelty of using street view big data with spatial regression models

In previous studies on restorative perceptions, most scholars have started by designing restorative perception questionnaires and conducting questionnaires on a small group of volunteers. The survey results may be more accurate, but the small sample size, time-consuming survey, and small survey scope have limited the research on restorative perceptions. With the development of various disciplines and technology, VR technology and the popularity of various types of big data have provided strong support for the study of restorative perception, but most scholars have used multiple linear regression for the interpretation of restorative perception data, without comprehensive consideration of the spatial heterogeneity of the data. In this study, SegNet is used to segment the visual elements of the Street view, and a random forest model is used to predict the restorative perception scores of urban streets. The process of interpreting restorative perception first utilizes OLS to determine whether the restorative perception data are smooth in space, and then to determine whether a spatial regression model is needed. Secondly, two spatial regression models, GWR and MGWR, were used to compare the explanatory strength of restorative perception, and the MGWR model with the highest explanatory strength was used to explore the connection between restorative perception and visual elements, and to identify the role of each element on restorative perception and the heterogeneous effect in space. This study combines deep learning techniques with spatial regression model, which means that it breaks through the limitations of the traditional approach, expands the scope of the study, reduces the cost of investigation, and increases the sample size of the survey, and also treats the restorative perception using spatial regression model with higher explanatory strength than the traditional single multiple linear regression, which makes the study tends to be refined and accurate. This provides a strong help for urban planners and research scholars to conduct research on the restorative perception of urban streets.

5.5. Limitations and future work

Several limitations that will be addressed in future work should be identified and discussed. First, data deviation is a common concern in such studies when perceptual data are collected from cloud servers based on the restorative perception factor scale. We found differences in the classification results of the street view restorative perception in the same part of the city by different volunteers. Here, we used machine learning methods to predict the global perception by excluding parts with restorative perception differences and rather than using data without differences. However, what is more meaningful and exploitable are regions with perceptual differences, or the classification results of multiple acquisitions to obtain the average of the recovered perceptions for the same region. In addition, Shenzhen is one of the most developed cities in China with the highest mix of urban functions; thus, the validity of the results of this study have not been investigated in other cities in China or other parts of the world. Thus, the generalizability of our findings must be investigated using additional research data for other regions. Finally, the impact on the perception of urban restorative is a multifaceted process that influenced by multiple factors. Thus, various other factors that influence perceived urban restorative properties should be further discussed. The future combines, for example, the application of the conclusions of Cervero et al. who concluded that density, diversity, and design are the three basic metrics for assessing 3Ds in street environments (32). To measure the relationship between the urban environment and the restorative perception more comprehensively. It can be used to investigate different methods to enhance the perceived urban restorative properties from multiple perspectives. POI-based facility distribution, spatial distribution data of transit stops should also be added to add to the discussion, and these approaches can be used to investigate ways to enhance perceived urban restoration from multiple perspectives.

6. Conclusion

The restorative properties of urban streets have a positive effect on the development and wellbeing of society and are required to facilitate the healthy and virtuous development of society. In this study, we systematically evaluated the perception of urban street restoration using a framework using street view big data, deep learning, and multiple regression models. Specifically, we performed semantic segmentation of the street view images using a deep learning method, and we evaluated the restorative perception of streets in the Nanshan District using a random forest algorithm based on the restorative factor scale. Finally, regression analysis was performed using the OLS, GWR, and MGWR models to explore the correlation between restorative perception and visual street elements in an urban space in detail. This method is more logical in terms of interpretation because it considers the possible spatial heterogeneity effect of the data. We suggest that this methodology can be used as a foundation for urban redevelopment to improve the overall recovery of the city. In addition, we believe that our findings will have important practical implications for the urban street reconstruction and urban computational science fields. The analysis of different regression models in this study showed that the R^2 of MGWR is 0.756, the R^2 of GWR is 0.740, and the R^2 of OLS is 0.552. The MGWR model is more suitable than the OLS and GWR models in exploring the association between perceptions of urban street restorability and urban visual elements. The exploration of different models revealed the existence of the spatial heterogeneity of visual elements on street restorative perceptions by each street. Among them, we found that vegetation, roads, the sky, and sidewalks exhibited a positive relationship with restorative perception. In addition, we found that the other elements, such as buildings, fences, and cars, demonstrated a negative relationship with restorative perception. They can be combined with spatial heterogeneity for comprehensive treatment in future urban transformation processes. We believe that this innovative approach can support the reconstruction of the built environment on the street by linking restorative perception studies with new data and emerging technologies. We expect that this will have important implications for the study of restorative perception in urban environments.

Data availability statement

The datasets presented in this study can be found in online repositories. The names of the repository/repositories and accession number(s) can be found in the article/supplementary material.

Author contributions

XH and LW: conceptualization and writing—original draft. XH: resources. JH and TJ: supervision. LW: validation. All authors contributed to the article and approved the submitted version.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Publisher's note

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Campus outdoor environment, learning engagement, and the mental health of college students during the COVID-19 pandemic: From the perspective of students in different grades

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Introduction: During COVID-19, the mental health of Chinese university students has been a pressing concern. But the internal mechanism of perceived campus outdoor environment and learning engagement affecting college students' mental health during the COVID-19 pandemic has not been fully discussed.

Methods: The current study used cross-sectional data from 45 Chinese universities to explore the relationship among perceptions of campus outdoor environments, learning engagement, and college student mental health, and focused on differences among college students in different grades.

Results: Our study revealed the mental health problems of Chinese college students during the COVID-19 pandemic were more severe. The mental health of postgraduates was generally poor, and their risk of depression was higher than that of undergraduates. More importantly, for postgraduates, the direct impact of the perceived campus outdoor environment on their mental health was stronger. For undergraduates, the indirect impact of learning engagement on the effect of the perceived campus outdoor environment on their mental health was stronger.

Conclusion: The results of the study have implications for campus planners, landscape architects, and university planners to pay particular attention to the needs of postgraduates for campus outdoor environments, which is of great significance to improve the overall mental health of students during the COVID-19 pandemic.

KEYWORDS

mental health, perceived campus outdoor environment, learning engagement, college students, group differences

1. Introduction

There is a growing concern about the mental health of young adults and college students (1–5). Nowadays, college students face academic, interpersonal, financial, and cultural challenges (6). They have relatively high-stress levels and, in turn, are more likely to suffer from mental disorders such as anxiety and depression (5, 7). More and more college students are experiencing depression, anxiety, suicidal thoughts, and other health problems (8–10). The causes of these mental health problems among college students could be attributed to the unique university lifestyles with factors such as academic studies, social stress, financial difficulties, exam anxiety, degree selection, living alone for the first time, and free time management (3, 7, 11, 12). China has 2,852 universities with 37 million students in 2015 (13). Mental health problems caused by various inducements have become a widespread problem among Chinese college students. Significantly during the emergence of COVID-19, the potential for mental health problems among college students has increased due to the wanton spread of the novel coronavirus. (14–18). Adolescents are likely to experience high rates of depression even after the enforced isolation ends. The longer the isolation of students, the greater the risk of health problems (14). Therefore, in the context of the normalization of epidemic prevention and control, more research is needed on the mental health of college students to better understand this problem (19, 20).

With this rising concern of mental health problems, researchers investigate possible solutions from various fields. Among them, the perceived campus environment is one of the important observation factors. The campus environment is similar to the urban environment, which is composed of buildings, open spaces, and walking paths. It is a place for sports, entertainment, learning, and social activities (21). The outdoor environment significantly affects a person's physical and mental health. The relationship between the natural environment and mental health has been widely theorized and studied by scholars of many subjects (22), such as environmental psychology, geography, urban planning, medicine, and landscape architecture (23). Many studies have shown that green space quality can significantly improve mental health (24) and promote mental restoration among students (25). A more natural outdoor environment and green landscapes can have a positive impact on decreasing stress (26), fostering an overall sense of wellbeing (27), reducing depression (28), and improving cognitive ability and mental health (27, 29–32). The outdoor environment is one of the typical characteristics of the school. Unlike the indoor teaching space, it provides students with open space for physical activities and amusement, socializing with their peers, relishing the beauty of nature, and acquiring outdoor education (33). Although there is no unified definition of the campus outdoor environment, the existing research on campus open space mainly focuses on outdoor green spaces (34) or outdoor venues and facilities that affect sports activities (35). According to its functional nature, campus outdoor activity areas can be mainly divided into two categories: green spaces and outdoor environments for interaction and activity, including sports zones and game equipment, among others (36). On campus, green space is part of the overall student experience (37) and has positive implications for student health (38–40). Studies have also demonstrated that college outdoor green spaces provide an environment for students to release their frustrations, reduce stress levels (41), and improve mental restoration (42), mental and physical health, and quality of life and wellbeing (43, 44). The communication and activity in the outdoor environment of the campus shall engender a salutary effect on the mental health of college students, thus aiding in their recuperation. For instance, open spaces, athletic fields, and exercise amenities proffer college students convivial and reposeful domains for socializing and unwinding (45). The accessibility of green areas in outdoor scenes, the availability of facility structures, the existence and esthetics of sidewalks, and the multiplicity of physical facilities are positively correlated with participation in sports activities (46–48). Those who partake in more esthetically pleasing outdoor activities are more prone to attaining positive psychological dispositions and sound mental wellbeing (49). Sports and other outdoor recreational activities in outdoor communication and activity environments assist students in mitigating academic stress (50). More studies have pointed out that physical activities exposed to the outdoor environment of the campus are more beneficial than indoor physical activities to reduce adverse psychological problems such as tension, confusion, anger, and depression (51, 52). During the COVID-19 pandemic, even if Chinese college students did not have a complete control period, most of their actions were generally limited to campus. Under the long-term closed management, the campus has become the only living place for some college students (53). Finding strategies to strengthen the campus outdoor environment to enhance the quality of life and mental health of college students has essential practical significance. However, most current research on campus environment and mental health in China mainly focuses on walking environments and green spaces (54). Few studies have considered the link between campus outdoor activity environment, campus green spaces, and mental health, especially during the epidemic. There is still some space for research on the perceived campus outdoor environment and the mental health of college students in China (55, 56).

In addition to the subjectively perceived campus environment, learning engagement also plays an essential role in mental health. Learning engagement, a multi-dimensional, multi-level, and evolving concept first proposed by Schaufeli et al. (57) is an important indicator of the quality of students' learning process (58). It is mainly used to measure the effective time students invest in learning and students' commitment or dedication to learning activities (59). Some studies have confirmed the relationship between learning engagement and mental health (60–68). The adverse effects of learning engagement and academic performance can in turn affect students' overall mental health (17, 69). Studies have demonstrated that adults involved in lifelong learning have fewer chronic health problems and are more physically flexible, such as walking more around their city (70). This finding is consistent with the evidence linking lifelong learning participation to better overall life outcomes, especially in physical and mental health (61–74). In addition, some students who have learning problems such as lower learning efficiency, lower learning motivation, and weaker learning persistence are more likely to suffer psychological problems such as depression and anxiety in later life (75, 76).

Research on the correlation between learning engagement and campus environment reveals that for college students, investing time in outdoor settings is an expeditious and efficacious method for enhancing emotional wellbeing (77). Positive emotions can stimulate learning and foster heightened learning engagement (78). Spending more time in green spaces and even watching green landscapes has positive effects on students' attention and performance (30, 79–81). When students are mentally exhausted, they may become irascible and restless and may have difficulty concentrating or performing simple tasks (22). In the natural environment, students have higher motivation, fun, and participation (82) and can promote the intrinsic motivation of learning engagement and the persistence of learning interest of high school students (83). The social cognitive theory posits that individuals, behaviors, and environments interact and influence each other reciprocally (84). Learning is a social activity. College students spend a significant amount of time in the campus environment on a daily basis. A favorable outdoor campus environment maximizes interpersonal contact and ideational exchange among students, while also augmenting formal indoor learning processes (21). The improvement of communication behavior prompted by the environment and the increase in outdoor activities have enhanced the quality of engagement in learning at school (85). Mental health is complex. The influence of the campus environment on mental health is not direct and is often affected by a variety of factors. For college students, learning engagement is important for students 'daily life and learning activities. Learning engagement may be a bridge between the campus outdoor environment and mental health. Therefore, learning engagement can be used as a mediator between mental health and the campus outdoor environment. Nevertheless, few studies focus on college students in such studies, and few have explored learning engagement as an intermediary variable. In this context, the complex correlations between perceived campus outdoor environments, learning engagement, and Chinese college students' mental health have not yet been fully investigated.

Although many previous studies suggest that the campus environment is beneficial to students' both physical and mental health, the processes and factors behind the correlations between these two factors have not yet been fully investigated. The logical relationship between how the perceived campus outdoor environment affects the mental health of college students is still unclear. There is still a lack of comparative research on the perceived campus outdoor environment, learning engagement, and the mental health of college students. Therefore, it is necessary to incorporate the perceived campus outdoor environment and learning engagement into the mental health impact model of college students for systematic research. Identifying these relationships will not only improve our understanding of the relationship between students' learning engagement and perceived campus outdoor environment but also enhance our ability to plan and manage the physical environment of Chinese universities, which will improve the overall mental health of Chinese college students.

In addition, it is worth noting that some scholars have paid attention to the heterogeneity of mental health after the academic community generally recognizes the importance of college students' mental health. However, most studies focus on gender differences (1, 5, 86). There are also some studies on race/ethnicity, LGBTQ+ identity, college generation identity, social economy (87), parents with higher education (88, 89), STEM major, sector, and GPA (self-report, 4.0 points), which confirmed that these variables may be associated with mental health (87, 90–95). Although some scholars believe that over time, the rate of depression in college students has increased (96, 97), there are relatively few studies on the differences in the mental health of Chinese college students of different grades. Therefore, it is necessary to consider the differences in the mental health of students of different grades.

Thus, our study focuses on the problem of the perceived campus outdoor environment and mental health of Chinese college students and analyzes the differences among college students of different grades. We aim to better understand the relationship between the perceived campus outdoor environment, learning engagement, and the mental health of college students. In this way, we can put forward targeted suggestions for the improvement of the mental health of students of different grades. Our research mainly raises the following questions:

1. Are there grade differences among the mental health, perceived campus outdoor environment, and learning engagement of Chinese university students?
2. Whether perceived campus outdoor environment and learning engagement are associated with self-efficacy?
3. Are there grade differences in the relationship between perceived campus outdoor environment and learning engagement with the mental health of college students?

2. Materials and methods

2.1. Study population

The survey was conducted from 1 October 2021 to 30 January 2022. All investigations were carried out during the morning on weekdays. Our horizontal section data were collected using a questionnaire of 1,261 students from 45 universities in China. In order to enhance the representativeness of the sample, the selection of the sample was based on a sampling principle that prioritized diversity in geographical location, university classification, and region, among other factors. All the participants completed an online survey and answered specific related questions, including the evaluation of their mental health, campus outdoor environmental perceptions, and learning engagement. The questionnaire star survey platform[1] was our electronic questionnaire release. Prior to the formal distribution of the questionnaire, we conducted a pilot study with 10 students and engaged in in-depth discussions regarding the rationality of the questions in the questionnaire. Based on their feedback, we made appropriate revisions to the questionnaire. To ensure the validity of the data, we set up strict requirements for the validity of the questionnaire and removed the invalid questionnaires that were randomly filled out and maliciously received rewards to obtain a truly effective questionnaire. The specific measures include: we have multiple restrictions and multiple screening in terms of questionnaire access, question setting, real-name lottery, repeated IP screening, and setting the shortest answer time, and the deans, teachers, and other leaders of each school and college assist the questionnaire. The survey objects were undergraduate, postgraduate, and doctoral students. The survey covered 45 universities, 20 provinces, and 30 cities in China. Under the effective organization of university leaders, we obtained a total of 1,236 valid samples, with an effective rate of 98% (see Table 1 for the sample statistics).

2.2. Measurement

2.2.1. Dependent variable: Mental health of college students

Mental health issues have received widespread attention from many scholars since the novel coronavirus pandemic (98). According to previous studies, depression assessment has become the most important indicator of mental health. According to the World Health Organisation (WHO), depression is defined as a common mental illness that usually leads to low mood, loss of interest, feelings of inferiority, lack of energy, and inattention (99). The impact of the novel

1 https://www.wjx.cn/app/survey.aspx

TABLE 1 The sample demographics.

Demographics	N	%
Grade freshman	440	35.6
Sophomore	213	17.2
Junior	206	16.7
Senior	201	16.3
Master	158	12.7
Doctor	18	1.4
Gender		
Male	553	45.16
Female	683	54.84
Subject		
Liberal arts	313	6.42
Sciences	923	8.19
Monthly living expenses		
Less than 1,000 yuan	118	9.5
1,000–2,000	762	61.7
2,000–3,000	270	21.8
3,000–5,000	60	4.9
5,000–8,000	14	1.1
More than 8,000	12	0.9
Self-assessment of health		
Very bad	23	1.9
Bad	82	6.6
General	530	42.9
Better	442	35.8
Very good	159	12.9
Father's level of education		
Elementary school and below	124	10
Junior high school	387	31.3
High school or technical secondary school or technical school	326	26.4
Junior university	169	13.7
Undergraduate	197	15.9
Master's degree or above	33	2.7
Mother's level of education		
Elementary school and below	221	17.9
Junior high school	377	30.5
High school or technical secondary school or technical school	308	24.9
Junior university	161	13
Undergraduate	142	11.5
Master's degree or above	27	2.2

coronavirus pandemic on college students' mental health is particularly prominent and severe in terms of depression (100). Therefore, in the emotional factors affecting the mental health of college students, this study mainly focuses on depression. The depression we studied was assessed by the WHO-5 Happiness Index (WHO-5), a tool used to assess participants' mental health benefits, which is highly effective and reliable in screening for depression (101–105). The Happiness Index Scale includes five positive emotional items: (1) feeling happy and comfortable, (2) feeling calm and relaxed, (3) feeling energized, (4) waking up feeling awake and well-rested, and (5) everyday life is full of exciting things. Participants were asked about the frequency of these positive emotions in the recent 2 weeks. A score ranged from 6 to 0. Less than 13 points indicate depression. The higher score indicates better mental health.

2.2.2. Independent variable: Perceived campus outdoor environment

The campus outdoor environment in our study mainly referred to students' subjective perceptions of the campus environment. Although there are differences in the specific indicators of the perception of the outdoor environment of the campus, the standard formulas of accessibility, convenience, esthetics, safety, satisfaction, and comfort are applicable to outdoor space (106–108). Our research combined existing findings and divided the campus outdoor environments into two sections consisting of a total of nine issues. Section one (campus green spaces) contained four questions, including greening comfort, reasonable layout, beautiful scenery, and plant diversity. In the second section (campus outdoor activity environment), we referenced the perceptual environmental scale developed by Mujahid et al. (109). This section contained five questions, including sufficient outdoor spaces, reasonable layout, complete facilities, reasonable lighting design, and physical exercise places and equipment. In each item, the response ranged from 1 to 5 (1 = completely disagree, 2 = disagree, 3 = neutral, 4 = agree, 5 = completely agree), and the higher score indicated the higher the respondents' recognition of all aspects of the campus outdoor environment.

2.2.3. Intermediary variables: Learning engagement

Our research referred to the schoolwork engagement scale (110, 111), and used four items to measure learning engagement, including "I feel energized when I study," "I am enthusiastic about my studies," Time flies when I'm studying," and "I feel happy when I devote myself to study.." All the items were rated on a 5-point scale (1 = never, 2 = rare, 3 = sometimes, 4 = often, 5 = always). The higher scores suggest a higher level of learning engagement.

2.2.4. Control variables

In the conceptual model of this article, gender, parental education level, students' education level, subject, and monthly expenditure were included as control variables. Education levels were assigned as follows: 1: freshman; 2: sophomore; 3: junior; 4: senior; 5: Master1; 6: Master2; 7: Master3; 8: 1st Year PhD student; 9: 2nd Year PhD student; and 10: 3rd Year PhD student and above. The item of parental education level was scored on a scale of 1 to 7 (1: elementary school and below, 2: junior high school, 3: senior high school, technical secondary school, and technical school, 4: junior college, 5: bachelor, 6: master, and 7: doctor). The subjects are as follows: 1. Humanities and 2. Science. The item of monthly expenditure was scored on a scale of 1 to 6 (1: less than 1,000 yuan, 2: 1,000–2,000 yuan, 3: 2,000–3,000 yuan, 4: 3,000–5,000 yuan, 5: 5,000–8,000 yuan, and 6: more than 8,000 yuan).

TABLE 2 The fitness fitting index of the full sample model.

	X^2/df	GFI	AGFI	CFI	RMR	NFI	TLI	RMSEA
The full sample model	3.545	0.948	0.932	0.978	0.043	0.969	0.973	0.045
Ideal standard	<5	>0.9	>0.9	>0.9	<0.05	>0.9	>0.9	<0.08

TABLE 3 Variable validity and reliability test.

Measurement model (CFA)	Observed variable	Model parameter estimates				Convergent validity			
		Non-standardized factor loadings	Standard error (S.E.)	C.R. *t*-value	*P*	The standardized factor loadings	SMC	C.R.	AVE
Campus outdoor environment	Campus outdoor activity environment	1.000				0.943	0.889	0.971	0.792
	Campus green spaces	0.858	0.046	18.761	***	0.822	0.676		
Campus green spaces	GS1	1.003	0.022	45.137	***	0.905	0.819	0.951	0.828
	GS2	1.025	0.021	48.448	***	0.939	0.882		
	GS3	1.027	0.019	53.172	***	0.927	0.859		
	GS4	1.000				0.867	0.752		
Campus outdoor activity environments	AE1	1.058	0.027	38.897	***	0.884	0.781	0.941	0.763
	AE2	1.058	0.026	40.784	***	0.908	0.824		
	AE3	1.107	0.026	41.952	***	0.922	0.850		
	AE4	1.026	0.029	34.940	***	0.823	0.677		
	AE5	1.000				0.827	0.684		
Learning engagement	LE1	1.050	0.025	42.288	***	0.925	0.856	0.927	0.761
	LE2	1.079	0.026	41.652	***	0.916	0.839		
	LE3	0.943	0.028	34.199	***	0.810	0.656		
	LE4	1.000				0.831	0.691		
Mental health	MH1	1.000				0.893	0.797	0.948	0.784
	MH2	1.070	0.018	60.207	***	0.904	0.817		
	MH3	1.093	0.019	58.183	***	0.936	0.876		
	MH4	1.058	0.031	34.462	***	0.863	0.745		
	MH5	1.106	0.030	37.162	***	0.909	0.826		

***represents significant at the 1% level.

2.2.5. Statistical analysis

This study discussed the relationship between the perceived campus outdoor environment, learning engagement, and college students' mental health. We validated the multi-factor analysis of all measurement models in the conceptual model. The result showed that all the measurement models' compositional reliability was greater than 0.6; the average variance extraction was greater than 0.5; the factor load of the observed variables was greater than 0.6; the reliability coefficient was greater than 0.36 (112), and all the measurement models had good reliability and validity. Relevant studies have shown that the X2/degrees of freedom ratio is partially affected by the sample size (113). As a large sample size model with a sample size greater than 750, the x2/df in our study can be slightly relaxed. Our x2/df is 3.545, below the recommended level of 5 (114). Other fit quality indexes (GFI > 0.9, AGFI>0.9, RMR > 0.9, NFI > 0.9, CFI > 0.90, TLI > 0.90, RMSER<0.08) achieved the criteria, which showed that the model was fit (Table 2).

After dividing all observed variables in our study into high and low groups based on the 27th and 73rd percentiles and conducting t-tests (115), we found significant differences between the high and low groups. Therefore, all variables exhibit good discriminant validity. Given that the sample size for our study is 1,236 (>1,000) and the sample mean is approximately normally distributed, we utilized the asymptotically distribution-free (ADF) statistical method. Consequently, the sample data in our study is appropriate for SEM analysis.

Multiple-factor confirmatory analysis was conducted on the measurement model of the conceptual model. The composite reliabilities of the five measurement models, namely campus outdoor environment, campus green space, campus outdoor activity environment, learning engagement, and mental health, were 0.971, 0.951, 0.941, 0.927, and 0.948, respectively, all exceeding the standard of 0.7. The average variance extracted (AVE) for each measurement model were 0.792, 0.828, 0.763, 0.761, and 0.784, all exceeding the standard of 0.5 (116). The standardized factor loading and SMC of the observed variables were all greater than or close to the standards of 0.6 and 0.36 (Table 3). All measurement models exhibited good reliability and validity and were suitable for structural equation modeling analysis.

3. Results

3.1. Descriptive statistics

The depression rates among different grades are shown in Table 4. It shows that most Chinese college students' mental health is general during the COVID-19 pandemic. In general, 27.3% of the respondents suffer from depression. The incidence of depression in freshmen is 20.0%, in sophomores to seniors is 30.8%, and in postgraduates is 33.0%. Obviously, the mental health of freshmen is the best and that of postgraduates is the worst. By and large, the higher the grade, the worse the mental health and the higher the incidence of depression among college students.

TABLE 4 The comparison of depression prevalence among different groups.

Different groups of college students		Depression percentage %
Grade	Freshmen	20.0
	Sophomore to senior students	30.8
	Postgraduate	33.0

The descriptive statistics of variables are shown in Table 5. The overall evaluation of college students in campus outdoor environments is relatively good. The mean values of students' satisfaction with campus green spaces are higher than 3.7, and the mean values of satisfaction with campus outdoor activity environment are higher than 3.4. Meanwhile, the mean values of students' satisfaction with outdoor activity environments are lower than that of campus green spaces.

The higher the grade, the better the learning engagement of students. In the control variables, the average education level for college students is sophomore, the father's education level is above senior high school, the mother's education level is above junior high school, and the monthly expenditure of college students is 1,000–2000 yuan or more.

3.2. Analysis based on the models of full sample

To verify if there is a mediating effect of learning engagement on the impact of campus outdoor environment and college students' mental health, this study employs three methods, the Bias-Corrected Confidence Interval (CI) method using Bootstrap, the Percentile CI method, and the *Z*-test method. The use of all three methods ensures

TABLE 5 Variable descriptive statistics.

	Observed Variables		All		Grades (mean)		
			Mean	S.D.	Freshmen	Sophomore to senior students	Postgraduate
The mental health of college students	MH1		3.44	1.26	3.71	3.30	3.27
	MH2		3.28	1.33	3.60	3.12	3.07
	MH3		3.29	1.32	3.60	3.13	3.08
	MH4		3.13	1.38	3.41	2.98	2.98
	MH5		3.24	1.37	3.54	3.06	3.10
Campus environment	Campus outdoor activity environment	AE1	3.53	1.02	3.34	3.52	3.66
		AE2	3.51	1.00	3.29	3.48	3.69
		AE3	3.48	1.02	3.19	3.48	3.65
		AE4	3.45	1.07	3.21	3.42	3.67
		AE5	3.56	1.03	3.34	3.53	3.75
	Campus green spaces	GS1	3.83	0.93	3.74	3.77	3.99
		GS2	3.76	0.91	3.61	3.72	3.94
		GS3	3.81	0.93	3.64	3.77	3.98
		GS4	3.75	0.97	3.59	3.71	3.93
Learning engagement	LE1		3.63	0.82	3.25	3.57	3.99
	LE2		3.63	0.85	3.25	3.54	4.01
	LE3		3.79	0.84	3.48	3.72	4.11
	LE4		3.75	0.87	3.50	3.65	4.10
Control variable	Father education level		3.03	1.34	2.88	2.98	3.24
	Mother education level		2.77	1.34	2.61	2.70	3.01
	Cost		2.30	0.86	2.28	2.25	2.41
	Education		2.71	1.80	1.00	2.98	6.03
	Gender		1.55	0.50	1.39	1.64	1.64
	Subject		1.75	0.43	1.91	1.63	1.76

TABLE 6 The mediating effect test of learning engagement in the influence path of campus outdoor environment on college students' mental health.

Variables	Point estimates	Product of coefficients		Bootstrap			
				Bias-corrected 95% CI		Percentile 95% CI	
		SE	*Z*	Lower	Upper	Lower	Upper
Campus outdoor environment–Mental health	Total effect						
	0.603	0.051	11.823	0.518	0.686	0.518	0.686
	Direct effect						
	0.282	0.052	5.423	0.199	0.371	0.197	0.370
	Indirect effect						
	0.321	0.039	8.231	0.261	0.391	0.260	0.390

TABLE 7 The standardized effect value of the full sample model.

Independent variable	Intermediate variable	Dependent variable		
	Learning engagement	Mental health		
		Total effect	Direct effect	Indirect effect
Campus outdoor environment	0.50***	0.43***	0.20***	0.23***
Learning engagement	–	0.46***	0.46***	–

***means significant at the 1% confidence level.

the rigor of the study (117). In the path of the influence of campus outdoor environment on mental health, under the 95% confidence interval, the lower-to-upper values of the total effect and indirect effect of the two test methods do not include 0, and the *Z*-value is greater than 1.96, indicating that the mediating effect exists, that is, learning engagement has a mediating effect in the path of campus outdoor environment affecting mental health. The lower to upper values in the direct effect does not include 0, and the Z-value is greater than 1.96, indicating that the intermediary is partial. The campus outdoor environment positively affects the mental health of college students through the partial intermediary of learning engagement. The statistical details of the intermediary effect test are shown in Table 6.

Model-fitting results for the entire sample are shown in Table 7 and Figure 1. After controlling for education, parental education level, monthly expenditure, and gender, the total effect value for perceived campus outdoor environment and learning engagement on the mental health of college students are 0.43 and 0.46 in sequence. The effect value for the perceived campus outdoor environment on the learning engagement of college students is 0.50. The direct and indirect values for the perceived campus outdoor environment on the mental health of college students are 0.20 and 0.23 in sequence. College students' mental health is impacted in direct and indirect ways by the perceived campus outdoor environment, indicating that there may be intermediary variables on this path. The intermediary effect value of learning engagement is 0.23. It shows that the positive impact of the perceived campus outdoor environment on college students' health is related to learning engagement.

3.3. Comparison of model differences among different income groups

Table 8 and Figure 2 compared the model fitting results based on samples of different grades of college students. The data of freshmen, sophomore to senior students, and postgraduate groups were substituted into the model for group comparison. The fitting result of the freshmen group model showed that the fitting result of the second-order measurement model of the campus outdoor environment was faulty, and the factor loading of the campus outdoor activity environment exceeded one. Therefore, the freshmen group model was modified to integrate the measurement model of the campus green spaces and outdoor activity environments into one variable, and thereafter, the model was re-fitted. This resulted in an adequately fitting result, as presented in Figure 2.

The comparison of the fitting results of different grades shows that the mental health of college students in different grades is significantly positively affected by the perceived campus outdoor environment and learning engagement. The direct and indirect effect values of perceived campus environment on the mental health of freshmen are 0.14 and 0.23, respectively, and the total effect was 0.37. The effect value of learning engagement on the mental health of freshmen is 0.45. The effect value of the perceived campus outdoor environment on freshmen's learning engagement is 0.52. The direct and indirect effect values of the perceived campus outdoor environment on the mental health of sophomore to senior students are both 0.24, and the total effect is 0.48. The effect value of learning engagement on the mental health of sophomore to senior students is 0.47. The effect value of the perceived campus outdoor environment on sophomore to senior students' learning engagement is 0.51. The direct and indirect effect values of the perceived campus environment on the mental health of postgraduates are 0.30 and 0.19, respectively, and the total effect is 0.49. The effect value of learning engagement on the mental health of postgraduates is 0.47. The effect value of the perceived campus outdoor environment on postgraduates' learning engagement is 0.40. This result indicated that the positive effect of the perceived campus outdoor environment on the mental health of students of different grades needs to be realized by improving their learning engagement.

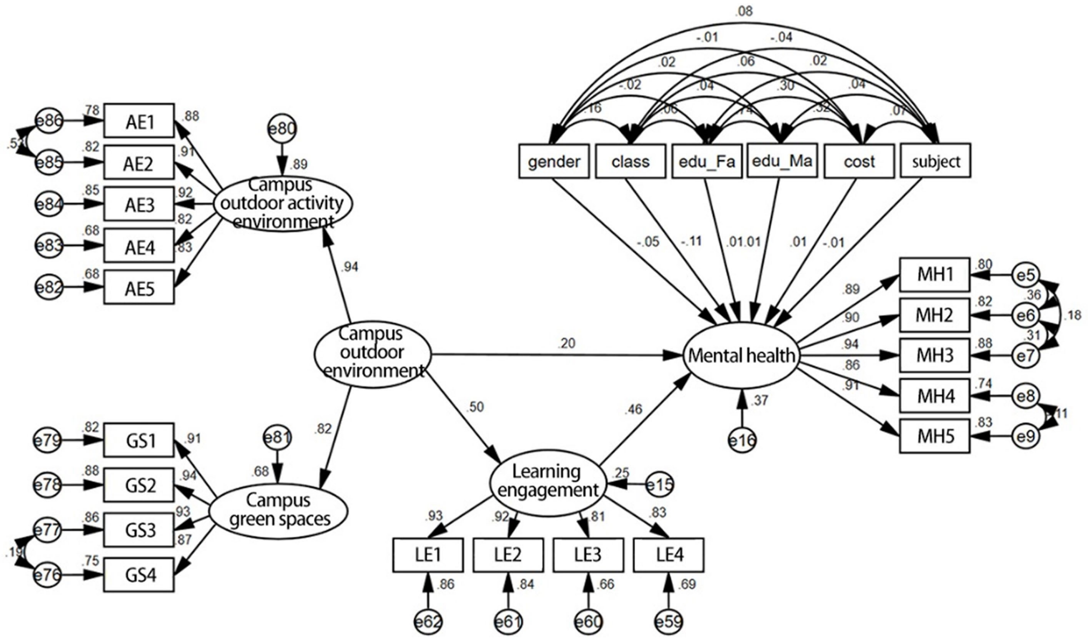

FIGURE 1
Standardized path diagram for the whole sample model.

TABLE 8 Comparison of path coefficients for different university student groups model.

Argument			Intermediate variable: Learning engagement	Dependent variable: Mental health – Total effect	Dependent variable: Mental health – Direct effects	Dependent variable: Mental health – Indirect effects
Grade	Freshmen	Campus outdoor environment	0.52***	0.37***	0.14***	0.23***
		Learning engagement	–	0.45***	0.45***	–
	Sophomore to senior students	Campus outdoor environment	0.51***	0.48***	0.24***	0.24***
		Learning engagement	–	0.47***	0.47***	–
	Postgraduates	Campus outdoor environment	0.40***	0.49***	0.30***	0.19***
		Learning engagement	–	0.47***	0.47***	–

***represents significance at the 1% level.

4. Discussion

Our study explored the mechanism of the effects of perceived campus outdoor environment and learning engagement on the mental health of college students during the COVID-19 pandemic. Furthermore, we compared the differences in the mechanism among college students of different grades. Our aim was to propose suggestions and feasible measures from the perspective of the outdoor environment and college management to improve the mental health of college students of different grades.

Our study found that the mental health problems of Chinese college students during the COVID-19 pandemic were more severe, and 27.3% of college students suffered from depression. In consequence, finding effective ways to intervene and improve the mental health issues of this special group was worthy of attention. More importantly, there were significant differences in mental health among different groups of college students. The mental health of college students deteriorates with the increase in grades. The mental health of postgraduates was generally poor, and the risk of depression was higher than that of undergraduates.

We confirmed that the outdoor environment on campus is positively correlated with the mental health of college students, which is consistent with the study before the novel coronavirus epidemic (40, 54, 118–121). Especially during the COVID-19 epidemic, when

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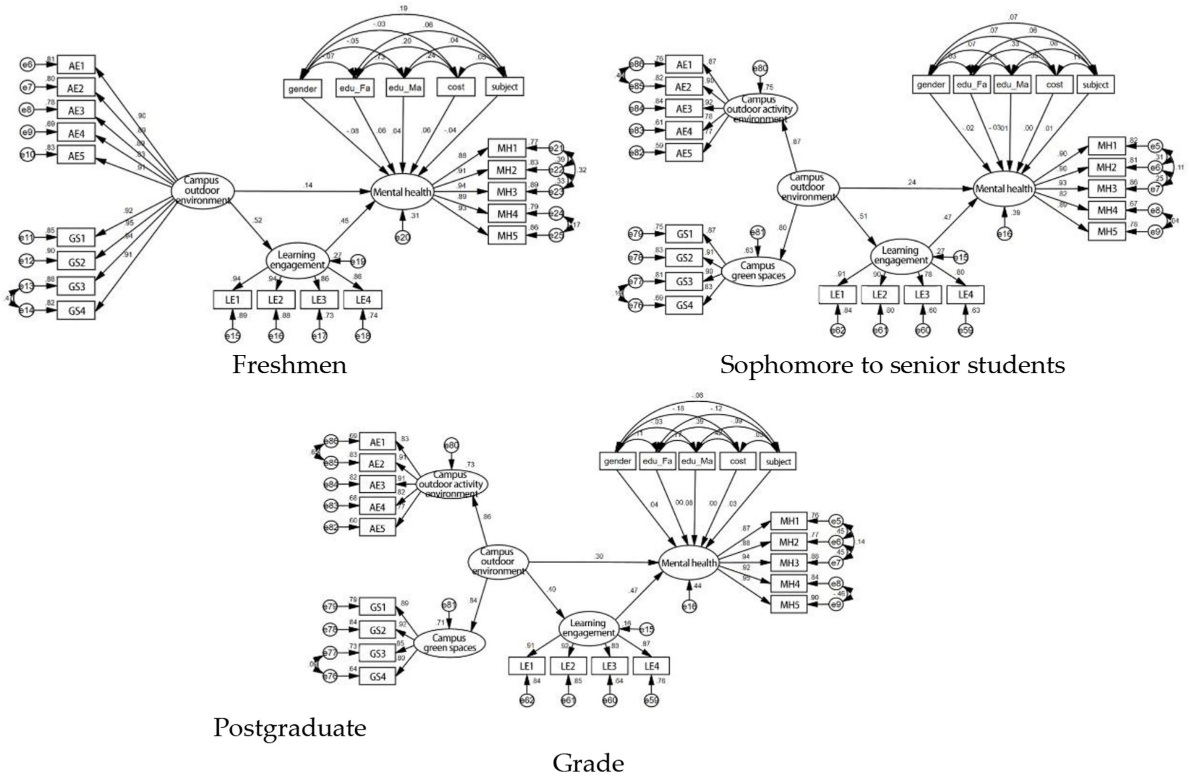

FIGURE 2
Comparison of standardized road maps of different university student population models.

colleges generally implemented closed management, college students stay longer on campus. At this time, the campus outdoor environment may play a more important role in the mental health of college students. From the existing literature, more scholars have focused on the impact of the epidemic on students 'mental health (122), but there is a lack of attention to the influence of the perceived campus outdoor environment on college students' mental health. Finding factors that can improve the mental health of college students to intervene may be more beneficial to solve this problem. Therefore, our research conclusion is a supplement to the current literature and a useful reference for how to improve the mental health of college students.

Although our research was aimed at the specific place of the campus environment, many scholars have studied other environments from a broader perspective. Their findings also confirmed the impact of human settlements on mental health (123). Some scholars also pointed out that special attention should be paid to vulnerable groups such as the older adults people and the poor (124). More relevant studies have studied the heat-related impacts on daily functions (125) and incorporated future climatic uncertainties into the consideration of the built environment (126). Some studies compared how outdoor design features are used by students with how these features are reported as being used (127). Planners should put forward targeted suggestions for environmental transformation and construction. Our study confirmed the correlation between campus outdoor environments and mental health, especially among postgraduates in China. Therefore, in the subsequent campus design and planning, special attention should be paid to the construction of the campus greening environment, enriching the content of outdoor activities and making a more reasonable layout design for the greening landscape and activity places of outdoor space.

Furthermore, we found that the perceived campus environment affects college students' mental health through the mediating effect of learning engagement. Some studies have confirmed the link between campus environment and learning engagement (82). Our research further confirmed that the increase in the natural environment on university campuses and the improvement of outdoor activity environment and infrastructure will have a positive impact on students' learning engagement during the COVID-19 pandemic. Existing research has confirmed that learning engagement is closely related to college students' mental health problems (60), and our research also proved this. Therefore, to improve the mental health of college students, it is necessary to focus on various aspects, including the quality of the campus outdoor environment and students' engagement in learning.

On the whole, learning engagement played an important mediating role in the path of campus outdoor environment affecting the mental health of college students, and its role was even stronger than the direct impact of campus outdoor environment on mental health. This showed that the impact of the campus environment on college students' mental health was mostly achieved by improving learning engagement. Learning engagement was an important predictor of the mental health of college students, not only because it had a high impact on mental health but also because it was also an important intermediary variable for external support factors such as campus outdoor environment.

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More importantly, we found that the influence of campus outdoor environment and learning engagement on the mental health of different groups of college students was different. For postgraduates, the direct impact of the campus outdoor environment on mental health was greater than that of undergraduates, while the intermediary impact of learning engagement on mental health was slightly lower than that of undergraduates. In addition, some perceived campus outdoor environment measurements of higher-grade students are higher than lower-grade students. This difference may be related to the different times students enter school. Compared with the lower-grade group, the higher-grade group tends to have a longer campus life, higher recognition, and emotional dependence on the campus environment, so their evaluation of the campus outdoor environment is relatively high. It also helps us to deeply understand and explain our research conclusion, that is, the mental health of higher-grade students who live longer in school is more affected by the campus outdoor environment.

Consequently, to improve the mental health of college students, it is particularly necessary to attach special attention to the needs of groups with relatively poor mental health and put forward specific opinions and strategies. First, the improvement of the campus outdoor environment is extremely important for students of different grades. Campus outdoor environment plays a positive role in promoting the mental health of college students. Creating a campus outdoor environment that promotes positive emotions can effectively alleviate stress among college students, thereby improving their mental health. The improvement of the campus environment needs to start from various aspects. Postgraduates' mental health is lower than undergraduates, and their depression is relatively higher than undergraduates. Therefore, postgraduates need special attention in campus groups. Their mental health is more directly affected by the campus outdoor environment. Improving the campus outdoor environment can greatly improve the mental health of this group. As a consequence of that, schools should pay special attention to the special requirement of postgraduates for campus outdoor environment, and improve the recognition of campus green spaces and outdoor activity environment. Moreover, actively creating outdoor facilities and activity spaces that facilitate communication and interaction, rather than solely considering their availability, can effectively enhance the mental health of graduate students from multiple perspectives.

Previous research on the relationship between campus outdoor environments and learning engagement remains inadequate. The underlying processes and factors linking campus outdoor environments, learning engagement, and the mental health of college students have yet to receive sufficient study. Our research incorporates the perception of the campus outdoor environments and learning engagement into a model assessing the impact on the mental health of college students. This supplements existing research in this area and provides a new avenue for improving the mental health of college students. Furthermore, we addressed the issue of heterogeneity in mental health. We found that the influence of the perceived campus environment and learning engagement on the mental health of college students differs across different grades. This facilitates targeted campus design interventions for students of varying grades to improve their mental health. Nevertheless, this research has a few shortcomings. First, our research is based on cross-sectional data, which is difficult to accurately clarify the causal relationship among perceived campus outdoor environment, learning engagement, and college students' mental health, and requires follow-up longitudinal studies. Second, we have not achieved complete random sampling, thus, there will be a certain deviation in the representativeness of the samples. Third, the survey scope and the number of the sample are limited. This research could not represent all campus outdoor environments in China because only a few colleges are selected for an in-depth survey. In future, more empirical studies need to be conducted. In addition, the evaluation of the campus outdoor environment is subjective, and cannot represent the objective campus environment in China. To better evaluate the campus environment in China, future investigations on this subject may consider objective measurements. In addition, our research was conducted during a period of normalization of the epidemic in China. This period was relatively stable and there were no point or concentrated outbreaks. Basically, there were no special circumstances such as being locked in dormitories among our interviewees. But despite this, there are still differences between different specific situations. Finally, more nuanced research is needed to explore whether the campus outdoor environment influences learning engagement through its impact on student communication and teacher–student interactions. In addition, further research is required to investigate whether campus outdoor activity environments can promote physical activity among students, leading to increased learning engagement and ultimately, improved mental health.

5. Conclusion

The results of this study reported that the mental health problems of Chinese college students during the COVID-19 pandemic were more severe. The mental health of college students deteriorates with the increase in grades. The mental health of postgraduates was generally poor, and the risk of depression was higher than that of undergraduates.

This study found that the campus outdoor environment affects the mental health of college students through the mediating role of learning engagement. More importantly, we found that for postgraduates, the direct influence of the campus outdoor environment on their mental health was stronger. For undergraduates, the indirect impact of learning engagement in the effect of campus outdoor environment on their mental health was stronger.

Therefore, in future construction and transformation of campuses, it is necessary to put forward different environmental transformation strategies according to the different grades of college students. We should especially pay attention to the needs of postgraduates with poor mental health for the campus outdoor environment, which is of great significance to improving the overall mental health and the quality of life of students during the COVID-19 pandemic.

Data availability statement

The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding author.

Author contributions

NS and ZZ: conceptualization, resources, and writing—review and editing. NS: writing—original draft preparation, software, funding acquisition, and supervision. NS, ZZ, and WL: methodology, validation, data curation, visualization, and project administration. All authors have read and approved the final manuscript and contributed to the article and approved the submitted version.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Publisher's note

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Research on the psychologically restorative effects of campus common spaces from the perspective of health

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Contemporary college students are suffering from increasingly serious psychological health problems, such as attention fatigue, psychological stress and negative emotions. A growing body of evidence has revealed that restorative environment design is conducive to psychological health. As the main choice of venue for students' daily activities, campus common spaces are supposed to be restorative to some extent. Given the above, the author studied 22 common spaces in the South China University of Technology (SCUT) Wushan Campus from the perspective of college students' behavioral patterns based on theories pertaining to restorative environments, then constructed a structural equation model (SEM) analyzing the psychologically restorative effects exerted by the characteristics of campus common spaces upon college students through a scale design and questionnaire survey. With the analysis of 478 valid questionnaires, the research found that the characteristics of campus common spaces with psychologically restorative effects mainly comprise the architectural environment, landscape environment, rest facilities and activity facilities. Among them, the characteristics of activity facilities and the landscape environment have the greatest impact on psychologically restorative effects, accounting for 33 and 30% of the total effects, respectively; they are followed by those of the architectural environment, which accounts for 21% of the total effects; those of the rest facilities have the least impact, accounting for 16% of the total effects. The research also found that the characteristics of campus common spaces can both directly influence college students' psychological recovery and produce psychologically restorative effects mediated by college students' behavioral patterns. The mediation effect of college students' behavioral patterns accounts for approximately 41% of the total effect of psychological restoration, in which the psychologically restorative effect of dynamic exercise behaviors is 2.5 times that of static leisure behaviors. The research reveals how the characteristics of campus common spaces promote the psychological restoration of college students, and it provides inspiration for healthy environment design in campus common spaces.

KEYWORDS

campus common spaces, healthy community, healthy environment design, college students, behavioral patterns, psychologically restorative effects

1. Introduction

College students are at a high risk of developing psychological conditions, according to relevant research. Global cross-sectional studies conducted from 2016 to 2020 indicated that 29–40% of college students experience psychological problems (anxiety, emotional disorders, academic stress, etc.), and the percentage is rising with each passing year (1–3). The *2022 National Depression Blue Book* reveals that 50% of the people with depressive disorder in China are students, with psychological stress as the main cause (4). Compared with other groups, college students are more likely to suffer from attention fatigue and psychological stress as they are required to spend a large amount of time acquiring professional knowledge and participating in scientific research projects, hence exerting a negative impact on psychological health (5). Relevant research has indicated that stress reduction and attention restoration are the key mechanisms that promote psychological health (6). Therefore, college students are in urgent need of means that can help to alleviate their attention fatigue, release their stress and regain their psychological health.

Campus common spaces, as a choice of location for daily activities, are crucial to the healthy development of college students, both in mind and body. However, the design of common spaces in many colleges still lags behind the psychological needs of students. Due to limited construction time, the development of college campuses in China tends to merely focus on the completion of main buildings and lacks the in-depth consideration of common spaces in terms of functional planning, activity planning and atmosphere fostering. This prevents the formation of an emotional bond between college students and the campus environment, leading to a low degree of space activity and involvement. The State Council, the National Health and Family Planning Commission and the Publicity Department of the CPC Central Committee have successively issued policies addressing the psychological needs of college students and the existing problems of campus spaces. Documents such as the *Outline of the Healthy China 2030 Plan and the Healthy China Action (2019–2030)* emphasize the task of building healthy campuses and provide guidelines for the psychological health of college students (7). It is evident that, faced with global crises (8, 9), psychological health is receiving increasingly more attention from the Chinese government. Building campus spaces that can facilitate college students' psychological restoration has become an urgent need.

Scholars at home and abroad have, in recent years, participated in extensive discussions and studies on how to build a spatial environment conducive to psychological health. Relevant researchers have revealed that a restorative environment can effectively help individuals to restore their consumed attention, relieve psychological stress and embrace a series of positive changes in both body and mind (10, 11). There have already been research works confirming that campus common spaces can effectively accelerate the physical and psychological restoration of college students. Nonetheless, existing research mainly focuses on the evaluation and comparison of the restorative ability and restorative effects of different types of spaces, lacking systematic research on the restorative elements of campus common spaces. Current empirical studies mostly adopt simple linear relationships to explain the association between the campus environment and restorative effects. Their evidence is relatively simple, and they ignore the impact of students' space use and behavioral patterns on psychologically restorative effects. Therefore, it is in some ways necessary for empirical studies to identify how the characteristics of campus common spaces affect college students' behavioral patterns and consequently psychological restorative effects.

In this context, the author studied the South China University of Technology (SCUT) Wushan Campus and employed structural equation modeling (SEM) to analyze the results of college students' psychological restoration contributed by the characteristics of campus common spaces under different behavioral patterns. The research attempts to answer the following questions: (1) Which characteristics of campus common spaces are conducive to college students' psychological restoration? (2) Are the characteristics of campus common spaces and the mechanism promoting college students' psychological restoration subject to the impact of college students' behavioral patterns? What are the influence effects? (3) Based on the answers to the above two questions, are there suggestions for the design optimization of existing campus common spaces?

2. Literature review and research hypotheses

2.1. The theory of the restorative environment

"Restorative environment" refers to an environment that enables people to better recover from psychological fatigue and stress (12). Two major theories have been developed since this concept was proposed, i.e., Attention Restoration Theory (ART) and Stress Reduction Theory (SRT). The ART, proposed in 1989 by the Kaplans, who are renowned in the field of environmental psychology, pointed out that a decline in an individual's ability to concentrate can lower their work or study efficiency and accuracy and lead to psychological fatigue; if the environment in which an individual exists is engaging in some way, it can help the individual to avoid fatigue-causing thought tasks and restore the consumed attention to a certain extent (13). The SRT, proposed by Ulrich, a scholar in the field of rehabilitation architecture, put forward that a clear state of stress perception can lead to negative emotions among individuals, as well as a decline in their cognitive and behavioral abilities (14). An environment that contains positive factors can effectively relax the individuals within it, reduce their sense of stress and transform negative emotions into positive ones. Kaplans et al. have proven that a restorative environment normally has four characteristics (Figure 1), i.e., being away, extent, fascination and compatibility (13), which contribute to individual attention restoration and stress reduction in a time-sequence-based progressive manner (15, 16).

2.2. Psychologically restorative effects of campus common spaces

Research by Kaplan shows that people constantly consume certain physiological, psychological and social resources in daily life, study and work, which produces a need for restoration when they are physically and psychologically exhausted (12, 13). Laumann and Bratman et al. pointed out that a spatial environment restores the psychological health of individuals mainly from two perspectives, i.e., "attention restoration," specifically the improvement of attention and

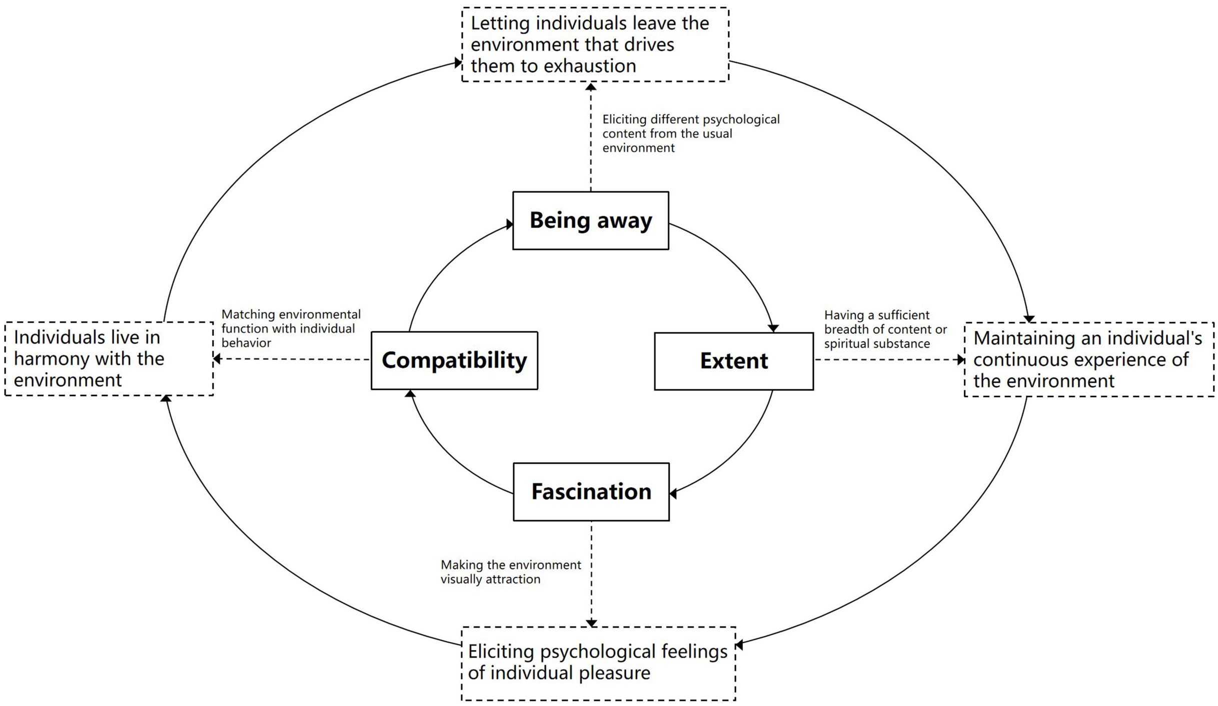

FIGURE 1
Four characteristics of restorative environment (15, 16).

memory (17), and "stress reduction," specifically the reduction of negative emotions and the promotion of positive emotions (18). According to research by Zhang, the resilience of a spatial environment refers to the ability of the characteristics and elements of a spatial environment to support the effective restoration of individuals, which determines whether individuals can obtain effective restoration in such a spatial environment (15). In campus common spaces, the characteristics of common spaces and the existence of their various elements will either facilitate or hinder the restoration of college students in these spaces, thus affecting their psychological restoration. Therefore, "the facilitating (or hindering) effect of the environmental characteristics of campus common space on the psychological restoration of college students" can be defined as "psychologically restorative effects." The psychological restorative effects of campus common spaces are related to the characteristics of the spatial environment and the behavioral patterns of college students in using these spaces.

2.3. Characteristics of campus common spaces

Campus common spaces are where teachers and students live and communicate, referring to mainly campus landscape spaces (vegetation and waterfront landscape), squares, courtyards and sports fields. In the planning and design of college campuses, common spaces are spatial nodes of different scales and forms enclosed by campus buildings. Their quality can be upgraded through landscape design, and they are equipped with rest and activity facilities. Therefore, the characteristics of campus common spaces are mainly formed by those of the architectural environment, landscape environment and facility support.

In recent years, some scholars have begun to turn their attention to the restorative effect of the characteristics of the architectural environment. Japanese architect Ashihara studied the building enclosure width (D) and building height (H) in common spaces and concluded that the ratio of D/H = 1 ~ 2 is appropriate to elevate people's positive emotions and spatial experiences (19). Based on machine learning simulation, Xiang et al. concluded that the shape and layout of building enclosures in common spaces are significantly related to people's emotions (20). Lindal, Weber and Masullo et al. believed that the number of turns in architectural outlines and historical elements in the architectural environment, and rich changes in building facades, can arouse people's interest and divert their attention from their daily needs and spiritual content and help them to achieve psychological restoration (21–26). In addition, there is ample evidence that increases in the quantity, type and color of vegetation in campus landscape spaces and sports fields is significantly related to enhanced psychological restoration (27–29). The degree of tree cover and green window views in campus have a significant positive relationship with the health, well-being and academic performance of college students (30, 31). For instance, Yang et al. believe that the type and distribution range of trees in a campus are related to the mental health levels of college students (32). Elsadek and Guo et al. proved through research that green and yellow plants can cause individuals to feel comfortable and peaceful, relieve stress and attention fatigue and improve work efficiency (33, 34). Wang et al. believed that extensive lawn spaces have restorative characteristics, and that looking at a green lawn free of people can evidently reduce stress and psychological fatigue (35). Research by Lu and Rout et al. shows that the accessibility and aesthetics of water bodies are significantly and positively associated with psychologically restorative effects (36, 37). Other researchers show that the rest facilities and activity facilities in campus common spaces can all significantly promote the psychological restoration of college students. For instance, research by Du and Nordh et al. shows that a sufficient number of comfortable and hygienic rest seats and seats with a natural view in campus common spaces can significantly increase the stay time and frequency of college students, which is conducive to producing restorative effects (38, 39). Research by Skärbäck shows that the number of activity facilities, and the compatibility and support of activity fields, can promote college students' physical activities, helping them to relieve their psychological stress and restore their attention (40).

The above researchers prove that the characteristics of the architectural environment, landscape environment, rest facilities and activity facilities in campus common spaces can all significantly promote the psychological restoration of college students. Therefore, the author puts forward the following hypothesis: H1—The characteristics of campus common spaces have a direct and significant positive impact on the psychologically restorative effects upon college students.

2.4. College students' behavioral patterns in campus common spaces

The environmental characteristics of campus common spaces have a significant impact on college students' behavioral patterns. Hipp, Markevych and Wang et al. proposed that the quality of the landscape environment in campus common spaces is positively related to college students' behavioral activities, and that a campus waterscape with a natural embankment is attractive to college students who prefer static rest activities such as reading, meditation and view appreciation, while a landscape with a hard pavement appeals more to those who enjoy dynamic exercise activities such as walking and running (41–43). Yu et al. put forward that sufficient sports fields and complete sports facilities on campus can secure the environment required for and promote college students' dynamic exercise behaviors (44). In addition, research by Altaher et al. shows that highly comfortable rest facilities with views can facilitate college students' static leisure behaviors such as meditation, reading and viewing, and help them to achieve emotional regulation and psychological restoration (45). As such, the author puts forward the following hypothesis: H2—The characteristics of campus common spaces have a direct and significant positive impact on college students' behavioral patterns.

Relevant studies have shown that behavioral activities have higher health promotion effects. Research by Holt et al. shows that college students who actively participate in outdoor activities on campus on a regular basis tend to be energetic and less sensitive to stress (46). Pasanen, Yuan and Herranz-Pascual et al. proposed that memory and emotional restoration are positively correlated with physical activities, and they pointed out after their research that a 30-min walk or meditation on a square can remarkably improve emotion and attention, and that a walk in a natural environment can relieve stress and anxiety and improve cognitive levels (47–51). Chawla, Sun and Yang et al. found, through observation and interviews, that the leisure and exercises activities of college students in campus landscape spaces can positively affect their emotions, and they indicated that stress reduction and attention restoration are associated with the leisure activity choices of college students (52–54). Although some studies have shown that individuals who engage in dynamic behavior activities (such as fitness, ball games and running) in the same environment enjoy greater restoration benefits than those performing static behavior activities (such as meditation) (55), the ART proposed by Kaplan demonstrates that behavioral patterns either supported by the environment or with a high degree of feedback can add to the restoration benefits (56). Static leisure behaviors (such as meditation, breathing in fresh air, contact with nature, etc.) can improve the level of restoration from psychological stress by promoting the collaboration between multiple senses (vision, hearing, and smell) (57). Based on the above research, the author puts forward the following hypothesis: H3—Behavioral patterns (static and dynamic exercise behaviors) have a direct and significant positive impact on the psychological restoration effects upon college students.

According to existing studies, the characteristics of the architectural environment, landscape environment, rest facilities and activity facilities in campus common spaces can promote the psychological restoration of college students. The characteristics of campus common spaces give rise to different behavioral patterns among college students, which lead to varied restorative effects. It can be inferred that college students' behavioral patterns play a mediating role in the relationship between the characteristics of campus common spaces and the psychologically restorative effects, hence leading to the following hypothesis: H4—The characteristics of campus common spaces can produce a positive impact on psychologically restorative effects through the mediation of college students' behavioral patterns.

The hypothesis model (Figure 2) of this research was produced based on the above hypotheses.

Based on the hypothesis model, the aforesaid four research hypotheses are divided into four sets of hypotheses (Table 1).

3. Research methodology

3.1. Overview of the researched area

The SCUT Wushan Campus is located in Tianhe District (Figure 3), Guangzhou, accommodating approximately 29,000 students on its 1.83 million square meters of land. The campus features an integrated north–south central axis extending from the south gate to the Liwu SciTech Building. It is divided into five areas: the Central Area, East Area, South Area, West Area and North Area. The campus common spaces are composed of vegetation landscape spaces, waterfront landscape spaces, squares, courtyards and sports fields (Figure 4). The research covered 9 sites in the Central Area, 7 in the West Area, 4 in the North Area, 1 in the South Area and 1 in the East Area, all selected based on the distribution characteristics of campus functions and college students' extracurricular activities. These 22 common spaces included 1 vegetation space, 4 waterfront spaces, 2 squares, 8 courtyards and 7 sports fields. The research targeted the characteristics of the architectural environment, landscape environment, rest facilities and activity facilities in these spaces, as

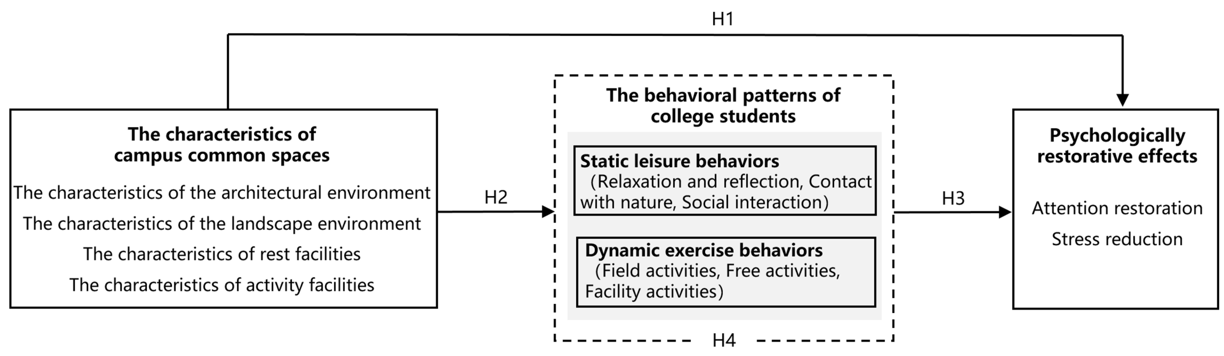

FIGURE 2
Hypothetical model of the psychologically restorative effects of campus common spaces.

well as the behavioral activities of and the psychologically restorative effects upon the college students in these spaces. The characteristics of the common spaces selected in the research are typical, covering all types of campus common spaces, hence providing a representative research sample.

3.2. Questionnaire design

The measurement scale in this research is based on the results of previous research performed by others, with some measurement items adjusted and redeveloped as per the hypothesis model (58). The quantity of measurement items references the widely recognized standards in the academic community, i.e., 2 indicators are acceptable, 3 indicators are better, and 4 indicators are the best (59). Therefore, in the scale developed for the research, each measurement variable contains 3–4 measurement indicators, which constitute a total of 7 measurement indicators. The Likert 5-level scale evaluation method was adopted, where "1" means strongly disagree, "2" means disagree, "3" means neutral, "4" means agree and "5" means strongly agree. The surveyed college students rated relevant descriptions based on their true ideas. In January 2022, the author distributed the questionnaires in the common spaces of the SCUT Wushan Campus and retrieved a total of 133 valid ones for pre-research; then, based on the results of the pre-research, the author amended the measurement scale and eventually determined the formal research scale and questionnaire.

3.3. Data collection and analysis methodology

In October 2022, the author conducted a formal questionnaire survey at the SCUT Wushan Campus, randomly distributing paper questionnaires to college students at the 22 surveyed sites. According to the principle wherein the ratio of the sample size to the quantity of observed variables should be at least 10:1 ~ 15:1 (60), a total of 500 questionnaires were distributed, while 478 valid ones were retrieved, hence yielding an effective retrieval rate of 95.6%. The specific composition of the retrieved questionnaire samples shows that the surveyed students were reasonably distributed in terms of age, grade and major and relatively evenly distributed in gender, so the overall sample structure was reasonable and fairly representative.

Structural equation modeling (SEM) was adopted to test the previously proposed hypothesis model. First, the influencing factors and path coefficients of the restorative effects of campus common spaces were analyzed quantitatively; second, the mediation effects of college students' behavioral patterns were tested. The most popular approach to mediation effect testing is the Baron and Kenny method, which, however, has been criticized and questioned continuously in recent years. Therefore, the more widely recognized Bootstrap method was employed instead for a direct test of the coefficient product. Chinese scholars Wen et al. have analyzed relevant topics and summarized the specific mediation effect analysis process (61) (Figure 5), which was referred to in this research.

4. Model test and results analysis

4.1. Analysis of data reliability and validity

The survey data were brought into the SPSS 26.0 and AMOS 26.0 statistical software for confirmatory factor analysis (CFA), which tests data reliability and validity. According to the test results, the Cronbach's α coefficient of the total scale is 0.958, while those of all latent variables are above 0.85, indicating that the observed variables for each latent variable are well designed, hence indicating the relatively high reliability of the questionnaire. The Bartlett's sphericity test and KMO value analysis of the survey data showed that the p-value was 0.000 ($p < 0.001$), passing Bartlett's sphericity test, and the KMO value was 0.949, greater than 0.7, meaning that the sample data were suitable for factor analysis. As shown in Table 2, the factor loads of all observed variables on the corresponding latent variables were greater than the standard value of 0.5, indicating a statistically significant subordination between the latent variables and the observed variables. In the overall correlation analysis of the project, the corrected item-total correlation (CITC) coefficients were all greater than 0.4, and the composite reliability (CR) coefficients of all latent variables were greater than 0.7, denoting the relatively high internal consistency of the measurement questions of each latent variable. The average of variance extracted (AVE) values of all latent

TABLE 1 Research hypotheses of the psychologically restorative effects of campus common spaces.

No.	Research hypotheses
H1	The characteristics of campus common spaces have a direct and significant positive impact on the psychologically restorative effects upon college students.
H1a	The characteristics of the architectural environment have a direct and significant positive impact on the psychologically restorative effects upon college students.
H1b	The characteristics of the landscape environment have a direct and significant positive impact on the psychologically restorative effects upon college students.
H1c	The characteristics of rest facilities have a direct and significant positive impact on the psychologically restorative effects upon college students.
H1d	The characteristics of activity facilities have a direct and significant positive impact on the psychologically restorative effects upon college students.
H2	The characteristics of campus common spaces have a direct and significant positive impact on the behavioral patterns of college students.
H2a1	The characteristics of the architectural environment have a direct and significant positive impact on the static leisure behaviors of college students.
H2a2	The characteristics of the landscape environment have a direct and significant positive impact on the static leisure behaviors of college students.
H2a3	The characteristics of rest facilities have a direct and significant positive impact on the static leisure behaviors of college students.
H2b1	The characteristics of the architectural environment have a direct and significant positive impact on the dynamic exercise behaviors of college students.
H2b2	The characteristics of the landscape environment have a direct and significant positive impact on the dynamic exercise behaviors of college students.
H2b3	The characteristics of activity facilities have a direct and significant positive impact on the dynamic exercise behaviors of college students.
H3	College students' behavioral patterns have a direct and significant positive impact on the psychologically restorative effects upon college students.
H3a	Static leisure behaviors have a direct and significant positive impact on the psychologically restorative effects upon college students.
H3b	Dynamic exercise behaviors have a direct and significant positive impact on the psychologically restorative effects upon college students.
H4	The characteristics of campus common spaces can produce a positive impact on the psychologically restorative effects upon college students through the mediation of their behavioral patterns.
H4a1	The characteristics of the architectural environment can produce a positive impact on the psychologically restorative effects upon college students through the mediation of their static leisure behaviors.
H4a2	The characteristics of the architectural environment can produce a positive impact on the psychologically restorative effects upon college students through the mediation of their dynamic exercise behaviors.
H4b1	The characteristics of the landscape environment can produce a positive impact on the psychologically restorative effects upon college students through the mediation of their static leisure behaviors.
H4b2	The characteristics of the landscape environment can produce a positive impact on the psychologically restorative effects upon college students through the mediation of their dynamic exercise behaviors.
H4c	The characteristics of rest facilities can produce a positive impact on the psychologically restorative effects upon college students through the mediation of their static leisure behaviors.
H4d	The characteristics of activity facilities can produce a positive impact on the psychologically restorative effects upon college students through the mediation of their dynamic exercise behaviors.

variables were greater than 0.5, indicating the relatively high convergence validity of the measurement variables.

4.2. Model test

In this research, the parameter estimation result and standardized path coefficients (Figure 6) of the model were obtained using the maximum likelihood estimation (MLE) method. From the fit indices of the measurement model (Appendix 1), it can be seen that the $\chi 2/df$ value was 1.993, smaller than 2, meaning that the model was well fitted; the GFI and AGFI values were 0.921 and 0.901, respectively, both greater than the recommended value of 0.9, indicating that the model was acceptable; the RMSEA value was smaller than 0.05, and the CFI, NFI and IFI values were all greater than 0.9, so the goodness of fit was relatively high. The above values proved that the structural equation model constructed was relatively ideal, and the hypothesis model had a fairly good fit measure overall.

4.3. Analysis of path coefficients

The magnitude of the standardized path coefficients shows the relationship between the measurement variables and the influence degree of each measurement indicator. Whether the path coefficients between the measurement variables are significant can be simply judged by the *t*-value test and *p*-value. Specifically, as long as the *t*-value is greater than 1.96 or the *p*-value is smaller than 0.05, the path coefficients can be deemed significant. It can be seen from the test results of the path coefficients (Table 3) that hypothesis H2a1 (the characteristics of the architectural environment have a significant positive impact on static leisure behaviors) is not accepted, while the other hypothesis results are valid.

Table 3 shows that the standardized path coefficients of F1 (the characteristics of the architectural environment), F2 (the characteristics of the landscape environment) and F3 (the characteristics of rest facilities) to F5 (static leisure behaviors) are 0.75, 0.483, and 0.286, respectively. The *p*-value of F1 (the characteristics of

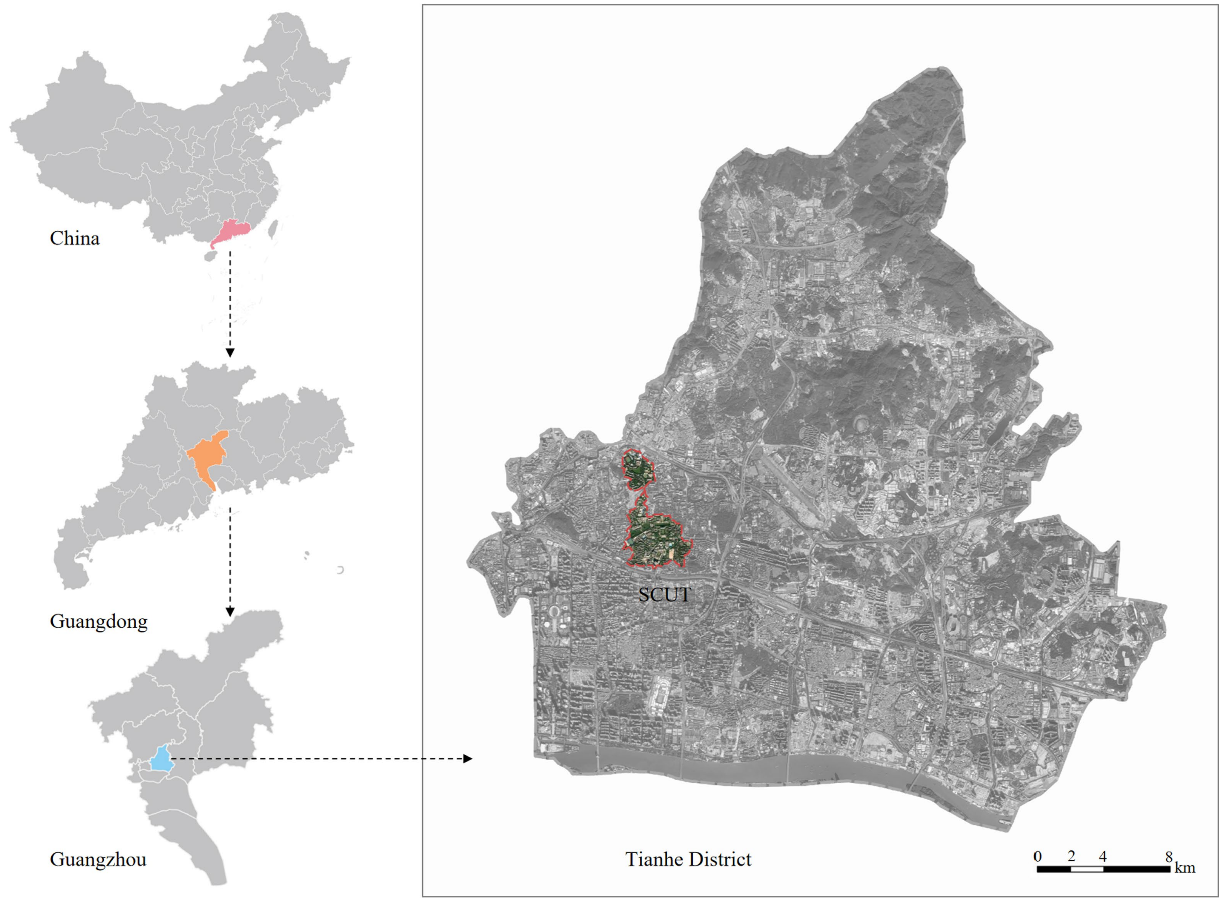

FIGURE 3
Location map of SCUT Wushan campus.

the architectural environment) is 0.104, greater than 0.05, which is insignificant, indicating that F1 (the characteristics of the architectural environment) has no significant impact on F5 (static leisure behaviors). The p-values of F2 (the characteristics of the landscape environment) and F3 (the characteristics of rest facilities) are both smaller than 0.05, reaching a significant level, indicating that F2 (the characteristics of the landscape environment) and F3 (the characteristics of rest facilities) both have a significant positive impact on F5 (static leisure behaviors). Among them, F2 (the characteristics of the landscape environment) has the largest standardized path coefficient, meaning that F2 (the characteristics of the landscape environment) has the greatest impact on F5 (static leisure behaviors). The standardized path coefficients of F1 (the characteristics of the architectural environment), F2 (the characteristics of the landscape environment) and F4 (the characteristics of activity facilities) to F6 (dynamic exercise behaviors) are 0.247, 0.239, and 0.527, respectively. Their p-values are all smaller than 0.05, reaching a significant level, indicating that F1 (the characteristics of the architectural environment), F2 (the characteristics of the landscape environment) and F4 (the characteristics of activity facilities) all have a significant positive impact on F6 (dynamic exercise behaviors). Among them, F4 (the characteristics of activity facilities) has the largest standardized path coefficient, meaning that F4 (the characteristics of activity facilities) has the greatest impact on F6 (dynamic exercise behaviors).

The standardized path coefficients of F1 (the characteristics of the architectural environment), F2 (the characteristics of the landscape environment), F3 (the characteristics of rest facilities) and F4 (the characteristics of activity facilities) to F7 (psychological restorative effects) are 0.145, 0.156, 0.124, and 0.178, respectively. Their p-values are all smaller than 0.05, reaching a significant level, indicating that F1 (the characteristics of the architectural environment), F2 (the characteristics of the landscape environment), F3 (the characteristics of rest facilities) and F4 (the characteristics of activity facilities) all have a direct impact on F7 (psychologically restorative effects). Among them, F4 (the characteristics of activity facilities) has the largest standardized path coefficient, meaning that F4 (the characteristics of activity facilities) has the greatest direct impact on F7 (psychologically restorative effects).

The standardized path coefficients of F5 (static leisure behaviors) and F6 (dynamic exercise behaviors) to F7 (psychologically restorative effects) are 0.159 and 0.297, respectively. Their p-values are both smaller than 0.05, reaching a significant level, indicating that F5 (static leisure behaviors) and F6 (dynamic exercise behaviors) both have a significant positive impact on F7 (psychologically restorative effects). Among them, F6 (dynamic exercise behaviors) has the largest standardized path coefficient, meaning that F6 (dynamic exercise behaviors) has the greatest impact on F7 (psychologically restorative effects). Based on the analysis of the above path coefficients, the

FIGURE 4
Master plan of SCUT Wushan campus and 22 researched common spaces.

structural equation model diagram supported by the data was drawn, as shown in Appendix 2.

4.4. Test of mediation effects

In this study, the mediation effect analysis process summarized by Wen et al. was adopted to test the mediation effects of college students' behavioral patterns. The Bootstrap method was employed to acquire 5,000 samples, obtain the standardized estimated values and standard errors among the variables and eventually calculate the significance level of the total effects, direct effects and indirect effects (Table 4). As long as the bias-corrected percentile and percentile estimated effect sizes do not contain 0 within the lower limit and upper limit of the 95% confidence interval, the *z*-value is no smaller than 1.96 and the Sig (two-tailed) *p*-value is smaller than 0.05, the effect size can be deemed significant. First, according to the results of the total effects in Table 4, independent variables F1 (the characteristics of the architectural environment), F2 (the characteristics of the landscape environment), F3 (the characteristics of rest facilities) and F4 (the

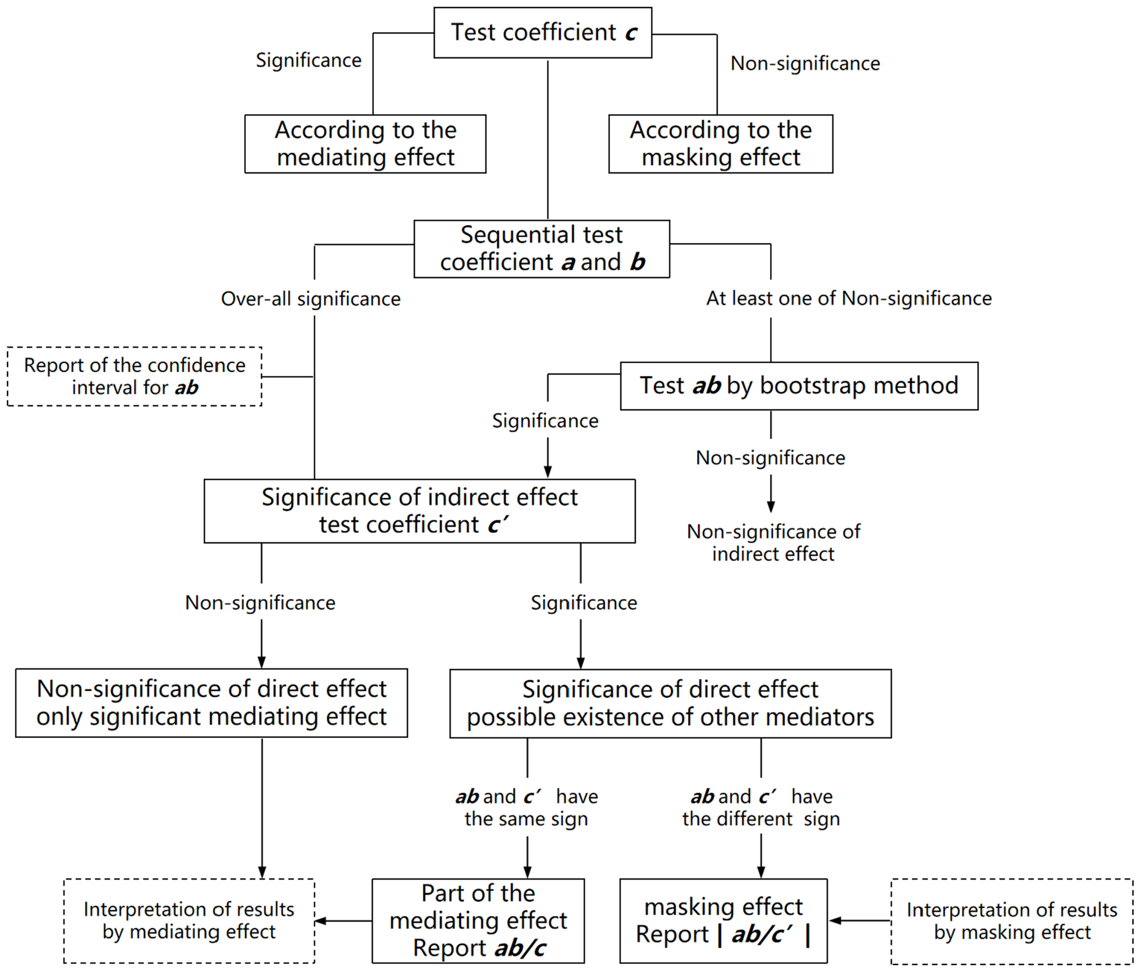

FIGURE 5
Test process of mediation effects (61). Coefficient *c*: the total effect of an independent variable on a dependent variable; Coefficient *a*: the effect of an independent variable on a mediating variable; Coefficient *b*: the effect of a mediating variable on a dependent variable after the influence of the independent variable is controlled; Coefficient *c′*: the direct effect of an independent variable on a dependent variable after the influence of the mediating variable is controlled.

characteristics of activity facilities), respectively, have a significant total effect on dependent variable F7 (psychologically restorative effects). Their lower and upper limit values do not contain 0, their *z*-values are all greater than 1.96 and the *p*-values are all significant at level 0.05. Second, according to the results of the direct effects in Table 4, only the lower and upper limit values of the standardized direct effect of F1 (the characteristics of the architectural environment) to F5 (static leisure behaviors) contain 0, the *z*-value of F1 is smaller than 1.96 and the *p*-value is greater than 0.05. The results are insignificant, consistent with the results of the abovementioned path analysis indicating that the F1 → F5 hypothesis is not valid, while the other hypotheses are valid. Finally, according to the test results of the indirect effects, the indirect effect *z*-values of independent variables F1 (the characteristics of the architectural environment), F2 (the characteristics of the landscape environment), F3 (the characteristics of rest facilities) and F4 (the characteristics of activity facilities), respectively, to dependent variable F7 (psychologically restorative effects) through mediating variables F5 (static leisure behaviors) and F6 (dynamic exercise behaviors) are 1.091, 1.973, 2.139, 2.219, 1.960, and 2.294, respectively, and their *p*-values are 0.138, 0.024, 0.016, 0.013, 0.025, and 0.011, respectively. Only the lower and upper limit values of the standardized indirect effect of F1 (the characteristics of the architectural environment) to F7 (psychologically restorative effects) through F5 (static leisure behaviors) contain 0, the *z*-value is smaller than 1.96 and the *p*-value is greater than 0.05. The results are insignificant; the path hypothesis of F1 → F5 → F7 is not valid, while other hypotheses are valid.

The above results show that the characteristics of campus common spaces, i.e., F1 (the characteristics of the architectural environment), F2 (the characteristics of the landscape environment), F3 (the characteristics of rest facilities) and F4 (the characteristics of activity facilities), respectively, have significant total and direct effects on F7 (psychologically restorative effects), and significant mediation effects through college students' behavioral patterns F5 (static leisure behaviors) and F6 (dynamic exercise behaviors). This indicates that the mediation effects in this research are incomplete, and that the college students' behavioral patterns play only a partial mediation role. As indicated in Table 4, the total effect exerted by the characteristics of campus common spaces on college students' psychological restoration is 1.025, the direct effect is 0.603, and the

TABLE 2 Analysis results of model reliability, validity, and CFA.

Latent variables	Observed variables	Standardized factor loadings	CITC	C.R.	AVE	Cronbach's α
F1 The characteristics of the architectural environment	A1 Appropriate scale of building enclosure	0.806	0.625	0.893	0.676	0.891
	A2 Diverse forms of building enclosure	0.850	0.584			
	A3 Strong architectural historical atmosphere	0.805	0.637			
	A4 Varied building facades	0.661	0.606			
F2 The characteristics of the landscape environment	A5 Abundant plant types	0.806	0.674	0.916	0.733	0.915
	A6 Rich plant colors	0.778	0.688			
	A7 Extensive lawn coverage	0.797	0.634			
	A8 Highly ornamental waterscape	0.773	0.659			
F3 The characteristics of rest facilities	A9 Plentiful rest facilities	0.791	0.615	0.903	0.700	0.901
	A10 Comfortable rest facilities	0.848	0.627			
	A11 Rest facilities with view	0.809	0.597			
	A12 Hygienic rest facilities	0.748	0.603			
F4 The characteristics of activity facilities	A13 Plentiful activity fields	0.820	0.701	0.906	0.706	0.902
	A14 Abundant types of activity fields	0.780	0.674			
	A15 Accessible activity fields	0.794	0.673			
	A16 Sufficient number of fitness facilities	0.675	0.664			
F5 Static leisure behaviors	B1 Relaxation and reflection	0.793	0.625	0.890	0.729	0.890
	B2 Contact with nature	0.761	0.660			
	B3 Social interaction	0.813	0.601			
F6 Dynamic exercise behaviors	B4 Field activities	0.566	0.757	0.887	0.723	0.887
	B5 Free activities	0.686	0.729			
	B6 Facility activities	0.700	0.716			
F7 Psychologically restorative effects	C1 Restoration of consumed energy	0.760	0.737	0.915	0.730	0.922
	C2 Mitigation of psychological fatigue	0.687	0.805			
	C3 Relief of anxiety and stress	0.678	0.741			
	C4 Regulation of negative emotions	0.689	0.760			

$N = 478$.

mediation effect of college students' behavioral patterns is 0.422, indicating that the characteristics of campus common spaces are improved by 1 unit, while the psychological restoration effects upon college students are improved by 1.025 units (with 0.422 being the effect exerted by the characteristics of campus common spaces on college students' psychological restoration through their behavioral patterns and 0.603 being the direct effect exerted by the characteristics of campus common spaces on college students' psychological restoration), so the mediation effect accounts for approximately 41% of the total effects. However, most of the existing research only focuses on the direct effect exerted by the characteristics of campus common spaces on college students' psychological restoration, ignoring the mediation effects of college students' behavioral patterns, which should be given more attention in future research. The mediation effect sizes of F5 (static leisure behaviors) and F6 (dynamic exercise behaviors) are 0.122 and 0.300, respectively. Among them, F6 (dynamic exercise behaviors) has the largest mediation effect size, meaning that F6 (dynamic exercise behaviors) has the greatest mediation effect. The psychologically restorative effect produced by the mediating path of dynamic exercise behaviors is 2.5 times that by the static leisure behavior path. Therefore, the dynamic exercise behavioral pattern should be considered in the design of campus common spaces.

5. Discussions

The research proposes four sets of hypotheses, and the empirical research results well support the hypothesis model. The research confirms that there are three paths for campus common spaces to influence the psychologically restorative effects upon college students, namely "Path 1: characteristics of campus common spaces → psychological restorative effects," "Path 2: characteristics of campus common spaces → static leisure behaviors → psychological restorative effects," and "Path 3: characteristics of campus common spaces → dynamic exercise behaviors → psychological restorative effects." Based on the above three paths, the paper discusses the psychological restoration influence paths and the effects of the characteristics of the architectural environment, landscape environment, rest facilities and activity facilities in campus common spaces, and concludes that more

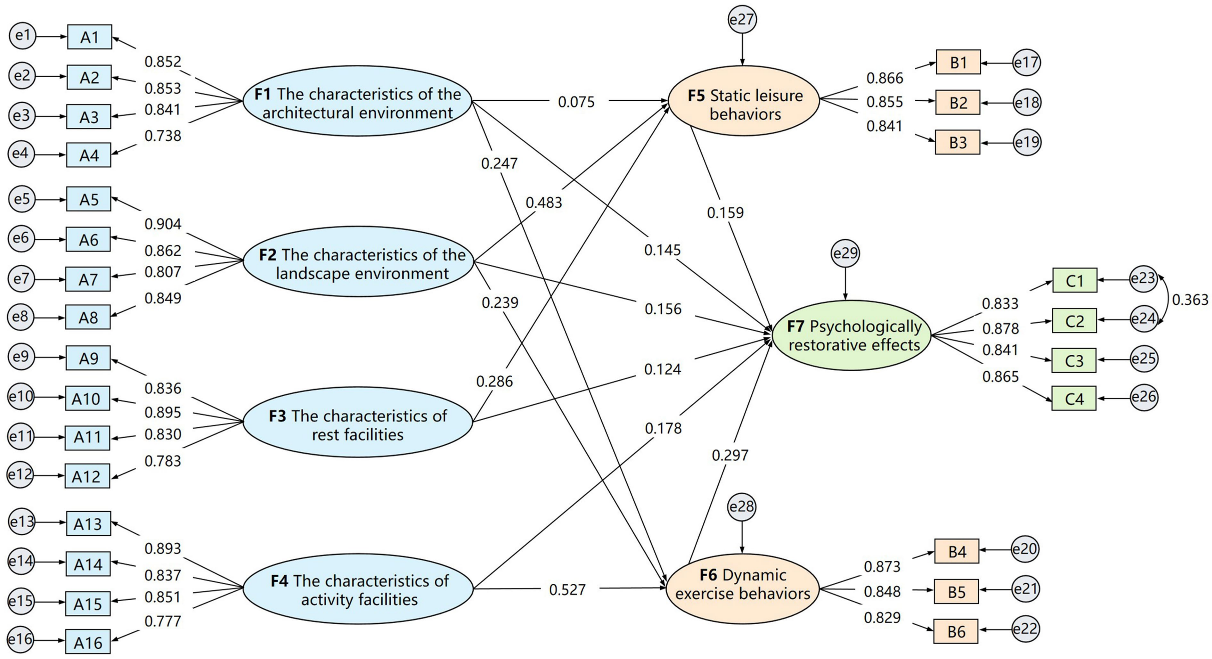

FIGURE 6
Diagram of standardized parameter estimation paths of the model for the psychologically restorative effects of campus common spaces.

TABLE 3 Analysis results of paths between variables.

Hypothesis	Regression path of the measurement model	Unstandardized estimate	Standardized estimate	S.E.	C.R. (t-value)	*p*	Conclusion
H1a	F1→F7	0.136	0.145	0.043	3.140	0.002	Supported
H1b	F2→F7	0.152	0.156	0.050	3.046	0.002	Supported
H1c	F3→F7	0.134	0.124	0.047	2.879	0.004	Supported
H1d	F4→F7	0.168	0.178	0.057	2.940	0.003	Supported
H2a1	F1→F5	0.075	0.075	0.046	1.628	0.104	Not supported
H2a2	F2→F5	0.499	0.483	0.055	9.151	***	Supported
H2a3	F3→F5	0.330	0.286	0.059	5.599	***	Supported
H2b1	F1→F6	0.251	0.247	0.045	5.566	***	Supported
H2b2	F2→F6	0.249	0.239	0.041	6.107	***	Supported
H2b3	F4→F6	0.534	0.527	0.049	10.975	***	Supported
H3a	F5→F7	0.149	0.159	0.045	3.289	0.001	Supported
H3b	F6→F7	0.276	0.297	0.068	4.023	***	Supported

"***" Means significant at level 0.001; $N=478$.

restorative campus common spaces can be designed according to the characteristics of college students' behavioral patterns.

5.1. Influence paths and effects of the characteristics of the architectural environment

The effect size of the characteristics of the architectural environment to psychological restorative effects is 0.218 (Table 4), accounting for 21% of the total effects. Through the comparison of the path coefficients in Figure 7, it can be seen that the effect size of the characteristics of the architectural environment to dynamic exercise behaviors is 0.247. Among the four measurement indicators, the path coefficients of "A2 Diverse forms of building enclosure" (0.853) and "A1 Appropriate scale of building enclosure" (0.852) in the characteristics of the architectural environment are the highest. This result indicates that the building enclosure form and scale are the factors that have the greatest impact on the dynamic exercise behaviors of college students. Previous

TABLE 4 Direct, indirect and total effects of the standardized hypothesis model.

Hypothesis	Path	Standardized estimate	Product of coefficient		Bootstrapping				P (Two-tailed significance)	Conclusion
					Bias-corrected Percentile 95%CI		Percentile 95%CI			
			SE	Z	Lower	Upper	Lower	Upper		
Standardized direct effects										
H2a1	F1→F5	0.075	0.053	1.415	−0.029	0.180	−0.026	0.182	0.079	Not supported
H2b1	F1→F6	0.247	0.059	4.186	0.131	0.364	0.135	0.371	0.000	Supported
H1a	F1→F7	0.145	0.068	2.132	0.015	0.282	0.014	0.281	0.017	Supported
H2a2	F2→F5	0.483	0.070	6.900	0.344	0.618	0.342	0.618	0.000	Supported
H2b2	F2→F6	0.239	0.053	4.509	0.141	0.350	0.137	0.341	0.000	Supported
H1b	F2→F7	0.156	0.069	2.261	0.021	0.292	0.020	0.291	0.012	Supported
H2a3	F3→F5	0.286	0.074	3.865	0.141	0.432	0.133	0.427	0.000	Supported
H1c	F3→F7	0.124	0.059	2.102	0.010	0.248	0.009	0.247	0.018	Supported
H2b3	F4→F6	0.527	0.061	8.639	0.406	0.647	0.404	0.646	0.000	Supported
H1d	F4→F7	0.178	0.083	2.145	0.023	0.352	0.005	0.332	0.016	Supported
H3a	F5→F7	0.159	0.069	2.304	0.034	0.302	0.028	0.296	0.011	Supported
H3b	F6→F7	0.297	0.119	2.496	0.077	0.543	0.084	0.554	0.006	Supported
Standardized indirect effects										
H4a1	F1→F5→F7	0.012	0.011	1.091	−0.002	0.043	−0.003	0.039	0.138	Not supported
H4a2	F1→F6→F7	0.073	0.037	1.973	0.018	0.161	0.017	0.160	0.024	Supported
H4b1	F2→F5→F7	0.077	0.036	2.139	0.018	0.160	0.013	0.151	0.016	Supported
H4b2	F2→F6→F7	0.071	0.032	2.219	0.021	0.149	0.018	0.142	0.013	Supported
H4c	F3→F5→F7	0.045	0.023	1.960	0.012	0.104	0.008	0.095	0.025	Supported
H4d	F4→F6→F7	0.156	0.068	2.294	0.043	0.310	0.042	0.310	0.011	Supported
Standardized total effects										
	F1→F7	0.218	0.062	3.516	0.109	0.356	0.114	0.363	0.000	
	F2→F7	0.304	0.061	4.984	0.191	0.432	0.190	0.430	0.000	
	F3→F7	0.169	0.064	2.641	0.058	0.307	0.052	0.300	0.004	
	F4→F7	0.334	0.070	4.771	0.202	0.473	0.191	0.465	0.000	

Standardized estimation of 5,000 bootstrap samples;"0.000" means significant at level 0.001; $N=478$.

researchers have not satisfactorily revealed the effects of students' behavioral activities on psychological recovery. This research confirmed that an appropriate spatial scale can promote college students' dynamic exercise behaviors, promoting psychological restoration through the mediation of dynamic exercise behaviors. The research also shows that historical buildings in campus common spaces can facilitate the free activities of college students, such as walking, playing and picture-taking, and have a positive impact on emotions and restoration from stress. This is consistent with the research results of Weber, Masullo, Reece and Guo, which revealed that architectural environments with a strong historical and cultural atmosphere are conducive to enhancing people's spatial experiences and promoting psychological restoration (22–25).

In addition, the research results show that varied building facades have a relatively small impact on the dynamic exercise behaviors of college students. However, research on the urban streetscape by Lindal and Yang showed that the degree of variation and number of decorations on building facades are significantly related to attention restoration (21, 26). The main reason for this discrepancy is that the environment of campus spaces and that of the urban streetscape differ significantly in characteristics. Facade forms in the urban streetscape are diverse and dynamic; thus, they can notably attract visual attention and guide behavioral activities. In the planning and design of university campuses, architectural interfaces and building heights are subject to unified design standards, so facade forms tend to be unified and less changeable, having little impact on college students' vision and behavioral activities.

5.2. Influence paths and effects of the characteristics of the landscape environment

The research results show that the total effect size of the characteristics of the landscape environment to psychological restorative effects is 0.304 (Table 4), accounting for 30% of the total effects. According to the comparison of the path coefficients in Figure 8, the effect sizes of the characteristics of the landscape environment to static leisure behaviors and dynamic exercise behaviors are 0.483 and 0.239, respectively, indicating that the influence effect of the characteristics of the landscape environment on college students' static leisure behaviors is higher than that on dynamic exercise behaviors. Previous research mostly adopted simple linear relationships to explain the association between the characteristics of the campus landscape environment and restorative effects, which ignore the impact of students' space use and behavioral patterns on the psychologically restorative effects. This research further demonstrates that the characteristics of the campus landscape environment and the mechanism promoting college students' psychological restoration are subject to the impact of college students' behavioral patterns by examining the mediating effect of college students' behavioral activities. Among the path coefficients of the four measurement indicators of the characteristics of the landscape environment, "A5 Abundant plant types" (0.904) is the most important influencing factor, indicating that plant type has the greatest impact on the static leisure and dynamic exercise behaviors of college students. The research also shows that a visually pleasant waterscape can promote the static leisure and dynamic exercise behaviors of college students, who would frequently sit around the waterscape to relax, walk around, get together and chat. However, college students pay more attention to plant elements in common spaces, such as whether the proportion of green plants is high enough and whether the mix of plant types is rich. A survey by Lu and Fu showed that college students prefer campus water bodies to green plants (36). The reason for this difference could possibly be that the Wushan Campus is located in a climate zone with hot summers and warm winters, where college students tend to seek shaded spaces with abundant greenery when they are outdoors (62).

In addition, the research results indicate that the lawn coverage area has a relatively small impact on the static leisure and dynamic exercise behaviors of college students, which is consistent with the empirical results presented by Ha and Kim, i.e., plant and waterfront landscapes with high biodiversity on campus can better relieve stress and promote restoration than traditional lawns (63). The main reason is probably that lawns in many campus common spaces only serve aesthetic purposes and are not open for college student activities, resulting in little impact on college students' behavioral patterns and psychological restoration.

5.3. Influence paths and effects of the characteristics of rest facilities

According to the research results, the total effect size of the characteristics of rest facilities to psychological restorative effects is 0.169 (Table 4), accounting for 16% of the total effects. It can be seen from Figure 9 that the influence effect of the characteristics of rest facilities on static leisure behaviors is 0.286. Among the path coefficients of the four measurement indicators of the characteristics of rest facilities, "A10 Comfortable rest facilities" (0.859) represents the most important influencing factor. It can be inferred that in campus common spaces, the comfort level of rest facilities has the highest impact on college students' static leisure behaviors and psychological restoration needs. College students with a high demand for psychological restoration are more concerned about the comfort level of rest facilities in relaxing themselves, so comfortable seats can induce more static leisure behaviors. The quantity, location and orientation of rest facilities can create more opportunities for college students to rest and spend more time in campus common spaces. In addition, college students with psychological fatigue are more sensitive to environmental hygiene. Clean and tidy seats in campus common spaces can, to a certain extent, promote college students' static leisure behaviors.

5.4. Influence paths and effects of the characteristics of activity facilities

The characteristics of activity facilities mainly describe the configuration of sports fields and fitness facilities on campus. The research results show that the effect size of the characteristics of activity facilities to psychological restorative effects is 0.334 (Table 4), accounting for 33% of the total effects. Through the comparison of path coefficients in Figure 10, it can be seen that the influence effect of the characteristics of activity facilities on dynamic exercise behaviors is 0.527, the greatest impact compared with other characteristics of common spaces. Among the path coefficients of the four measurement indicators of the characteristics of activity facilities, "A13 Plentiful activity fields" (0.893) represents the most important influencing factor. It reveals that, compared with fixed fitness facilities, college students prefer flexible activity fields, which have a higher impact on their dynamic exercise behaviors. This is consistent with the research results of Yu et al., i.e., a sufficient number of sports fields on campus can

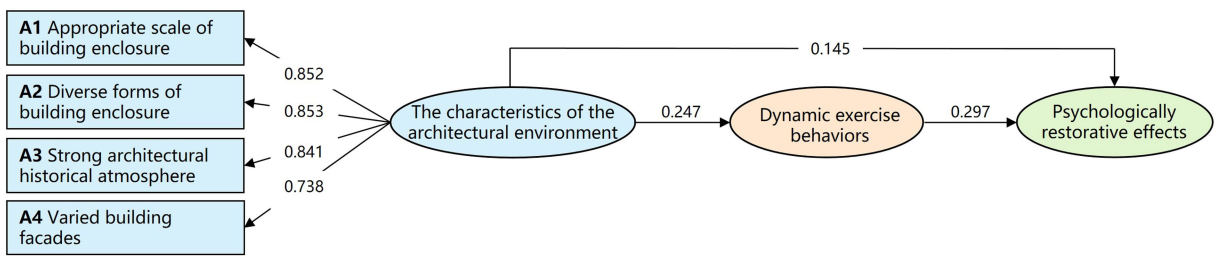

FIGURE 7
Influence effect illustration of the characteristics of the architectural environment.

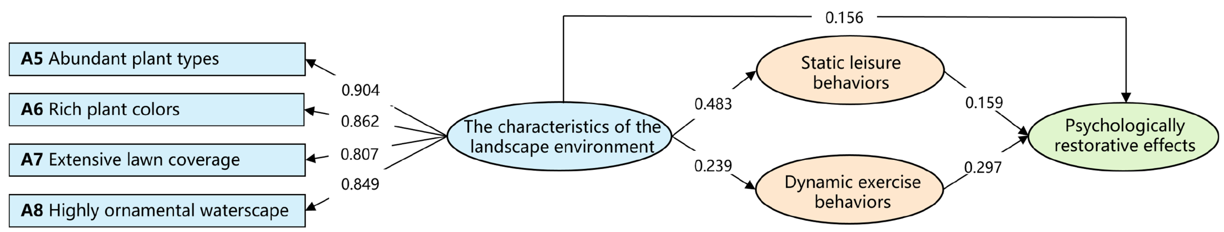

FIGURE 8
Influence effect illustration of the characteristics of the landscape environment.

promote college students' dynamic exercise behaviors (44). Some studies on community common spaces have shown that fitness facilities in common spaces can better promote dynamic exercise behaviors than activity fields (64). This discrepancy is mainly due to different research groups. The majority of community residents are middle-aged and older adults, who prefer mild or moderate fitness activities, while college students prefer more competitive, flexible and collaborative field activities. In addition, the accessibility of activity fields can increase the frequency of college students' exercise activities, while a great variety of them can improve the college students' choices and the duration of exercise activities, both playing a significant role in promoting psychological restoration.

5.5. Limitations in the research

Overall, the research reveals how the characteristics of campus common spaces promote the psychological restoration of college students. In particular, differing from existing studies, the research confirmed the direct and indirect effects of the characteristics of campus common spaces on psychological restoration, using college students' behavioral patterns as mediating variables. Nevertheless, some limitations were noted during the research, which require further improvement. First, the structural equation model constructed in the research needs further improvement. The observed variables for the characteristics of campus common spaces mainly extracted physical environment factors and did not cover perceived environmental factors, such as the security and privacy of the space. Future research should explore these factors that were not covered here. In addition, it is necessary to better identify the influence of campus common spaces' characteristics on the psychologically restorative effects on college students. It is important to explore more mediating factors, such as perceptual restorative and emotional responses, in future research. Second, the number of samples and the scope of the research were limited, so the universality of the research conclusions needs to be further verified; in addition, different campus environments have different impacts on college students, so the future research will further expand the scope of samples and conduct a comparative study of different types of campus common spaces. Finally, due to the limitations of the practical operating conditions, the research used mainly short questionnaires to measure college students' psychological restoration; in the future, biosensor technology should be employed to collect college students' ECG, EEG, ECOG, EMG and other autonomic nerve response data in campus common spaces, and the research should explore the rules regarding the impact exerted by the environmental characteristics of campus common spaces on college students' psychological restoration from both qualitative and quantitative aspects.

6. Conclusion

6.1. Main conclusion and innovation points

From the perspective of college students' psychological health, the author constructed a theoretical model for the psychologically restorative effects of campus common spaces based on a field survey of 22 common spaces in the SCUT Wushan Campus, as well as a follow-up analysis of spatial characteristics and the extraction of behavioral activities. Structural equation modeling (SEM) was adopted to test the theoretical model, with an analysis of the paths and effects by which campus common spaces influence the psychologically restorative effects upon college students. The main conclusions are as follows. First, the research confirms that the four characteristics of campus common spaces all have psychologically restorative effects. Among them, the characteristics of activity facilities and the landscape environment have the greatest impact on psychologically restorative effects; they are followed by those of the architectural environment; those of rest facilities have the least impact. Together, they constitute the four dimensions of the restorative environment of campus common spaces. Second, the research confirms that the environmental characteristics of campus common spaces not only directly affect the psychological restoration of college students but also produce psychologically restorative effects through the interaction between the characteristics of campus common spaces and college students' behavioral patterns. The mediation effect of college students' behavioral patterns accounts for around 41% of the total effects of psychological restoration, a relatively high proportion, in which the psychologically restorative effect of dynamic exercise behaviors is 2.5 times that of static leisure behaviors. Therefore, the psychologically restorative effects of campus common spaces are closely related to the behaviors of college students in common spaces. The design of a restorative campus environment should focus on not only spatial characteristics but also on the behavioral patterns of college students.

The research puts forward the viewpoint of addressing the psychological health problems of college students by guiding their

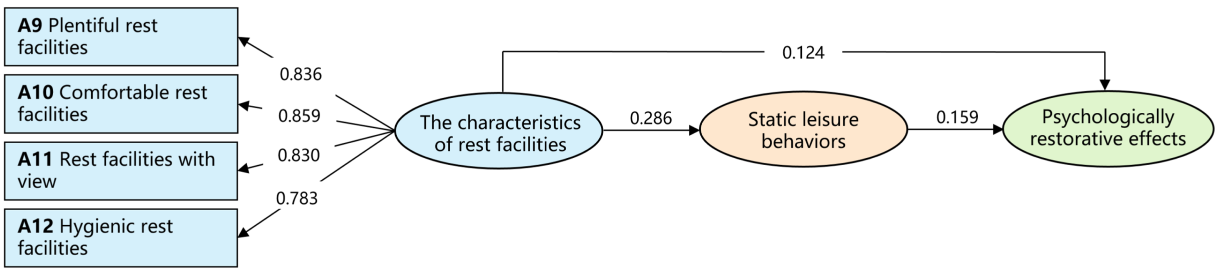

FIGURE 9
Influence effect illustration of the characteristics of rest facilities.

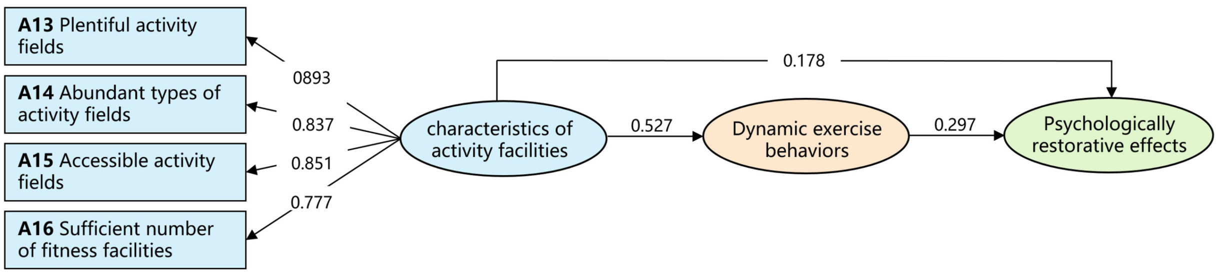

FIGURE 10
Influence effect illustration of the characteristics of activity facilities.

behaviors through the characteristics of campus common spaces, identifies the correlation between the environmental characteristics of spaces and psychologically restorative effects and realizes the quantifiable research of non-quantifiable factors through the construction of a structural equation model (SEM) for the psychologically restorative effects of campus common spaces from the perspective of college students' behavioral patterns. It effectively promotes related research on restorative environments on campus, and it provides new ideas for the construction of a healthy campus. The research results can guide the optimization of the design of campus common spaces and provide a theoretical basis and workable measures for the construction of campus common spaces that can meet the psychological health needs of college students.

6.2. Inspirations

As an integral part of and an important restorative place on a college campus, common spaces serve as an important form for the daily lives and communication of college students. Therefore, after identifying the psychological restoration mechanism of campus common spaces based on college students' behavioral patterns, the author puts forward recommendations for the design of campus common spaces from three aspects, i.e., architectural design, landscape design and facility configuration as per the "static leisure" and "dynamic exercise" behavioral patterns. The objective is to establish a health support mechanism for college students who suffer from psychological depletion, such as attention fatigue, stress and negative emotions.

6.2.1. Improve the diversity of building enclosures in common spaces

From the research results, it can be seen that the characteristics of the architectural environment in campus common spaces have an important impact on the dynamic exercise behaviors of and psychologically restorative effects upon college students. Within the category of the said characteristics, the building enclosure scale, form and cultural atmosphere are the crucial factors. Therefore, the design of campus common spaces should create multiple types of building enclosure spaces supporting behavioral activities through the building enclosure scale and form. For example, common spaces such as campus squares and courtyards may be divided into various functional areas. The resulting diversified types of common spaces can provide college students with a rational place to engage in public activities, promote their behavioral activities and thus facilitate psychological restoration. In addition, the design of campus common spaces should integrate the regional context and campus historical and cultural elements into architectural interfaces so as to enrich the cultural atmosphere of the common spaces, enable college students to perceive different spaces through characteristics of historical context, enhance their cultural and aesthetic experience in common spaces and thus promote their psychological restoration.

6.2.2. Enhance the full sensory experience of the landscape environment in common spaces

This paper proves that the characteristics of the landscape environment have a great impact on the static leisure behavioral patterns of and psychologically restorative effects upon college students. In the design of campus common spaces, the visual, auditory and tactile experience brought about by the landscape environment should be enhanced to induce college students' leisure behaviors and thus promote their psychological restoration. First, the enhancement of visual experience is necessary. Plant type and color are the landscape design elements that promote college students' visual experience. In landscape design, different colors, shapes and uses of plants should be leveraged and plant communities should be reasonably configured to foster a comfortable, pleasant spatial environment. Second, the enhancement of auditory experience is necessary. The design of campus common spaces should also focus on waterscapes by, for instance, creating visually and auditorily pleasing living water landscapes (such as cascades, fountains, and streams). Third, the enhancement of the tactile experience is necessary, by creating a landscape environment conducive to college students' active participation. For example, as many large lawns are present in the form of inaccessible green landscapes with a low utilization rate, lawns on campuses should be preferably opened up and integrated with the pedestrian road network to allow college students to sit on them and interact with others while enjoying a pleasant connection with nature.

6.2.3. Optimize the compatibility between facility configuration and behavioral activities in common spaces

This study indicates that the characteristics of activity facilities in campus common spaces have the greatest impact on the dynamic exercise activities of and psychologically restorative effects upon college students, with the quantity and accessibility of activity fields being the crucial factors. However, in previous campus designs, sports fields were either insufficient due to a shortage of land or far away from teaching and living areas, thus being less utilized or simply abandoned. Therefore, in the design of university campuses, it is necessary to not only provide a sports field that meets the basic exercise needs of students, but also create varied, continuous activity spaces in the front and back yards of buildings or idle spaces. It is also necessary to reasonably plan the service radius and spatial distribution of facilities for high-intensity sports (such as basketball courts, tennis courts and track and field) in the living areas of college students, and design facilities for low-intensity sports (such as badminton courts) on small squares and courtyards in the teaching area. In this way, more opportunities for diversified physical activities are made available for college students. In addition, the characteristics of rest facilities in common spaces have a certain impact on the static leisure behaviors of and psychologically restorative effect upon college students, with the comfort level and quantity of rest facilities being crucial factors. Therefore, in the configuration of rest facilities in campus common spaces, a proper number of comfortable rest facilities should be provided for college students to relax, read and rest, with a reasonable layout or movable seats to accommodate the college students' needs for relaxation, meditation or gathering.

Data availability statement

The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding author.

Ethics statement

Ethical review and approval was not required for the study on human participants in accordance with the local legislation and institutional requirements. Written informed consent from the participants was not required to participate in this study in accordance with the national legislation and the institutional requirements.

Author contributions

WG: conceptualization, resources, software, writing—original draft preparation, writing—review and editing. HW: conceptualization, methodology, software, validation, formal analysis, investigation, data curation, visualization, writing—original draft preparation, writing—review and editing. XL: conceptualization, methodology, visualization, software, writing—original draft preparation, writing—review and editing, funding acquisition. All authors contributed to the article and approved the submitted version.

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Conflict of interest

WG and XL were employed by Architectural Design and Research Institute Co., Ltd.

The remaining author declares that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Publisher's note

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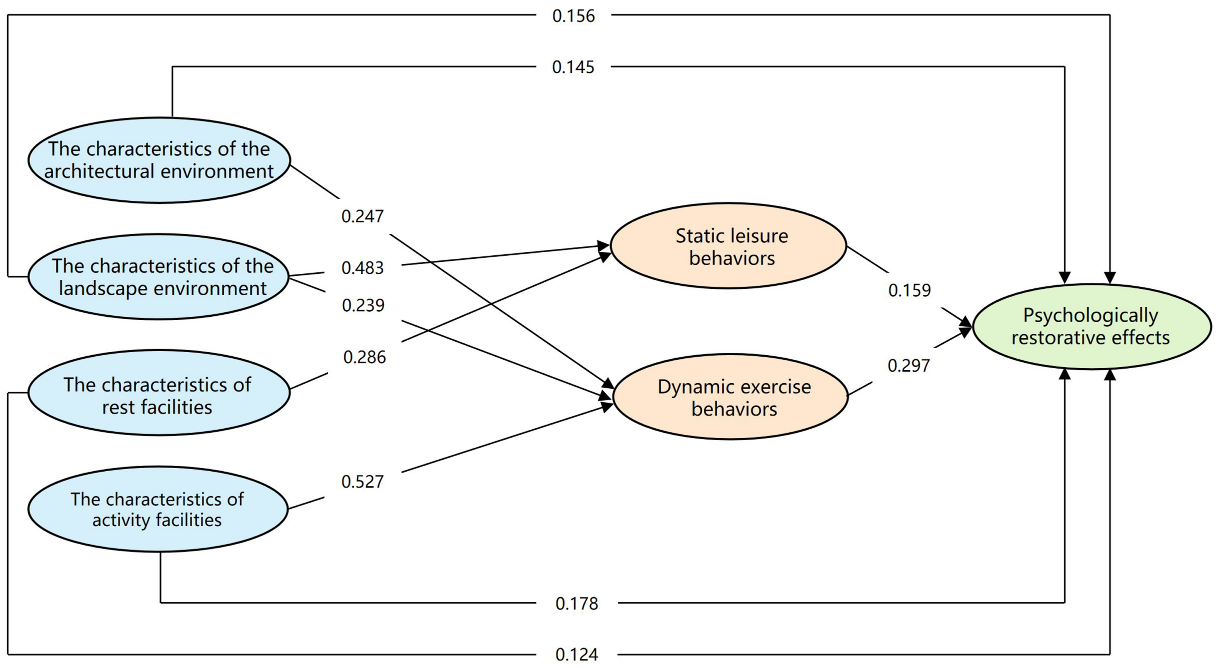
Appendix

APPENDIX 1 Goodness-of-fit test of the structural equation model.

Fit indices	Reference value	Model value	Overall model fit
χ^2		558.151	
df		280	
χ^2/df	<2.00	1.993	Yes
GFI	>0.90	0.921	Yes
AGFI	>0.90	0.901	Yes
PGFI	>0.50	0.735	Yes
RMR	<0.05	0.016	Yes
RMSEA	<0.05	0.046	Yes
CFI	>0.90	0.972	Yes
NFI	>0.90	0.946	Yes
RFI	>0.90	0.937	Yes
IFI	>0.90	0.972	Yes
TLI	>0.90	0.968	Yes

APPENDIX 2 Test of path model.



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Detecting informal green, blue, and street physical activity spaces in the city using geotagged sports-related Twitter tweets

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Introduction: Finland's natural physical environment and climate support a wide variety of informal outdoor sports, thereby motivating the population to do physical exercise in scenic environments. The vast majority of Finns enjoys outdoor recreational activities, and could thus be encouraged to post accounts of their year-round activities on social media. Our aim was to find out in what kind of areas and spaces, spatially, users are tweeting about sporting activities.

Methods: We use geotagged Twitter tweets filtering for 16 sporting activity keywords in both English and Finnish. The case study was conducted in the Helsinki Metropolitan Area, Finland, with an emphasis on cross-country skiing as a sports activity when there is snow. In a secondary analysis we concentrated on the sports people were practicing in these locations when there was no snow. The location spaces are split in to three land cover types: green, blue, and street spaces.

Results: We found that approximately half of the 150 skiing-related tweets were geotagged in green spaces, and half in street spaces. This finding related to street space was attributable to a spatial scale error: when we checked the results manually we noticed that they referenced the sporting location in the green space. Hence, then over 90% of the 745 non-ski-related tweets were geotagged in a street space.

Discussion: We conclude that Twitter is a beneficial tool for detecting spaces used for informal physical activity. A shortcoming in current Finnish national sporting policies is that spaces for informal physical activity are not explicitly mentioned- we use the term informal with reference both to the space and to the sporting activity, whereby public spaces are used for physical activity. This new knowledge of sporting locations will help city planners and sports planners to improve informal sports facilities, which in turn will promote healthy exercise in cities.

KEYWORDS

geotag, informal sports, physical activity, Twitter, urban planning, wellbeing

1. Introduction

There is an abundance of free informal outdoor space for physical activity (PA) in Finland, ranging from volleyball on the beach to ice skating on the frozen sea and lakes. We interpret informal sport to encompass any urban and nature-based lifestyle PA that takes place in a publicly accessible space away from fee-paying official sports facilities. Although informal sport is not a new concept in academic literature, as Chalip et al. (1984) already having studied the overall enjoyment of participation, it was only quite recently that it began to gain traction in official policy making, such as reported in Jeanes et al. (2019). This strengthening of focus in policy making could reflect the fact that participation in informal sport is said to be in decline (Coakley, 2017).

Therefore, as we point out in this article, there is a need to investigate where people engage in PA to establish the demand in urban locations. We use social-media data, coming from public geotagged Twitter messages, meaning that the location attribute is already attached to the messages. Our main analysis focuses on key words related to cross-country skiing, and is geographically limited to the Helsinki Metropolitan Area (HMA) in southern Finland. The secondary analysis concerns other sporting activity in the same locations as in the skiing tweets. The HMA comprises the cities of Helsinki, Vantaa, and Espoo, and the town of Kauniainen. These four areas combined constitute the largest urban concentration in Finland. It is not a typical urban area in that it contains many urban green (such as public parks, forests, or nature reserves) spaces and urban blue (such as rivers, lakes, or the sea) spaces that are suitable for PA. Additionally, the majority of Finnish cities are designed to allow everyone access to places where they can engage in PA, regardless of whether or not they like to do so outdoors (Neuvonen et al., 2018).

Our main research question is: "How can geotagged Twitter tweets detect informal PA spaces?" and our sub-question is "In what type of urban public space do people engage with in their informal PA?." We split the tweet analysis by skiing related key words in both English and Finnish, whereby skiing in Finland means cross-country skiing but can also include downhill skiing if done at a physical facility. Skiing in the HMA is an interesting research topic because, even though it is an urban environment, there are numerous opportunities for skiing in public green, blue, and even street PA spaces. We extend the analysis by comparing the skiing tweets to other sporting tweets within the same location to find out what sports people engage in when there is no snow.

The literature on informal participation in sport focuses on the improvement of overall health and wellbeing (Bowler et al., 2010). We do not separate the terms "sport," "exercise," and "participation" here, because in our view any type of PA is beneficial in terms of having an active and healthy lifestyle in the city. We therefore use the term "physical activity" from here on, following the World Health Organization (WHO) definition: "physical activity refers to all movement including during leisure time, for transport to get to and from places, or as part of a person's work" (WHO, 2020). Children in Finland are encouraged to engage in outdoor play from a young age, going outside in all weathers while at kindergarten (Iivonen et al., 2019). Furthermore, our case study area, the HMA, has many outdoor play parks, averaging almost one per neighborhood, which is not the norm in many other countries. These parks promote exercise in natural environments whilst honing children's independent mobility through to adulthood (King and Sills-Jones, 2018). However, even though Finns seem to have an ingrained habit of engaging in PA year-round, around 70% of the adult population (over 18 years old) are not reaching the recommended weekly target of ≥150 min activity of moderate-to-vigorous-intensity PA (Bennie et al., 2017).

Kolu et al. (2022) point out the economic burden of a sedentary lifestyle in Finland: the total cost of low PA behavior came to approximately € 3.2 billion in 2017, and the costs attributable to high sedentary behavior totaled around € 1.5 billion. According to the Finnish Institute for Health and Welfare (2022), around 70% of men and 60% of women in Finland are overweight, meaning that they have a body mass index (BMI) of 25 or more, and a third of the population are obese, having a BMI of 30 or more: a score of 18.5–24.9 is healthy. It was found in a similar recent study conducted by the Helsinki and Uusimaa Hospital District that the annual healthcare costs for an obese person were approximately € 2,665 (Vesikansa et al., 2022). Rose et al. (2008), in turn, reported that spending two or more hours outdoors helps to prevent children from becoming short sighted in the near future, which also eases the burden on health care. Therefore, the provision of free public spaces that allow the population to be active outdoors is one among many simple and effective ways of improving health and simultaneously lowering the negative costs attached to being inactive. It is suggested in current literature based on PA rates and the impact of the COVID-19 pandemic that there is a general tendency to be less active (e.g., Engels et al., 2021; Ronkainen et al., 2021; Semple et al., 2021). However, according to the Ministry of the Environment (2021) there is a strategy to increase the recreational use of natural habitats in Finland as part of Prime Minister Sanna Marin's government program. Survey results have shown that, in fact, the COVID-19 pandemic increased the motivation of Finns to exercise in local nature-based surroundings, whereby almost everyone (96%) enjoys outdoor activities: this adds to the relevance of our article.

Researchers have found it difficult to establish participation rates for informal lifestyle sport (Gilchrist and Wheaton, 2011). PA of this type does not typically go on in a fixed place such as a physical sports facility, hence usual practices such as counting tickets are not possible. Consequently, for this article we focused our analysis on already geolocated Twitter tweets to detect the demand for informal sport by location, meaning that the PA takes place in an informal setting away from physical sports facilities. It should be borne in mind that not all PA takes place by or in green or blue urban spaces, and that street spaces also exist. Finland has a national database of sports facilities (LIPAS, 2022), which also includes informal sports infrastructure comprising street spaces (any location not in green or blue spaces) such as outdoor table-tennis tables and basketball courts. We therefore distinguish between three informal urban PA spaces which are also land cover types: (1) green, (2) blue, and (3) street.

2. Background

2.1. Defining informal spaces for physical activity

For the purpose of this article we focus on informal PA spaces, given that Finland already has a national open database of sports facilities and their conditions, namely LIPAS (LIPAS, 2022). User demand for formal PA facilities can be tracked by means of ticket purchases or by scanning sports cards, but this is not the case for informal spaces, hence it is more difficult to estimate user demand in each location. Table 1 shows varying definitions of informal

TABLE 1 Definitions of informal sports.

References	Informal sport definition	Mentions location (Yes/No)
Coakley (2017)	Informal games exist when young people come together and agree to organize themselves for the sake of having fun and maximizing action.	N
Kokolakakis et al. (2017)	The distinction between formal and informal definition is based on the frequency and context of participation- formal sport implies doing sport in a club, or through organized competition.	N
Wheaton and O'Loughlin (2017)	A defining feature of lifestyle sports is their self-organized and spontaneous nature, with participation in predominantly informal settings, often without external regulation or institutionalization.	**Y**
Deelen et al. (2018)	Typical informal and flexible sports settings are commercial health centers and gyms, with informal groups and individual participation in the public space, all of which make participants less dependent on formal structures such as membership obligations, opening hours and the availability of specific sports facilities.	**Y**
Jeanes et al. (2019)	Traditional recognized sporting forms, played by groups who are not affiliated to sporting bodies or pay membership fees.	N
Mathisen et al. (2019)	Informal sports do not require adolescents to be part of organized official sports clubs but may involve high levels of leisure time vigorous PA.	N

sports, and whether they mention the location of the PA. We use the term "sport" rather than "physical activity" because the majority of literature refers to informal sport, the assumption being that participation is informal (Wheaton and O'Loughlin, 2017).

However, as Deelen et al. (2018) point out, participation in sport may be within sport clubs, gyms, or public spaces, with a focus on the "settings" in which the sporting activity is located. The authors also suggest that most informal sport goes on in public spaces and natural environments, and we follow this same distinction. In our case this even applies to downhill skiing slopes, which have specific opening times and require entrance tickets but are still classed as informal because the public can choose what time to visit within the specified period. Therefore, even though there is no fixed definition of informal sport, it typically simply means being self-organized. According to Coakley (2017), for example, formal sport is "rule-centered" and informal sport is "action-centered," whereby the latter relies on group decision-making among the participants to be self-sustaining: however, this definition omits individual sports. One variation is that the difference is simply a matter of the frequency and context of participation, whereby formal sport takes place at regular times, requires club membership and involves taking part in organized games and competitions (Kokolakakis et al., 2017).

On the grounds that the distinction between formal and informal sport is not yet fully adopted in either government or non-government agencies, Jeanes et al. (2019) define formal sports as any activities that take place in affiliated sports clubs and within official sports structures, for which participants pay a fee and compete in leagues. They further define informal sports as any traditional sporting activity, such as cricket, football, or basketball, whereby participants do not pay membership fees and play in places such as local parks or community spaces. They omit sports such as surfing, skateboarding, and parkour, which they refer to as a "lifestyle" or "leisure" sport that evolved from resistance to traditional sport. According to Mathisen et al. (2019), club sport increased in Finland from 1992 to 2010, and general PA participation expanded with the introduction of new informal sports such as cross fit, hiking, and skateboarding. We focus here on the location of the informal sporting activity, which seems to have been omitted in existing definitions.

2.2. Interpreting green, blue, and street urban spaces

Green and blue urban spaces have been gaining traction in academic literature (see Korpilo et al., 2021; Tan et al., 2021). It is becoming increasingly common to study how and where people exercise in a city. Locations in which physical activities take place that are scenic and in natural surroundings tend to motivate people to improve their overall wellbeing (Loureiro and Veloso, 2014; Bell et al., 2015). Finland is a suitable country in which to conduct research on where people engage in PA given the large amount of land used as green and blue spaces. Green areas, specifically forests, comprise more than 75% of the country's land (Ministry of Agriculture and Forestry, 2022). Blue spaces, namely water bodies, are particularly high in recreational value among Finnish citizens. Inland water bodies such as lakes and rivers cover ~10% of the country's total surface area, accounting for 34,539 km^2 (Ministry of Agriculture and Forestry, 2020). These two statistics exemplify the suitability of Finland for studying where people exercise outdoors in nature, as even urban spaces are encompassed by both green and blue spaces. According to a survey of around 1,250 residents of Helsinki and Tampere conducted by the Finnish Forest Research Institute, over 80% of them thought that the green spaces improved their residential area, and over 90% said their favorite place was in nature, in a forest, on a shore or in another type of green space (Tyrväinen et al., 2007). This has led to the term "green exercise," which has recently arisen to emphasize the positive effects of combining PA and exposure to nature (Shanahan et al., 2016; Mnich et al., 2019). It also has an effect on people's emotions, particularly when walking or otherwise exercising in a forest environment (de Brito et al., 2020).

Having included three different types of informal urban space in this article, namely green, blue, and street, we thought it important to understand how others used these terms and what in particular made the PA informal compared with traditional or formal sports. We now turn to our third and final urban space, namely street space. Street-based sports have, in the recent past, been associated with rebellion against more traditional informal sport, encompassing skateboarding or parkour (see e.g., Angel, 2016; Rannikko et al., 2016). We define street space PA here as any physical activity that does not take place on or around green or blue space, but on asphalt, concrete, or similar hard surfaces, including those on which outdoor open sports parks are built. Outdoor public spaces in Finland have varying uses depending on the season. Gravel parks, for example, are used in summer for boules and football, and in winter for ice skating. There are 943 street workout parks in Finland, of which 326 (35%) are within the HMA (LIPAS, 2022), and there are many more outdoor street PA opportunities ranging from obstacle courses to frisbee golf and workout step hills (Kivistö, 2022). Indoor public sport facilities were forced to close to the public during the winter of 2020–2021 due to the COVID-19 pandemic, and only outdoor public spaces were allowed to remain open. Thus, even under the heavy restrictions related to the pandemic there were still many outdoor-exercise opportunities that allowed the general public to remain active.

Recent research has focused on the impact of the COVID-19 pandemic and the resulting increasingly sedentary lifestyles among the population (Du et al., 2020; Dunton et al., 2020; Yamada et al., 2020; Ronkainen et al., 2021). There was still access to green space in Helsinki, and as Korpilo et al. (2021) found, in fact some forest areas nearby were over-crowded, which had a negative impact upon the environment. Informal sport is not often explicitly mentioned in policies: in Finland, for example, the Sports For All policy is still centered around organized sports focusing on diversity (Ministry of Education and Culture, 2018). It would therefore be useful to know where in urban spaces people are doing their PA. Urban spaces tend to be associated with a decreasing amount of green space and with discouraging people from exercising, which could fuel an increase in sedentary living (Triguero-Mas et al., 2022). Our focus here, however, is on how urban areas could still give access to a variety of outdoor sports.

A healthy city, as defined in the Zagreb Declaration (WHO Regional Office for Europe, 2009), is one that "provides conditions and opportunities that encourage, enable and support healthy lifestyles for people of all social groups and ages." Li et al. (2022) conducted a review to distinguish any differences between green and non-green exercise: they found that green exercise did, in fact, have psychological advantages. Since then, social media has been used as a novel source of data to capture the usage of green space during the COVID-19 pandemic (Fagerholm et al., 2021; Korpilo et al., 2021; Cui et al., 2022). However, these studies omit other urban spaces in which informal PA takes place outdoors in fixed locations, such as outdoor gyms, skate parks, and table-tennis facilities. Moreover, outdoor informal sports such as cycling, kayaking, and walking do not take place in fixed locations. It would therefore be useful for municipalities to know where their populations were engaging in PA.

2.3. Previous usage of geotagged Twitter tweets

Geotagged Twitter messages have been successfully used in previous academic studies spanning many research topics, such as for analyzing political events (Tear, 2018) or human mobility (Jurdak et al., 2015). Huang and Carley (2019) refer to Twitter as a useful proxy for understanding people's mobility and social events. Tweets are naturally occurring data, the main purpose of which is not for analysis (Sloan and Morgan, 2015). This makes it potentially more suitable for further analysis given that data collected from online users as a by-product are said to be more reliable than survey or questionnaire data in which people might give false answers (McLaren and Shanbhogue, 2011). Tweets typically include a hashtag (#) alongside a phrase or term, which researchers follow spatially, temporally, and socially. Crampton et al. (2013), for example, followed "#LexingtonPoliceScanner" to find out how riots spread online in the US. They suggest that researchers go beyond the geotag and focus on the space associated with the geolocation and not just the point on the map, but it should be borne in mind that they were focusing on a localized event in one fixed location. We argue against this practice, as we have found that the geolocation, which for us is the most important aspect, is often omitted in secondary research analyses.

Key words that link "sports" and "Twitter" on web search engines, at least in the English language, typically identify research focusing more broadly on sports journalism, and on finding sports events. These results are linked to how the art of journalism has had to adapt to reporting news in different ways (Schultz and Sheffer, 2010), for example, or how social media can be used alongside humans as real-time sensors to find out when sporting events are taking place (Lanagan and Smeaton, 2011; Zhao et al., 2011b). Smith et al. (2019) point out that sports fans enhance their live sports viewing by using Twitter. This is a sentiment that has been noted in other studies, not only among fans but also among coaches, athletes, and sports media associates, originating in particular at the London Olympics in 2012, which was known as the "first social media Olympics" (Mann, 2012). In summary, the kind of volunteered geographic information mentioned above has long been used on other social-media platforms such as Flickr photos and Google Maps placemarks, which Crampton et al. (2013) call the "geographies of the geoweb."

However, what is missing from these examples is the vital aspect of our research, namely where these tweets about sporting and news events are produced (Gritta et al., 2018), especially those in non-fixed locations. A similar result would be found in data from mobile network infrastructures, called transactional data, which Raun et al. (2023) cite has the potential to reveal activity spaces for second home usage, but still with a focus on the "where" and "when" of fixed locations. Although some sporting events are obvious, this is not the case with less widely known or news events, or informal leisure sports. The "where" of an event should be attached to a specific and unique location, and this spatial aspect (geolocation) is available as a geotag on Twitter (Middleton et al., 2018). We are aware that users post about and interact with sporting events, and we wonder if people in general also tweet about their own physical activities. Then "when" is not so important in our case, given that many previous studies have focused on this, such as Zhao et al. (2011a) as well as Lanagan and Smeaton (2011).

Previous geotagged Twitter tweet studies have begun to uncover land use functions including sport-related urban land use, such as Iranmanesh et al. (2022), but they do not mention which sporting activities and still omit the land cover type that the activity is occurring on. There should hence be more emphasis on the more specific "where," which yields information for our study about which urban PA locations are popular in terms of user demand, and could help municipalities to keep up their maintenance or improve the usability of locations in the HMA. We are aware that the City of Helsinki already uses some people counters in specific outdoor PA spaces (Rämö, 2022), but although this example includes outdoor gym demand, it omits all other types of PA that might go on in the HMA. Members of the public have also noted that the maintenance of outdoor gyms could be improved, and that this could correlate directly with user demand. Therefore, Twitter messages would be a more well-rounded data source of skiing tweets among a wider population, as well as of other sports-related key words in the same locations.

3. Methods

3.1. Study area

We tested our approach in the case-study area, namely the Helsinki Metropolitan Area (HMA), with a total population of 1.2 million (Statistics Finland, 2020). Figure 1 shows each of the four areas as situated within the HMA. According to the LIPAS database, the HMA has a total of 5,084 sports facilities (LIPAS, 2022). Helsinki (2,775 facilities), Espoo (1,266), and Vantaa (1,002) are the top three municipalities in Finland in terms of sports facilities, the fourth being Kuopio (980) in the east, and the fifth Oulu (977) in the north (LIPAS, 2022). Kauniainen ranks 240th out of 308 municipalities, with 41 facilities in its 6 km^2 area (LIPAS, 2022). We consider the HMA to be one borderless research unit, as residents typically live, work, and spend their leisure time freely across the four areas (Kepsu and Vaattovaara, 2008; Di Marino et al., 2018, 2021). The respective municipalities therefore need to know the locations in the HMA in which people engage in PA and spend their leisure time outdoors, as well as the respective demands. Finland's climate is of the continental type, being cold and with a long winter in the north and the interior, and relatively milder along the western and southern coasts. The HMA lies on the southern coast but still averages temperatures below freezing and has snow most winters, although the weather is becoming less predictable and these conditions cannot be guaranteed.

3.2. Data

We used two main types of data: (1) Twitter tweets data and (2) information from LIPAS sports facilities. The Twitter tweets comprise two combined secondary data sets: one was collected by the Digital Geography Lab at the University of Helsinki (DGL, 2022) and the other was part of an archive from the Digital OnLine Life and You (DOLLY) research project at the University of Kentucky (FloatingSheep, 2022). The total number of tweets amounted to 38,487,766 but it is worth pointing out that only a very small proportion (5.3%) of these contained geotags. The temporal range of both the data is between September 2006 and April 2020.

The LIPAS data on sports facilities are openly available for download and further analysis (LIPAS, 2022). LIPAS is a nationwide database containing information about sports facilities in Finland, which currently number around 42,000, and are all categorized. We chose five ski-related types of facility: (1) ski tracks (code 4402), (2) ski slopes and downhill ski slopes (code 4110), (3) ski-jumping hill for training (code 4310), (4) ski competition center (code 4630), and (5) cross-country ski parks (code 4640). We used these sports facilities locations in the results visualizations to find out if there were any matches between the sports and the tweet locations.

In the final visualization we display the individual tweets as points, a tactic that has been successful in other studies for activity mapping in terms of space (see Goličnik and Ward Thompson, 2010; Korpilo et al., 2021). It is an effective way of disseminating results to designers, for example, who are familiar with using visual material to influence decision-making. We additionally overlaid three land-cover, open polygon data sets from the Web Feature Service of the City of Helsinki: (1) lakes, (2) rivers, (3) sea, and (4) green space (Helsingin Karttapalvelu, 2022). The HMA boundary is as delineated in the Helsinki Region Map (Helsinki Region Environmental Services HSY, 2021).

3.3. Methodology

We followed the same methodology as Koivisto (2021) did, namely using both geotagged and geoparsed tweets, although we only used the geotagged tweets in this analysis. Geotagged tweets inherently contain location information, and are thus ready for further geographical analysis. Geoparsing is an additional method whereby a text location within the tweet is linked to geographical coordinates (Gritta et al., 2018). We used the programming language Python to identify the geotagged sports tweets, and the geographic information system software (QGIS) for manual data cleaning and analyzing the results visually.

Twitter stopped allowing followers to use the precise geotag feature in June 2019, although still keeping a general geotag feature, claiming that the majority of users did not use it (Hu and Wang, 2020). The precise geotag feature allowed the exact longitude and latitude coordinates to be utilized, whereas general geotags include a larger bounding box of a specific place such as a park or a city. We therefore include data from September 2006 to April 2020, although some tweets came after this date. Twitter still allows users to post a precise location through a third-party app such as Instagram or Sports Tracker, hence our results include these.

In order to extract the sporting information from the tweets we filtered the tweet texts for the sporting key words. To make the text in the tweets comparable, we then normalized the words by means of lemmatization, in other words returning to the dictionary form (Korenius et al., 2004). Next, we filtered the tweets by a list of sporting key words in both English and Finnish (see Table 2): tweets containing a word from this list were added to our data set. An additional data-cleaning task was to correct the filtered tweets

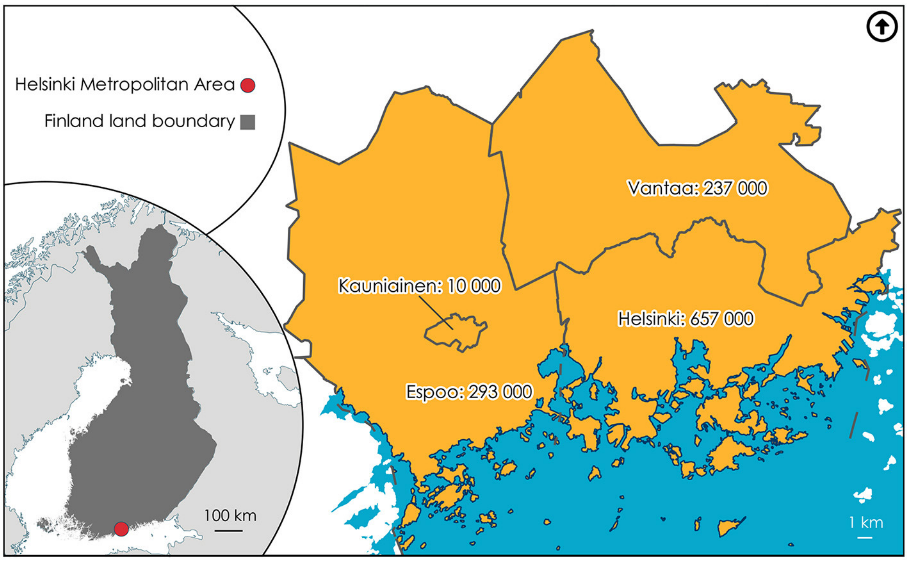

FIGURE 1
Helsinki Metropolitan Area: location and population counts.

TABLE 2 Ski-related tweets: summarized statistics.

Tweet language	Key word	Removed	Kept
English	Ski, skiing	71	105
Finnish	*Hiihto, hiihtäminen, hiihtää*	57	45
	Sum	128 (46%)	**150** (54%)

manually to make sure that the action of skiing was being carried out. We only kept the tweets whereby the tweeter was currently engaged in or had just completed the activity (in our case: skiing). We removed the tweets if the tweeter was tweeting about another person, or if it was in the future tense, as we could not conclude with certainty that they had completed the action. We were then left with first-person action tweets. We started with 278 skiing tweets, but after the data cleaning we ended up with 150.

We conducted a secondary analysis of tweets based on different key words that were located within a 100 m buffer zone as the remaining correct skiing tweets. We used the same 19 key words as in Koivisto's (2021) analysis, again restricting the languages to English and Finnish (their analysis included Estonian). We also removed the key words for ice-skating and ice-hockey in both the English and the Finnish tweets and kept only non-snow sports-related activities. Table 3 shows the resulting filtered sports key word options. We had 1,076 other sports-related tweets but following the data cleaning we removed 296 incorrect tweets, resulting in 745 correct ones. Tweets with more than one sports-related key word were counted again, hence the sum counts of key words is higher than the number of tweets. We counted the language of the key word and not the language of the tweet for the further analysis, for which we therefore had 798 sports-related key words.

4. Results and discussion

Our main research purpose was to find out how geotagged tweets detect informal PA spaces in the Helsinki Metropolitan Area (HMA), complemented with the sub-purpose of identifying the type of urban public spaces in which people did their informal PA. In Section 2.2, we introduced green, blue, and street spaces, which we explore below. We categorize the results in terms of the need for municipalities to know where people are exercising and spending their leisure time outdoors, and the respective demand. First, we give the results for the ski tweets, and then we discuss the non-ski tweets in relation to them. We chose five locations with a tweet in both the ski and the non-ski locations to give an example of a tweet with different features for analysis, such as mentioning a location, not mentioning a location, or sharing a tweet *via* a third-party application. There is an emphasis on what other types of informal activities are going on in these spaces that diverge from the space's intended purpose. We further discuss how our findings could help municipalities, including sports planners and city planners, to improve the conditions in locations in which user demand is calculated through tweet popularity. Figure 2 shows the ski-related tweets, and Figure 3 shows the tweets in the same locations but also includes other sports-related key words. Finally, Table 4 shows the counts of the overlapping tweets with the blue, green, and street spaces.

4.1. Ski tweets

4.1.1. Ski locations

Figure 2 shows the results of the ski tweets. Spatial location is very important when analyzing tweets as the majority (62% of the 150 ski tweets) do not include a specific location within the text. However, it turns out that when they are added to a map

TABLE 3 Non-snow-related sports tweets: summarized statistics.

English key word	Removed	Kept	Finnish key word	Removed	Kept
Basketball	5	2	*Koripallo, koris*	0	1
Bicycle, bike, biking, cycling	23	54	*Pyöräillä, pyörä, pyöräily, pyöräileminen*	10	23
Dance, dancing	40	33	*Tanssia, tanssi, tanssiminen*	10	4
Exercise, exercising, workout, training, sport, sporting	43	124	*Urheilla, treenata, treenaaminen, treeni, urheilu, liikunta*	21	23
Floorball	0	1	*Salibandy, sähly*	3	0
Football	29	9	*Jalkapallo, futis*	3	1
Gym	0	0	*Kuntosali*	2	4
Hike, hiking, trek, trekking	4	5	*Patikoida, patikointi, patikoiminen*	0	0
Run, running, jog, jogging	60	223	*Juosta, juoksu, juokseminen, lenkkeillä, lenkki, lenkkeily*	14	33
Sail, sailing, kayak, kayaking, canoe, canoeing, rowing	9	15	*Purjehtia, purjehdus, kajakki, meloa, melonta, soutaa, soutaminen*	0	0
Sweat, sweating	5	4	*Hiki, hikoilla*	2	4
Swim, swimming	10	11	*Uida, uinti, uiminen*	1	2
Tennis, badminton, squash, tabletennis	5	5	*Tennis, sulkapallo, squash, kössi, pingis, pöytätennis*	0	2
Volley, volleyball, beach volley	3	0	*Lentopallo, lentis*	0	0
Walk, walking	30	150	*Kävellä, kävely, käveleminen*	13	41
Yoga	0	21	*Jooga*	2	3
English sum	266 (28.8%)	**657** (71.2%)	**Finnish sum**	81 (36.5%)	**141** (63.5%)
			Overall sum	347 (30.3%)	**798** (69.7%)

output they are indeed in the correct location. This is a key finding because it is not self-evident from the text results. It is also a strong argument put forward by Sloan and Morgan (2015), who affirm that the geotag information is extremely valuable, in that the tweeter decides to tweet at some point during an event or at a location in real time. Although in Coakley's (2017) opinion informal sport participation is in decline, our study has shown that people do engage in informal cross-country skiing in the HMA, and they even tweet about it. As Figure 2 shows, there are overlaps with the ski tracks and the ski-related types of sports facility. There were tweets from close to six of the 10 ski-related facilities. With a capture rate of 60% resulting in 50 tweets ($\frac{1}{3}$ of total ski tweets), it is clear that these more formal facilities are also popular places for people to spend their free time. These results would not have come to light if only a textual analysis had been conducted—the "where" is thus a very important aspect of this analytical method. Additionally, two tweets mention the indoor ski tunnel at the Kivikko ski center in Helsinki. However, they are located in a street space even though the location of the ski center is within a green space. This shows that our analysis could be limited by the scale of the background data.

The fact that we only used pre-geotagged tweets raises a further discussion point in that we assume they are geotagged to a correct location that is mentioned within the tweet. However, some key definitions of informal sport in the current literature ignore the location, as shown in Table 1. Even though there is not yet a main emphasis on the location where sport happens, there were still two definitions that included it: Wheaton and O'Loughlin (2017) and Deelen et al. (2018) both use the term setting. Consequently, if we divide the HMA into green, blue, and street spaces, the tweet results, as shown in Table 4, are: 76 tweets (50.7%) in a green space, 69 (46%) in a street space, and five (3.3%) are in a blue space. This could be broken down further into tweets along ski tracks. Ski tracks in total have a combined length of 594.8 km, and they are maintained by the municipalities. Most of the paths are within a green space, accounting for 95.8% of all ski tracks. Hence, skiing in the HMA is also a form of green exercise in that the tracks go through parks and along forest paths. Additionally, people follow self-made tracks in the snow, which are not counted in the total length of tracks: they enable people to ski to the maintained tracks, or just close to their home since people can go cross-country skiing when there is enough snow on the ground.

Shanahan et al. (2016) make the overall claim that green spaces are important in terms of providing a location for physical activity, and in particular with an emphasis on green exercise with its better health and wellbeing benefits in comparison to PA in built-up or indoor environments. We do not focus on the specific health benefits in this article, but it is obvious that the HMA population has easy access to skiing tracks within green spaces. Next (Section 4.2.1), we consider which other sporting activities could be conducted in the same skiing locations when there is no snow.

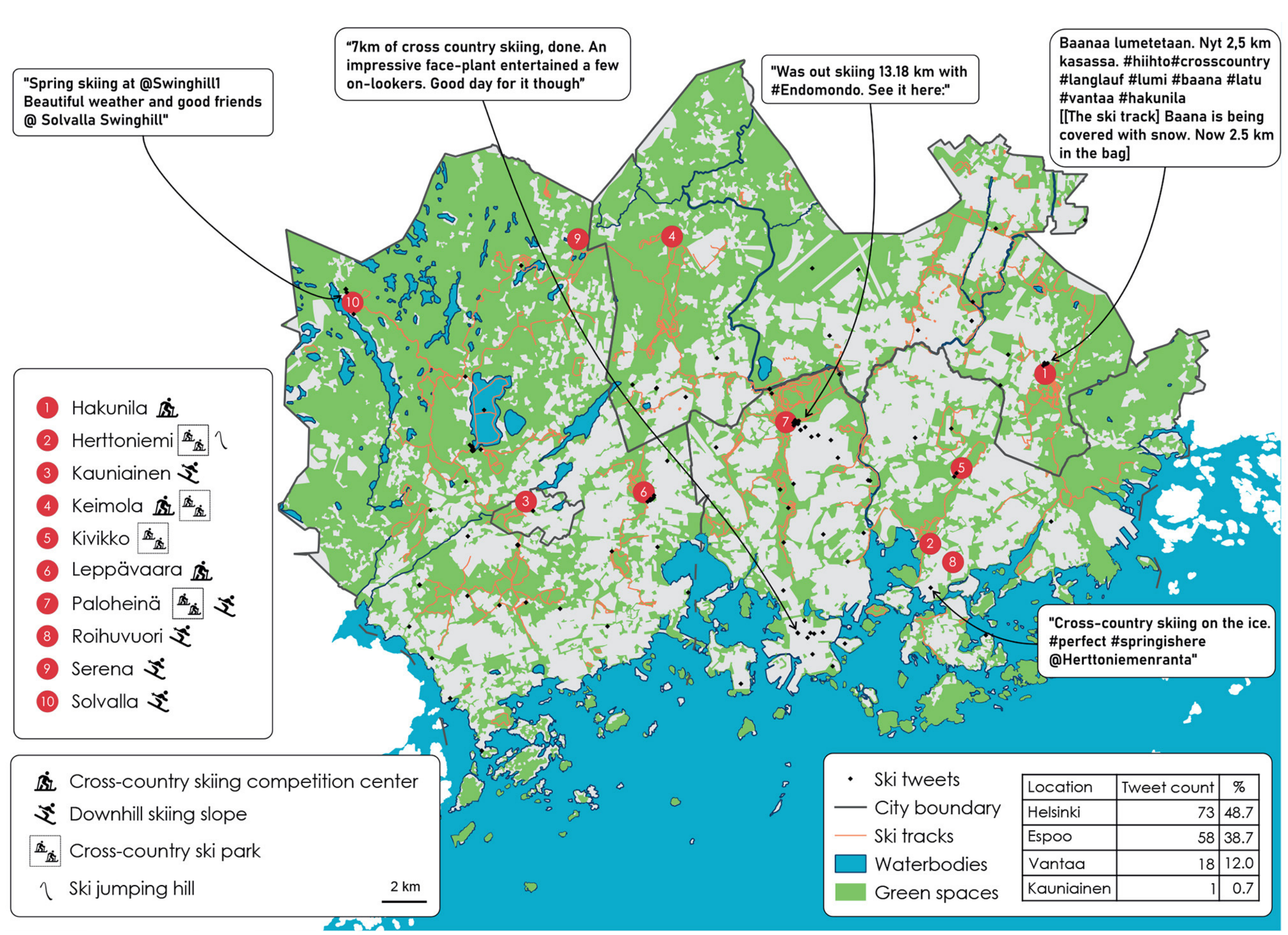

FIGURE 2
Skiing: tweet locations in the Helsinki Metropolitan Area.

4.1.2. Ski demand

Finland offers opportunities to engage in outdoor exercise even in winter, skiing being one major hobby, to keep up with the recommended weekly target of 150 min of moderate-to-vigorous-intensity PA—which according to Bennie et al. (2017) 70% of adult Finns do not achieve. The tweet counts match the population of the municipalities, Helsinki having the most and also the highest population count (see Figure 1). Helsinki yielded 73 tweets, Espoo 58, Vantaa 18, and Kauniainen one. There are other ways of tweeting than writing directly within the Twitter site. Of the 150 ski tweets 60 came via Instagram (accounting for 40%), 39 (26%) via Endomondo (a social fitness network-tracking application that closed down at the end of 2020), five (3.3%) from Foursquare Swarm, which is a location diary shareable with friends, and two from Charity Miles (1.3%), a sports-tracking application for fundraising. This leaves 44 (29.3%) that were directly written in Twitter[1]. As Figure 2 shows, people living in the HMA do not need to leave their local area to engage in winter sports or to do PA outdoors. An example tweet is highlighted in Solvalla Swinghill Ski Center. The user has tagged (linked the ski center's Twitter username) the tweet so it could be said that the user was there at some point in time. From the perspective of this paper, then, the additional information of location within the text is also beneficial. An overall supply of cross-country skiing locations is thus beneficial in promoting healthy cities: if the municipalities know where the demand is in specific locations they could improve the maintenance of the tracks and facilities nearby, such as providing more garbage bins, benches to rest on, and toilet facilities, for example.

A negative aspect of improving facilities is that the routes could become overcrowded, and this has a negative impact upon the environment. Korpilo et al. (2021) found that this occurred during the use of nearby forests throughout the COVID-19 pandemic in the HMA. Another negative aspect that is often cited is that urban spaces have decreasing amounts of green space (Triguero-Mas et al., 2022). However, 57.4% of the HMA is green space measured according to the green space layer, and even then street spaces are still used for PA, as these tweet results show. It has also been found that engaging in PA improves overall health and wellbeing (Bowler et al., 2010), without having the extra stress of formal sports, such as having to be present at a regular time each week and the extra costs involved. Bell et al. (2015) also found that if the PA area is scenic and in natural surroundings, people are motivated to work on their

1 The results sum to 100 when accounting for 0.3 recurring in the percentages.

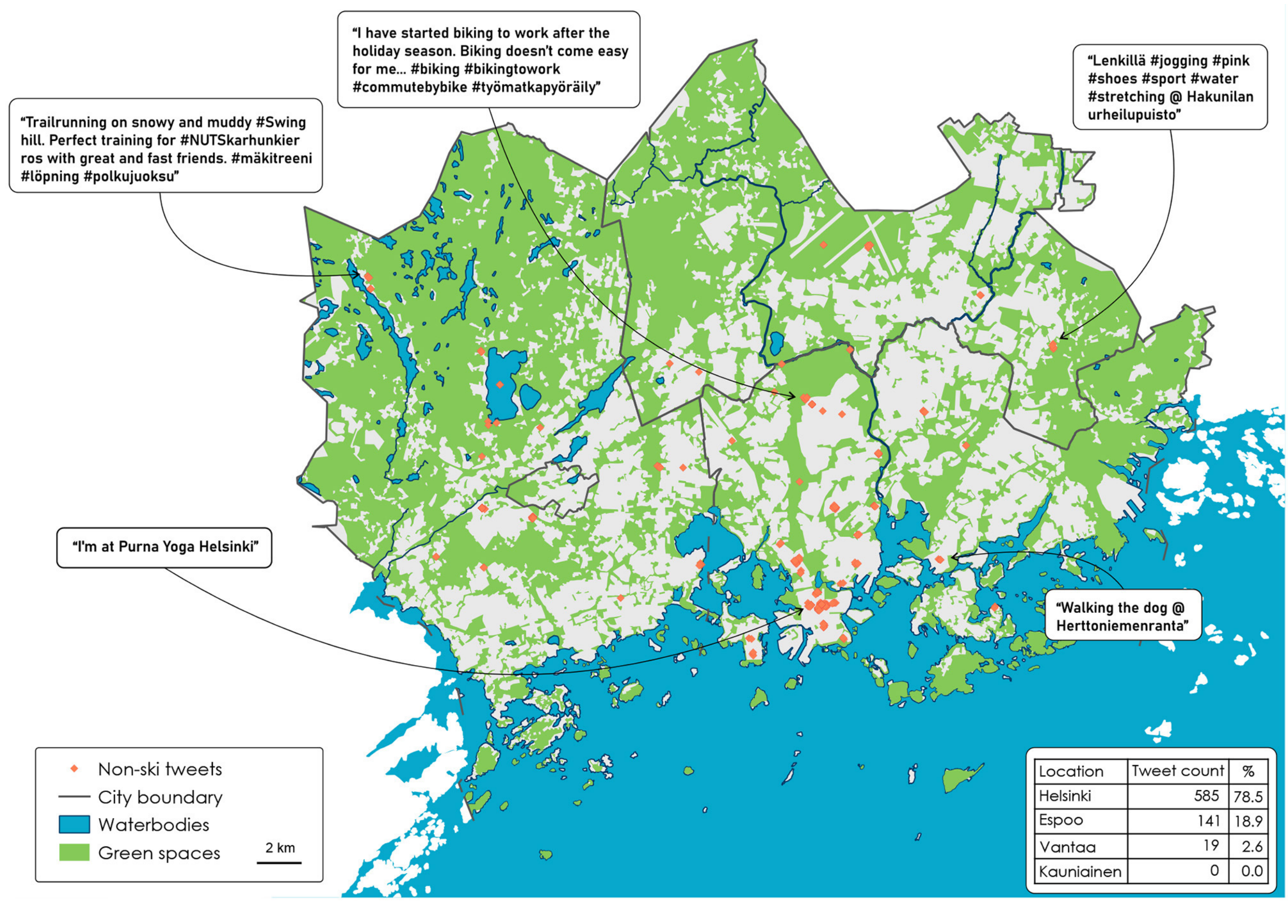

FIGURE 3
Other sports: tweet locations in the Helsinki Metropolitan Area.

TABLE 4 Land cover: summarized statistics.

Land cover	Ski tweets counts	Non-ski tweets counts
Green	76 (50.7%)	32 (4.3%)
Blue	5 (3.3%)	8 (1.1%)
Street	69 (46%)	705 (94.6%)
Sum	**150**	**745**

overall wellbeing. In general, then, engaging in PA outdoors could be considered an inherently positive activity.

4.2. Non-ski tweets

4.2.1. Non-ski locations

Next, we focused on what ski locations are used for when there is no snow. The green, blue, and street spaces are not just winter locations as they are open public spaces, which is very common in Finland. Figure 3 shows the results for the non-ski tweets. Following the green, blue, and street analysis, as shown in Table 4, 32 tweets (4.3%) were in a green space, eight (1.1%) tweets were in a blue space, and 705 (94.6%) in a street space. This is a big contrast to the ski-tweet results. The example tweet in the Espoo figure is for the Swinghill downhill ski center, and the tweeter is tweeting about trail running. Multi-use outdoor PA spaces are not unique in Finland, but they are plentiful in comparison to other countries, which was particularly evident during the peak of the COVID-19 pandemic: some countries, such as France, even restricted the use of urban parks (Geneletti et al., 2022). In England, aside from the pandemic, the Countryside and Rights of Way Act 2000 gives the legal right of public access only to about 8% of the countryside, which severely limits opportunities for informal PA (Horton, 2022). Finnish forest areas, such as Central Park ("Keskuspuisto" in Finnish) in Helsinki, have specific paths to be used for skiing during snowy weather (when cycling is not allowed), and during non-snowy weather there are specific paths for cycling, horse riding and walking. However, our results show only one tweet in this location. Of the 745 tweets, 362 (48.6%) mention a location. It is clear from this result that if the geotag were missing, the location of the remaining 51.4% of the tweets would remain a mystery, even with the additional step of geoparsing because there is no location to geoparse. This also reflects Hu and Wang's (2020) concern about the removal of Twitter's precise geotagged tweets and its research consequences.

Within the tweet location the results for non-ski tweets reveal a cluster in Helsinki city center, which is the largest in the southern part of the map. These tweets have the same coordinates (60.1708, 24.9375), which is the center of Helsinki, and therefore are located here when a tweeter tags Helsinki as a more general location than where they are located. This cluster comprises 220 tweets, with another 123 surrounding it (in total 46%). This type of tagging behavior is not so useful for further analysis because it means losing some of the data, but it benefits the tweeter in not revealing the exact location. Mapping individual points has proven to be beneficial for the mapping of open spaces by researchers such as Goličnik and Ward Thompson (2010), who mapped larger public parks and how their design limited user behaviors. They concluded that larger open spaces were used for team sports such as football and that paths were mainly used for walking or cycling, thus implying that urban design dictates how people should behave in a space. An example of unusual behavior in a park is then to cycle across a grass field if there are paths around the edge. This behavior setting extends to the inappropriate use of green spaces: if many people similarly misbehave, the result would be an area with muddy informal paths where the grass has been removed, which in turn would lead to environmental degradation. This scenario extends to urban forests: Korpilo et al. (2021) reported the overuse of nearby forests during the COVID-19 period in Helsinki.

4.2.2. Non-ski demand

There were 745 non-ski tweets: 585 in Helsinki, 141 in Espoo, 19 in Vantaa, and none in Kauniainen. In comparison to the ski results, there was a higher sum of tweets in Helsinki compared to the other three municipalities, accounting for 78.5% of all the non-ski tweets. In terms of where the tweets are posted from, 440 (accounting for 59.1%) were via Instagram, 103 (13.8%) via Endomondo, 27 (3.6%) via Foursquare Swarm, and 77 (10.3%) via Charity Miles. The remaining 98 (13.2%) were posted directly from Twitter. Figure 3 shows five examples of tweets representing four different types of sport, but in the same location as the examples of ski tweets given in Figure 2 (trail running, biking, jogging, walking, and yoga). Environmental decisions could promote healthy living in specific urban-design and social settings (Ward Thompson, 2013). If it is known where people engage in PA, municipalities could plan more effectively where to put more facilities, such as bike racks and starting routes from public-transport stops. Another example is where people follow specific routes created by the municipalities to both control and increase outdoor PA: decisions have to be made such as where to place garbage bins, toilets, and signposts to specific routes. There has recently been increasing interest in designing walkable cities as a consequence of the COVID-19 pandemic (Fagerholm et al., 2021). Knowing the tweet demand may help municipalities to improve locations to make people feel more comfortable and willing to spend longer outside.

The results in combination create a new and more comprehensive data set concerning the demand for informal sporting locations that the municipalities in the HMA could utilize to better allocate funding for improvements, such as those facilities mentioned above. In relation to Jeanes et al. (2019) who focus on sports policies, the data and information that have been produced from the tweet locations can serve as a tool that helps municipalities to include the practices of knowledge-based management into their daily work. The information can be used by city or sports planners when they know where informal sports and PA spaces are being utilized in order to help plan facilities and cities in such a way that access is equal for the population. This is a key idea and result as we have shown that a wide variety of sports are conducted in the same outdoor locations, even when restricting our study to 16 sports keywords. This further means that the population already feel welcome to use these locations at any time or location which formal sports might restrict, but improvements can still be made so that a wider population has access to outdoor PA spaces.

5. Conclusion

Gilchrist and Wheaton (2011) note the difficulty in finding out participation rates for informal sports, and we took this as an opportunity to gather a user-generated data set of Twitter tweets. We have shown that, even with a very small subset of an already limited portion of data that is geotagged, it is possible to obtain sound results for further analysis. We detected informal spaces for skiing activity that might otherwise be ignored in efforts to understand where people engage in physical activities in the HMA. Improving the health of the population through facilitating engagement in informal sports is a simple and cost-effective form of intervention to reverse the increase in illnesses related to physical inactivity, which costs the country billions annually. We further focused on other types of informal activities going on in these spaces that differ from the intended purpose, to shed light on the PA that goes on in the same locations when there is no snow.

The HMA is a very inclusive area from a sports facility perspective and therefore allows the population to have many different opportunities for maintaining active and healthy lifestyles. Our results support the suggestion put forward by Neuvonen et al. (2018) that the HMA has been designed and maintained so that everyone has equal access to outdoor spaces regardless of whether or not they realize they like to be outdoors doing PA. Informal sports do not require regular monetary or time commitments, and are therefore suitable for a larger proportion of the country's population. Informal sports often require less regular monetary or time commitment than organized sports and therefore may be suitable for a larger proportion of the country's population. Our research can therefore be expanded to a national level and a wider variety of sports to capture any variations between municipalities to locate which populations are less active in using social media to post about their PA. A further research aspect could be the impact of climate change upon the skiing possibilities in the HMA. Our results have already shown that the population do conduct other types of PA in the same locations, but it would be interesting to find the types of PA during a less snowy winter.

Finally, future research should focus on detecting PA spaces using the 90-plus percent of tweets that do not have a geotag. This involves complex geoparsing to add the missing locational information (Gritta et al., 2018), and in potentially revealing different demands of informal spaces that are not currently known could be a valuable method to test. It is difficult to create national policies focusing on informal sports because it means taking a step back and letting the population do their own thing away from formal sports facilities. The more traditional data-collection methods involve surveys, which are open to exaggeration on the part of the participants, or the giving of false information, as McLaren and Shanbhogue (2011) found. It is therefore more difficult to know how many people, and more specifically, who (such as the age, gender, or ethnicity) use the informal outdoor facilities, and if they even bring about change in sedentary lifestyles. Overall, we conclude that Twitter may be a beneficial tool in detecting year-round spaces for informal physical activity. The benefits could extend to city planners and sports planners aiming to improve informal sports facilities based on user demand, and thereby promote the development of healthy cities.

Data availability statement

The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding author/s.

Author contributions

CL, EE, SK, and PM: study design, reviewed the results, and approved the final version of the manuscript. CL: draft manuscript preparation. EE and SK: methodology, preparation of the results, and the analysis. PM: acquiring funding, supervision, and project coordination. All authors contributed to the article and approved the submitted version.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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Configuration paths of community cafe to enhance residents' well-being: fsQCA analysis of 20 cases in Shanghai

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Community cafes have emerged as a critical infrastructure for promoting communication and cultural construction in urban areas, and have gradually become an essential public place to enhance residents' well-being. However, despite their growing importance, more empirical research is needed on the emerging concept of community cafes, including the configuration analysis of their influencing factors. To address this gap, this study employs the fuzzy set qualitative comparative analysis (fsQCA) method to examine 20 community cafes in Shanghai, China. The configuration effects on residents' well-being are explored across five dimensions: activity quality, psychological cognition, physical quality, physical accessibility, and sociability. The findings reveal that sociability is necessary for high levels of residents' well-being. Three configuration paths are identified to generate high well-being, which can be classified into activity-based or acquaintance-based social interaction patterns based on spatial functions. Additionally, the study identifies five groups of non-high well-being configurations, in which lack of activity quality and sociability are core conditions. Overall, the study contributes to evaluating community public spaces and provides insight into the configuration of factors that contribute to residents' well-being. The study highlights that community public spaces can have significantly different impacts on residents' well-being, with sociability emerging as a significant factor. Therefore, it is necessary to clarify community public spaces' social orientation according to spatial conditions.

KEYWORDS
community public space, social interaction, residents' well-being, community cafe, fsQCA, configuration path

1. Introduction

Community cafes have become increasingly popular in recent years, as more people recognize their value in enhancing residents' well-being (1–3). In the research on public space, cafes as common consumption and leisure places in cities have received extensive attention from urban studies and social research. The intersection between cafes as physical spaces and their social-spatial significance has received particular attention (4–6). According to Oldenburg (7), cafes are a typical "third place" where people are bound by social norms but not totally ruled by society. In cafes, people are more likely to form social connections and encourage social interaction. Cafes have gradually become an important infrastructure for promoting communication, cultural construction, and carrying public life in the city (8–10). Unlike chain coffee shops, community cafes are located in communities and primarily serve the leisure needs of local population. Community cafes have developed into a unique cultural space for the production and expression of social relations, with diverse social groups conducting social activities in these spaces, which further exemplifies Hamas's concept of public space as a public sphere (11).

Urban planning has long been prioritized to improve the life quality and well-being of people. There are strong evidences that the urban-built environment has a profound impact on public health and well-being. For example, studies have found that access to public spaces can reduce stress and anxiety, increase physical activity, and improve social connections (12–14). An increasing number of scholars recognize the value of public space in enhancing urban vitality, strengthening residents' sense of belonging, and promoting their physical and mental health (15–17). In all scales of urban public space, the community and residents' daily life are inseparable, as the basic unit and cell of urban function. The quality of the community environment directly impacts residents' well-being (18–20). Therefore, community public spaces founded on commonality and neighborhood interaction are essential for preserving the social fabric of the neighborhood and enhancing residents' well-being (21, 22).

The term "community public space" refers to a physical area within a community that is equally accessible to all its members. While it covers both physical and social space, this study focuses on the latter as community public spaces have a strong social significance, providing a variety of social roles as places for social interaction. These spaces are directly connected to residents' daily life, which situate in the neighborhoods with strong interpersonal links and have a solid public nature. Scholars suggest that community public spaces play a crucial role in fostering community identity, promoting happiness, upholding neighborhood peace, and integrating social relationships (12–14). As a result, among the various forms of public spaces in communities, current studies particularly emphasize those that serve as places for social interaction, such as libraries, community centers, and different kinds of local shops that offer leisure and amusement activities. These places aim to strengthen cultural and communal ties in the neighborhood through specific spatial forms and public services (3, 23, 24).

From the perspective of public space, empirical research on community cafes is necessary. According to the 2022 China Ready-made Coffee Category Development Report released by Meituan (25), Shanghai ranks first in China in terms of the number of cafes, with community cafes taking up an important part, which provides this study with abundant local research objects. However, research on cafes has not yet identified the key factors that contribute to their significance as public spaces, especially for the emerging community cafes. The question is, what factors are the key to influencing the community cafe to enhance residents' well-being?

This study aims to explore the crucial factors that influence community cafes' ability to enhance residents' well-being. Public space theory and interaction and space theory provide a theoretical basis for finding the impact factor of community cafes. Public space is viewed as a multifaceted concept encompassing social characteristics, public sphere significance, and physical environment quality. As it possesses both physical and social environment qualities, its effect on residents' well-being is a complicated process involving several interrelated aspects. To clarify the multiple configuration paths of community cafes to enhance residents' well-being, this study adopts the fuzzy set qualitative comparative analysis (fsQCA) to deal with these complex cause-and-effect relationships. This paper integrates the five antecedents of activity quality, including psychological cognition, physical quality, physical accessibility, and sociability through a literature review and exploratory factor analysis (EFA) to study the relationship among various configurations of these five antecedents and residents' well-being. This paper attempts to answer the following questions: How do community cafes affect residents' well-being? What are the configuration paths of influence? Which paths are the dominant ones?

2. Literature review

This paper investigates community cafes and their configuration paths as community public spaces to enhance residents' well-being. This section aims to conduct theoretical modeling by combining the literature as the selection of condition variables. Although existing literature has studied public spaces, a gap exists in evaluating community-scale public spaces as a distinct research object. Typically, research on community-scale public space uses public space theory as a theoretical foundation and combines it with specific research questions. Given the emphasis on the social interaction attributes of community public spaces in this study, the theoretical modeling is mainly based on two theories: public space theory and interaction and space theory. Public space theory focuses on space's physical and social properties. The former represents the physical environment quality of space, while the latter is the main focus of this article due to its relevance to the community and social attributes. Interaction and space theory, which draws from behavioral psychology and architectural behavior, is suitable for refining the theoretical model. Based on these two theories, this study constructs the initial evaluation dimensions of community public space. To further refine the evaluation dimensions and focus on the community scale, exploratory factor analysis will be conducted. This section will delve into the three subcategories of related literature, including the physical environment quality, political philosophy, and interaction &space perspectives.

2.1. Physical environment quality perspective

As a physical form, public space's physical environment quality is the earliest influencing factor. Comfort, quality, and esthetic considerations have been identified as key variables for measuring the utilization of public spaces and are principally related to the physical and functional properties of the public space itself (26).

Comfort is considered one of the most important standards of public space (27), which is a subjective feeling of human beings to the physical space environment. It has an important influence on space behavior and is directly reflected in people's usage of space. Quality of service and facilities is another important factor that affects people's experience in public spaces and promotes social behavior (28, 29). The better people's needs in public spaces are met, the higher the quality of service and facilities. This is critical for improving residents' satisfaction (26). Furthermore, esthetics are important in attracting people's attention and increasing their pleasure (30, 31).

Moreover, safety is a fundamental human need and is also taken into consideration when creating public spaces (32–34). According to

Jacobs (35), safety is the fundamental principle of urban design. Safety is also the basic requirement in Maslow's theory (36). As the basic unit of urban function, community is the closest to residents' daily life and the concept of "home." Therefore, safety is particularly important for community public space. Referring to the framework of Pikora et al. (30), safety means providing safe physical environments for residents.

Additionally, hygiene is critical for crowded spaces. Hence, cleanliness and tidiness are one of the basic conditions of public space and will impact how well a public space functions (37–39). Congestion level is also considered to be an important factor influencing the quality of public space, as spatial density can intuitively affect people's experience in public space and hint at the allocation of public resources (26, 40).

2.2. Political philosophy perspective

Public space has deep roots in political philosophy due to its communal nature. Habib (41), a political scientist, summed up the public space theory into three main ideological models: H. Arendt's philosophical view on the public realm, the liberals' view on the legitimacy of power, and J. Habermas's public sphere theory. In the political philosophy of the built environment, accessibility in public space is the most important. This concept was first put forward by historian S. Howard, who thinks that accessibility, which means "accessible to all," is the foundation of the spatial entity of public space.

In summary, physical and psychological accessibility to public spaces are fundamental considerations for all public space planning (42). Many scholars have provided indicators of accessibility from these two aspects (43, 44). Physical accessibility is one of the most important indexes in evaluating public spaces (43–46). It refers to the effort made by residents to reach the public space from their starting point. The less effort required, the greater the physical accessibility (47). Psychological accessibility, on the other hand, focuses on the social nature of space, emphasizes the publicity and openness of space. It is also closer to Habermas's concept of the public sphere. According to Bertolini, an accessible public space is one that different people can come to and do different things: it is both a node and a place (48, 49). From this perspective, accessibility means inclusiveness, which is regarded as a prerequisite for urban public space by sociologist L. Lofland (50).

2.3. Interaction and space perspective

Interaction is a fundamental aspect of human sociality, and in the context of urban planning, the behavior of individuals within a community is a basic unit in the structure of social communication. As the Machu Picchu Charter states: "We believe that human interaction and communication are the essential reasons for the city's very existence. This reality must be reflected in urban planning and housing design (51)." The theory of interaction and space draws on environmental psychology and architectural behavior to regulate social interaction by examining the relationship between the environment and human psychological behavior. According to this theory, public space should focus on public life rather than just physical space, because human behavior is the most important factor in space (16).

One of the most widely recognized methods for evaluating the quality of urban public space and the public living conditions of citizens is called PSPL (Public Space and Public Life Survey) by Gehl (52). This approach evaluates both the physical quality of public space (PS) and the quality of behavior in space, which is the core of the approach (PL). The PS aspect represents the physical quality of the space, focusing on the protection and enjoyment of the space, with the former referring to people's perceived safety in the space and the latter denoting the space's potential to provide a positive sensory experience. The PL aspect evaluates the quality of behavior in space, as public space is the carrier of public activities, and the quality of activities determines whether people's physiological and emotional needs can be met. Gehl (52) categorizes human activities in public space as "necessary activities" when participants have no choice, "optional activities" when people are willing to participate, and the spatial conditions are suitable, and "social activities" when actions rely on the participation of others. Among them, the latter two, known as "unnecessary activities," are more easily affected by the quality of public space and can bring richer emotional experiences.

Similarly, Carr (53) emphasizes the centrality of human activity in public space, as the uniqueness of public spaces emerges from the various activities within them. He identifies five types of reasons for people's needs in public spaces: comfort, relaxation, passive engagement, active engagement, and discovery (47). The first two causes are related to people's perceived state of mind in public spaces. Comfort is the most basic need, as people feel their needs are met only when being comfortable. Relaxation is a more developed state of comfort in which both body and mind are at ease. The last three causes correspond to people's behavior in public spaces, with varying degrees of initiative and desire when interacting with the space and others in it.

In addition, Oldenburg (7) introduces the concept of the "third place," which refers to informal public gathering spaces outside of people's homes and workplaces, such as cafes, bars, and community centers. The "third place" is often regarded as a "neutral zone," with a high degree of inclusiveness and accessibility, allowing individuals to get psychological comfort and support while feeling comfortable. People can also engage in continuous dialog with each other in this space, making it a valuable forum.

However, it is worth noting that some scholars have raised concerns about the potential negative impact of excessive social interaction in public spaces on personal privacy, emphasizing the importance of prioritizing privacy in the design of public spaces (54–56). This can be achieved by increasing the physical distance between individuals or regulating the frequency and intensity of social interactions to allow for moments of solitude. Striking a balance between the public and private nature of public spaces is crucial, as inhibiting social interaction altogether may also have unintended consequences.

2.4. Hybrid perspective

In addition, some scholars have proposed comprehensive indicators for evaluating public spaces, drawing on the aforementioned perspectives. For example, Project for Public Spaces (PPS), a non-profit organization, has put forward four essential qualities that generate desired patterns of behavior, emotion, and measurable outcomes in public space after investigating more than 3,000 public spaces (53). These qualities include "social," "have a variety of uses and activities," "well-connected to their surroundings," and "comfortable and welcome." According to Erkip (26), factors affecting satisfaction of the users in public spaces are classified as accessibility, congestion levels, measures of comfort, the variety of activities and facilities. Indicators of quality, safety, physical attractiveness, or maintenance are classified as an esthetic consideration.

Based on the above literature, this paper constructs a list of impact factors of community cafes, as shown in Table 1.

3. Exploratory factor analysis

Based on the literature review, a total of 12 evaluation factors were identified and summarized in Table 1. To determine the condition variables, an exploratory factor analysis was conducted to remove any factors that were not relevant to the study object. Specifically, 113 residents and community-building scholars were inquired with questionnaires to assess the importance of factors in improving the well-being of residents in community cafes. The above 12 influencing factors were scored by Likert's five levels. KMO is 0.710, and the data passed the Bartlett test ($p < 0.05$), indicating that the data is suitable for factor analysis, as shown in Table 2.

Factor analysis extracted five dimensions, with the variance rate after rotation being 27.002, 22.462, 12.832, 9.044, and 8.374%, respectively, and the cumulative rate is 79.714%, as shown in Table 3.

As shown in Table 4, the relationship between each factor and the item is analyzed through factor loading. Variable 12 was excluded because its factor loading is less than 0.5. Finally, five factors, namely activity quality, psychological cognition, physical quality, physical accessibility, and sociability, are selected as condition variables, as shown in Table 5.

3.1. Activity quality

The quality of activities in a community public space is determined by various behaviors of individuals in the space. The higher the diversity and initiative of these activities, the better the quality. Additionally, the availability of services and facilities in the space plays a significant role in facilitating and enhancing the quality of activities. To measure "activity," the proportion of unnecessary activities in the public space is taken as the specific measurement index. A questionnaire is used to gather information on residents' activities, indicating their willingness and ability to participate in these activities. When measuring "quality," the specific measurement index is the score of 7-level Likert questionnaires on residents' satisfaction with services and facilities in public spaces.

3.2. Psychological cognition

The psychological impact of space on individuals is profound, and the emotions perceived by people in space will directly affect people's behavior in space and evaluation of space. When people feel "comfort," "safe," and "enjoyment" in the space, they will not reject the experience in the space. Since all three indicators are subjective, residents will use the Likert 7-level scale to answer how much they perceive these three mental states in the space.

3.3. Physical quality

Since community public space is first and foremost a physical space of a physical entity, its spatial quality directly impacts residents' well-being. "Esthetic considerations" refer to the physical space's esthetic features and whether they appeal to residents. "Cleanliness" refers to whether the environment of community public space is clean and tidy. "Congestion level" refers to whether there is enough space to support people's behaviors and activities. The specific measurement indicators of the above three items are all scored by the 7-level Likert questionnaire.

3.4. Physical accessibility

According to the relevant literature, "physical accessibility" means the convenience of residents to access the community public space. The specific measurement index is the travel time from the place of residence to the public space.

3.5. Sociability

The sociability of community public space implies a wide range of social interactions between people of various identities. Community public space is more than just a physical environment for residents to meet their needs; it is also a public domain open to all residents to promote communication, understanding, and integration. As a result, community public space should not be restricted to a specific demographic. "Inclusiveness" means that people of different identities participate in the activities of community public space. The specific measurement index is what residents score on the 7-level Likert questionnaire in the field of "inclusiveness." At the heart of "social interaction" is a conversation between people (7); the more vibrant the conversation in public space, the more likely people interact socially. The specific measurement index is the proportion of residents who engage in conversation in public spaces.

In summary, the relationship between condition variables and the outcome variable is shown in Figure 1.

4. Materials and methods

4.1. fsQCA

In the 1980s (58), American sociologist Ragin proposed a case-oriented asymmetric research method called qualitative comparative analysis (QCA) to solve complex causal phenomena. QCA, based on set theory and Boolean operation, investigates how the configuration of antecedent conditions affects the interpretation

TABLE 1 Evaluation factors of community cafes.

Number	Factor	Meaning	Definition	Literature
1	Comfort	The comfort feeling one perceives in the space.	A person's perceived comfort level in the space.	Pasaogullari and Doratli (42)
			People feel comfortable subjectively in the physical environment.	Vukmirovic et al. (27)
			People's mental state in the space.	Erkip (26)
			Get psychological comfort and support and feel comfortable.	Oldenburg and Brissett (7)
			The comprehensive feeling of people in the space.	Madden and Wiley-Schwartz (53)
			The mental state that one perceives in the space.	Carr (47)
2	Quality	The quality of services and facilities in the space.	The quality of service and facilities.	Pasaogullari and Doratli (42)
			Services and facilities can meet the needs of people in public spaces.	Erkip (26)
			Quality of services and infrastructure.	Stauskis (28)
				Stauskis and Eckardt (29)
3	Esthetic considerations	The physical space's esthetic features and whether they are appealing to people.	Physical attractiveness and maintenance.	Pasaogullari and Doratli (42)
			Physical attractiveness.	Erkip (26)
			Esthetic features of the physical environment and facilities.	Pikora et al. (30)
			Human esthetic preference for physical space.	Matsuoka and Kaplan (31)
4	Safety	The safe feeling one perceives in the space.	Personal safety.	Navarrete-Hernandez et al. (32)
			The safety of life shall not be infringed.	Burton and Mitchell (33)
			Avoid fear and outside risks.	Van der Burgt (34)
			Psychological safety and physical safety.	Jacobs (35)
			Provide a safe physical environment for residents.	Pikora et al. (30)
			People can feel safe in the space.	Gehl (52)
5	Cleanliness	The sanitary condition of the space.	Sanitary conditions in public Spaces.	Carmona (37)
			Clean and well maintained spaces.	Beck (38)
			Cleanliness of environment and facilities.	Williams and Green (39)
6	Congestion level	Whether there is enough space to support people's behaviors.	Spatial density.	Erkip (26)
			The coordination between spatial scale and behavior.	Gehl (52)
			Density of resource allocation in public space.	Webster (40)
7	Physical accessibility	The effort made by people to reach the space from their starting point.	Barrier-free experience in public places.	Brorsson et al. (44)
			The ease with which a building, place or facility can be reached by people and/or goods and services.	Lotfi and Koohsari (45)
			Distance and travel time.	Erkip (26)
			Whether it is easy to access public spaces.	Talen (43)
			Distance and time to public space.	Ward Thompson and Travlou (46)
8	Inclusiveness	People of different identities participate in the activities of space.	The public nature of space.	Bertolini (48)
			Public Spaces are accessible to different groups of people.	Bertolini and Dijst (49)
			Welcome to everyone.	Madden and Wiley-Schwartz (53)
			Open to all identities and groups.	Nadal (50)
			Everyone can come and go without restrictions.	Oldenburg and Brissett (7)
9	Activity	The variety of human activities in the space.	The activities that people can carry out in public space can be divided into necessary activities, optional activities and social activities.	Gehl (52)
			A variety of uses and activities.	Madden and Wiley-Schwartz (53)
			The variety of activities and facilities.	Erkip (26)
			People's initiative and desire when interacting with space and others in space can be divided into three levels: passive engagement, active engagement, and discovery.	Carr (47)

(Continued)

TABLE 1 (Continued)

Number	Factor	Meaning	Definition	Literature
10	Social interaction	Interact with other people in the space.	Engage in a heart-to-heart and ongoing conversation.	Oldenburg and Brissett (7)
			Interaction with others.	Madden and Wiley-Schwartz (53)
			Social activities that require interaction with other people.	Gehl (52)
11	Enjoyment	People's pleasure level in the space.	People keep a happy mood in the space.	Askari and Soltani (57)
			People feel ease and relaxation in the space.	Carr (47)
12	Privacy	Protect personal privacy in public Spaces.	Personal privacy is not subject to random inspection.	Easwara Moorthy and Vu Kim-Phuong (54)
			Personal information will not be disclosed.	Little et al. (55)
			Not to be disturbed by others.	Herzfeld (56)

TABLE 2 KMO and Bartlett's test.

KMO		0.710
Bartlett test	Approx. Chi-Square	638.940
	df	66
	p value	0

TABLE 3 Total variance explained.

Factor	Eigen		% of Variance (Unrotated)			% of Variance (Rotated)			
	Eigen	% of Variance	Cumulative % of variance	Eigen	% of Variance	Cumulative % of variance	Eigen	% of Variance	Cumulative % of Variance
1	3.24	27.002	27.002	3.24	27.002	27.002	2.684	22.37	22.37
2	2.695	22.462	49.464	2.695	22.462	49.464	2.48	20.668	43.038
3	1.54	12.832	62.296	1.54	12.832	62.296	1.695	14.128	57.166
4	1.085	9.044	71.34	1.085	9.044	71.34	1.689	14.072	71.239
5	1.005	8.374	79.714	1.005	8.374	79.714	1.017	8.475	79.714
6	0.809	6.739	86.452	–	–	–	–	–	–
7	0.445	3.711	90.164	–	–	–	–	–	–
8	0.371	3.093	93.257	–	–	–	–	–	–
9	0.319	2.658	95.914	–	–	–	–	–	–
10	0.201	1.674	97.589	–	–	–	–	–	–
11	0.166	1.38	98.969	–	–	–	–	–	–
12	0.124	1.031	100	–	–	–	–	–	–

of results. Compared to traditional causal inquiry methods, this method addresses issues such as causal asymmetry, multiple concurrent causal relationships, etc. Through consistency and coverage, QCA primarily evaluates the relationship between condition and outcome variables. Consistency refers to the extent to which cases with specific outcome variables share the configuration of a particular group of condition variables. When the consistency is more significant than 0.8, it shows that the configuration constitutes a sufficient condition for a specific result. It is necessary when the value is more significant than 0.9 (59).

The configuration of community cafes affecting residents' well-being is a complex process influenced by multiple factors. Because each factor is not isolated from the others, it is appropriate to use the QCA method to deal with complex causal problems. Since the condition variables are continuous variables representing degree, they are not ideal for clear set comparative analysis (csQCA) and multivalued set comparative analysis (mvQCA). Instead, this study uses fuzzy set qualitative comparative analysis (fsQCA) to transform all data into membership degrees from 0 to 1. This paper analyzes the influence of activity quality, psychological cognition, physical quality, physical accessibility, and sociability on residents' well-being using a sample of 20 community cafes in Shanghai, China.

TABLE 4 Factor loading (rotated).

Number	Factor loading					Communality
	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5	
1	**0.888**	0.213	−0.028	−0.023	0.049	0.838
4	**0.872**	0.167	−0.099	−0.239	−0.002	0.855
11	**0.887**	0.141	−0.156	−0.034	−0.072	0.838
3	0.04	**0.874**	0.064	0.239	0.067	0.831
5	0.143	**0.927**	0.07	0.098	0.002	0.895
6	0.246	**0.769**	0.022	0.099	0.02	0.662
2	−0.078	0.032	**0.879**	0.033	−0.039	0.782
9	−0.169	0.178	**0.817**	0.062	−0.041	0.733
8	−0.039	0.184	0.026	**0.885**	−0.094	0.828
10	−0.158	0.172	0.089	**0.873**	0.091	0.832
7	0.002	0.066	−0.042	−0.009	**0.983**	0.972
12	0.452	−0.267	0.449	0.067	0.136	0.5

Bold values represent factor loads greater than 0.5.

TABLE 5 The outcome of exploratory factor analysis.

Factor	Item number	Name
Activity quality	2	Quality
	9	Activity
Psychological cognition	1	Comfort
	4	Safety
	11	Enjoyment
Physical quality	3	Esthetic considerations
	5	Cleanliness
	6	Congestion level
Physical accessibility	7	Physical accessibility
Sociability	8	Inclusiveness
	10	Social interaction

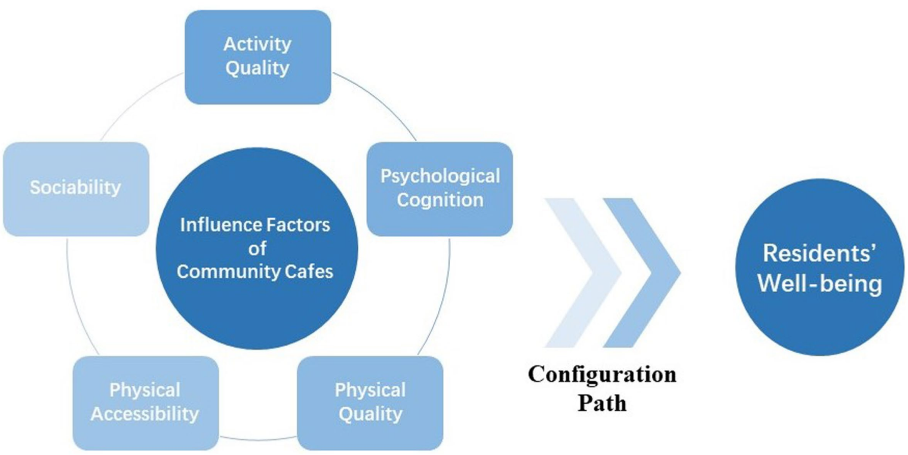

FIGURE 1
The relationship between condition variables and the outcome variable. Five interrelated condition variables form different configurations, so as to produce diverse paths for community cafes to affect resident's well-being.

4.2. Variable selection

The definitions and indicators of condition variables have been described in the previous section. The outcome variable needs to measure the well-being of residents.

From the philosophical notion of utility perspective, Diener and other scholars put forward that subjective well-being is one of the main methods to evaluate the quality of social life, with the other two being economic and social indicators (60). Subjective well-being includes cognitive experience and emotional experience, which is an important index to measure the quality of personal and social life (61–63). This paper adopts the Index of well-being, developed by Campbell et al. (64), and it is a mature and widely used well-being scale (62).

The scale consists of two parts, the first part is an index of general affect, including eight items, and the second part is an index of life satisfaction, which has only one item. When calculating the total score, the average score of the total general affect is added (weighted 1) with the life satisfaction score (weighted 1.1). The score ranges between 2.1 (the lowest well-being) and 14.7 (the highest well-being). Based on theoretical modeling and exploratory factor analysis, the final variables and their measures are shown in Table 6.

4.3. Data

Based on field investigation and the information from dianping.com, a third-party consumer review website, this paper selects 20 community cafes situated in non-commercial residential areas across Shanghai, China, as representative research samples, as shown in Table 7. These cafes have been widely discussed and praised for their community attributes on dianping.com. Through field investigation and online contact, a total of 206 questionnaires were distributed to the nearby residents who had visited these cafes. The questionnaire topics were designed according to the specific measurement indicators detailed in Table 6. The secondary indicators' scores are added to the condition variables' scores, and the final scores of the 20 cases were obtained by computing the average scores of the questionnaires. Finally, the score table of 5 condition variables and 1 outcome variable was obtained, as shown in Table 8.

4.4. Variable calibration

To convert the original data into set membership scores, the process of assigning set membership scores to cases and conditions is called calibration (65). The direct calibration method is used in this study. Combined with the numerical characteristics and referring to the commonly used QCA calibration anchors (66, 67), 95% quantile, 50% quantile, and 5% quantile are set as calibration anchors in this paper, which represents, respectively, full membership, the crossover point, and full non-membership, as shown in Table 9. Specific calibration results are shown in Table 10.

After calibration, a case with a 0.5 membership degree appeared. This is not included in the analysis because it's difficult to classify,

TABLE 6 Explanation and measurement of variables.

Variable type	Name	Secondary indicator	Explanation	Measurement
Condition variable	Activity quality	Quality	The quality of services and facilities in the space.	7-level Likert questionnaire for residents' sense of satisfaction with services and facilities in public space.
		Activity	The variety of human activities in the space.	The proportion of the types of unnecessary activities that people can do in public spaces to all types of activities.
	Psychological cognition	Comfort	Subjective feeling when people are in the space.	7-level Likert questionnaire for residents' sense of these three mental states in the space.
		Safety		
		Enjoyment		
	Physical quality	Esthetic considerations	The physical space's esthetic features and whether they are appealing to residents	7-level Likert questionnaire for residents' sense of these three factors.
		Cleanliness	The sanitary condition of the space.	
		Congestion level	Whether there is enough space to support people's behaviors and activities.	
	Physical accessibility	Physical accessibility	The convenience of residents to the community public space.	The time from the place of residence to the public space.
	Sociability	Inclusiveness	People of different identities participate in the activities of space.	7-level Likert questionnaire for residents' sense of inclusiveness.
		Social interaction	Interact with other people in the space. At the heart of "social interaction" is conversation between people.	The proportion of residents who engage in conversation in public spaces.
Outcome variable	Subjective well-being (SWB)	-	A subjective feeling includes both cognitive experience and emotional experience.	Campbell's index of well-being.

TABLE 7 Sample source and basic information.

Sample number	Name (abbreviations for privacy reasons)	Located community	Third-party consumer review website score (out of 5)
1	BA Cafe	Jiashan community	4.5
2	m Coffee	YOU + International Youth Community	4.2
3	p	Anshan fifth village	4.5
4	R Coffee	Yan Heng Riverside Garden	3.7
5	P1 Coffee	Jialanting	4.3
6	CL Coffee	Guoquan Road 333 Lane Community	4.7
7	W	Maoming South Road 163 Community	4.6
8	S1	Zhong He Apartment	4.2
9	B Cafe	SVA Expo Garden	3.8
10	P2 Coffee	West New Villa	4.0
11	TH Coffee	Beimengsan Community	4.8
12	LD Coffee	Zhengdan East Road Community	4.7
13	YY Coffee	Xiangyang South Road 510 Lane Community	4.6
14	AL Coffee	Xinyi Yayuan	4.3
15	ASC Coffee	Zhongshan Xintun	4.6
16	CA	Ruijin New Village	4.8
17	CBS	Julu Road 272 Lane Community	4.5
18	CS	No.2 Community, Lane 838, Beijing West Road	4.5
19	S2	Urumqi Road 148 Lane Community	4.5
20	M Coffee	Xinhu Qinglan International Community	3.9

which affects the final analysis results. Therefore, referring to the research of Fiss (59) and Wagemann et al. (68), all membership values less than 1 are increased by 0.001 in actual operation.

5. Results

In this study, fsQCA3.0 software is used to analyze the configuration path of improving residents' well-being in 20 community cafes. According to the suggestions of Fiss (59), Greckhamer et al. (69), and An et al. (70), the parameters are set: the original consistency threshold is 0.8, the PRI consistency threshold is 0.5, and the case frequency threshold is 1.

5.1. Necessity analysis of single conditions

The first step of QCA analysis is to analyze the necessity of single conditions, that is, to check whether the result set is a subset of a certain condition. The criterion of necessary condition analysis is that the consistency is higher than 0.9. As can be seen from Table 11, the necessity of sociability exceeds 0.9, which constitutes a necessary condition. The other condition variables do not constitute necessary conditions, which shows that the explanatory power of each single condition variable to the outcome variable is weak. Therefore, the configuration analysis of these condition variables will be carried out below.

5.2. Configuration analysis

fsQCA determines the intermediate and parsimonious solutions, as well as the core and marginal conditions. The core conditions that co-occur in the intermediate and parsimonious solutions significantly impact the results. Conditions that appear only in the intermediate solution are marginal.

The results of the QCA analysis are shown in Table 12, in which three configuration paths produce high SWB. The consistency indexes of the two configurations are 0.924585，0.913148, and 0.945302, respectively. The overall solution consistency is 0.904417, all of which are higher than 0.9, which shows that both configurations are sufficient conditions for high well-being. The overall solution coverage is 0.785251, indicating that the three configurations explain about 79% of the reasons for high well-being.

Meanwhile, considering the asymmetry of cause and effect, the reasons for the appearance and non-appearance of results are different, such that the conditions for opposite results must be examined separately. Because the condition variables and the outcome variable selected in the theoretical modeling part are positively correlated, it is assumed that the absence of any condition variable may lead to a lower level of well-being. The data is then subjected to another fsQCA operation. The results show that five configuration paths produce non-high well-being, that their consistencies are more significant than 0.9, and that the overall solution coverage is 0.753611, indicating that these five paths provide sufficient conditions for non-high well-being and explain approximately 75% of the causes. According to the

TABLE 8 Variables' original scores.

Sample	Condition variable					Outcome variable
	Activity quality	Psychological cognition	Physical quality	Physical accessibility	Sociability	SWB
1	6.68	17.93	14.67	4.5	3.6	9.89
2	7.03	19.31	19.33	5.56	7.11	11.85
3	6.77	18.7	18.5	5.75	7.42	11.25
4	6.5	18.08	18.49	5.67	7.23	12.38
5	7.64	17.24	16.86	6.14	7.86	13.35
6	7.21	18.86	14.71	6.43	7.29	13.2
7	7.35	19.13	19.1	4.18	7.27	11.86
8	7.21	17.16	15.64	6.75	7.75	13.43
9	7.21	19	18.7	3.7	7.1	12.66
10	6.87	17.32	17.82	4.45	6.73	12.47
11	7.12	18.19	18.96	4.24	7.08	13.07
12	7.17	18.23	18.5	4.23	7.05	13.11
13	7.16	18.74	18.67	4.76	6.96	12.49
14	7.2	17.95	18	4	7	12.33
15	7.4	18.93	18	3.4	7.6	13.41
16	7.41	19.72	19.57	4.83	7.24	13.98
17	7.75	20.1	20.4	2.8	7.4	14.28
18	7.65	19.45	19.16	2.17	8	14.23
19	7.3	18.6	18	5	7.8	13
20	6.88	19.08	18	3.8	7.2	13.16

TABLE 9 Calibration anchors.

Variable type	Variable name	Calibration		
		Full membership	Crossover point	Full non-membership
Condition variable	Activity quality	7.75	7.21	6.5
	Psychological cognition	20.081	18.72	17.164
	Physical quality	20.3585	18.495	14.672
	Physical accessibility	6.734	4.475	2.2015
	Sociability	7.993	7.235	3.7565
Outcome variable	SWB	14.2775	13.035	9.958

findings of the analysis, this study creates a configuration path model diagram of community public space to improve the well-being of residents (Figure 2).

(1) Activity-based space: configuration 2. Its core conditions are high activity quality, and the marginal conditions are high psychological cognition, high physical quality, and low physical accessibility. This suggests that, regardless of the sociability of the community cafe, residents will have a higher sense of well-being if other conditions are met, even if they have less convenience and take longer to reach. Activities in this type of space go beyond simply selling coffee and may include workshops, reading clubs, parent–child activities, pet activities, and more. Residents in this type of space can engage in various unnecessary activities that can provide new and pleasant psychological experiences. These activities help to stimulate diverse psychological experiences and create a solid social atmosphere (52). Furthermore, the larger spatial scale of this kind of community cafe in all samples allows it to accommodate more residents and pay more attention to decoration and space design, resulting in higher physical space quality. This demonstrates that high physical space quality helps improve the experience of social communication spaces (71). It is worth noting that due to the large space and high rent, this kind of community cafe is relatively remote and has poor physical accessibility. However, the other excellent qualities compensate for this flaw.

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TABLE 10 Calibration values.

Sample	Condition variable					Outcome variable
	Activity quality	Psychological cognition	Physical quality	Physical accessibility	Sociability	SWB
1	0.09	0.18	0.05	0.51	0.04	0.04
2	0.32	0.79	0.79	0.81	0.47	0.24
3	0.13	0.49	0.5	0.84	0.68	0.15
4	0.05	0.23	0.5	0.83	0.5	0.35
5	0.92	0.05	0.22	0.9	0.92	0.68
6	0.51	0.58	0.05	0.93	0.55	0.6
7	0.69	0.71	0.73	0.4	0.53	0.24
8	0.51	0.05	0.1	0.95	0.88	0.72
9	0.51	0.65	0.58	0.26	0.47	0.41
10	0.19	0.06	0.37	0.49	0.39	0.37
11	0.41	0.26	0.68	0.42	0.47	0.52
12	0.46	0.28	0.5	0.42	0.46	0.55
13	0.45	0.51	0.57	0.59	0.44	0.37
14	0.49	0.18	0.4	0.35	0.45	0.33
15	0.75	0.61	0.4	0.19	0.81	0.71
16	0.76	0.9	0.85	0.62	0.5	0.91
17	0.95	0.95	0.96	0.1	0.66	0.95
18	0.92	0.83	0.74	0.05	0.95	0.95
19	0.63	0.44	0.4	0.67	0.9	0.49
20	0.2	0.69	0.4	0.29	0.49	0.57

TABLE 11 Analysis of necessary conditions.

	High SWB		Non-high SWB	
Condition variable	Consistency	Coverage	Consistency	Coverage
Activity quality	0.847591	0.865462	0.607528	0.599598
~ Activity quality	0.607866	0.615737	0.863683	0.845618
Psychological cognition	0.733530	0.788583	0.620956	0.645243
~ Psychological cognition	0.670010	0.646490	0.796541	0.742884
Physical quality	0.752212	0.779816	0.716785	0.718247
~ Physical quality	0.728220	0.726791	0.780265	0.752699
Physical accessibility	0.683382	0.653195	0.800814	0.739849
~ Physical accessibility	0.727827	0.790812	0.624619	0.655983
Sociability	0.904621	0.794473	0.743642	0.631261
~ Sociability	0.580138	0.700713	0.757884	0.884798

(2) Acquaintance-based space: configuration 1 and 3. Both have high activity quality as their core condition and high sociability as their marginal condition. Still, configuration 1 has high psychological cognition, while configuration 3 has high physical accessibility and low physical quality. This difference is due to the different groups that each space serves. Configuration 1 consists of themed cafes that attract a specific group of people through a unique feature and therefore has no strict requirements for the quality and accessibility of the physical space. It mainly serves as a place for small groups to meet, focusing on people's psychological feelings and interaction within the space. On the other hand, configuration 3 has a small spatial scale in general and primarily sells high-quality coffee while also providing a small space for nearby residents to have social conversations. Due to space constraints, these cafes do not have enough room for large events, and they tend to be crowded and do not pay much attention to store decoration. However, residents often gather here to socialize, supporting Hall's (72) conclusion that

TABLE 12 Configuration results.

Configuration	Solution							
	High well-being			Non-high well-being				
	1	2	3	4	5	6	7	8
Activity quality	●	●	●	⊗	⊗	⊗	⊗	⊗
Psychological cognition	●	●			⊗	⊗	●	●
Physical quality		●	⊗	⊗		⊗	●	●
Physical accessibility		⊗	●	⊗	⊗		●	●
Sociability	●		●	⊗	⊗	⊗	⊗	●
Consistency	0.9246	0.913148	0.945302	0.96325	0.97076	0.987159	0.963091	0.997641
Raw coverage	0.6028	0.523107	0.530187	0.506613	0.506612	0.625636	0.398169	0.516378
Unique coverage	0.0446	0.0234022	0.159095	0.0193285	0.00590026	0.0791454	0.0417091	0.0463885
Overall solution consistency	0.904417			0.949743				
Overall solution coverage	0.785251			0.753611				

● and ● mean the conditions exist. ⊗ and ⊗ mean the conditions do not exist. ● and ⊗ denote the core conditions. ● and ⊗ denote the marginal conditions. White space denotes that the condition may or may not exist.

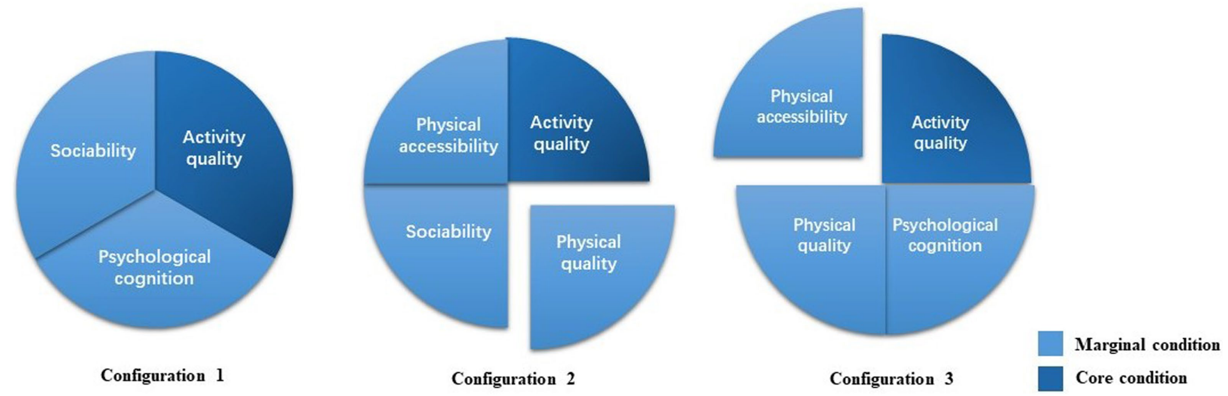

FIGURE 2
Configuration paths of community public space with high well-being. QCA results show three configuration paths producing high resident well-being. The core condition of configuration 1 is high activity quality, the marginal conditions include high sociability and high psychological cognition. The core condition of configuration 2 is high activity quality, the marginal conditions include high sociability, high physical accessibility, and non-high physical quality. The core condition of configuration 3 is high activity quality, the marginal conditions include high psychological cognition, high physical quality and non-high physical accessibility.

the distance between people identifies social relations in public space. As people's connections increase, the distance between them shrinks, and intimate crowding develops in public spaces. The nearby regular residents are the leading consumer group of this type of cafe, which is related to the higher physical accessibility. The easier for users to access a specific space, the higher the usage rate (52).

By comparing these two types, we found that both of them have high activity quality, but the main difference lies in their social function. The former is mainly activity-based, while the latter is primarily acquaintance-based. This further demonstrates the importance of community cafes as "the third space" (7). Furthermore, according to the coverage index, configurations 1 and 3 have slightly higher scores than configuration 2, indicating that they are more likely to improve residents' well-being. This fully demonstrates that for community public spaces, the physical attributes of the space itself are less important than the social attributes (73), and the deep interaction between people is the key to improving residents' well-being.

(3) The core conditions of configurations 4, 5, 6, and 7 are characterized by non-high activity quality, and the marginal conditions are also non-high sociability. While configurations 4, 5, and 6 lack positive conditions, configuration 7 has all the other positive conditions. This indicates that, regardless of other factors, a community cafe lacking high activity quality and sociability will inhibit residents' well-being. This further underscores the significance of activity quality and sociability in community public spaces.

Cases in configurations 4, 5, and 6 mainly consist of small shops that only provide coffee sales services. After customers drink coffee, they typically leave without engaging in other activities, resulting in an indifferent atmosphere. Additionally, some shops are located in remote areas that are challenging to spot. These community cafes often result in poor business and low foot traffic.

In contrast, cases in configuration 7 mainly consist of medium to large cafes that are situated near residential areas and have high-quality physical space. However, residents typically drink coffee or spend time alone without interacting with others. Configuration 8, while possessing all other positive conditions, lacks activity quality. This finding further emphasizes the importance of the behavioral perspective in enhancing residents' well-being. Referring to the original data, it was found that the sociability score of the configuration 8 cases had a higher inclusiveness score, which may explain the difference between configurations 8 and 7. Nonetheless, the cases in both configurations were similar in terms of lacking social interaction.

QCA causality is asymmetric, implying that different condition configurations are required to explain the occurrence of a result. Compared to the previous five configurations, the study revealed that the lack of activity quality and sociability in community cafes has a noticeable inhibitory effect on residents' well-being. The study also uncovered that psychological cognition, physical quality, and physical accessibility play a substitute role in explaining non-high well-being.

5.3. Robustness analysis

To verify the robustness of the analysis results, this study adjusted the consistency threshold according to the practice of White et al. (74) and changed the consistency standard from 0.8 to 0.85 and 0.72, respectively. The configuration path and parameters did not change substantially and passed the robustness test.

6. Discussion

The main results are as follows. Firstly, through theoretical modeling and exploratory factor analysis, it is found that community cafes have an important impact on residents' well-being through five aspects: activity quality, psychological cognition, physical quality, physical accessibility, and sociability. There are three main ways to produce high well-being, which demonstrates the multiple causal relationships of this impact.

Secondly, an analysis of the necessity of individual conditions reveals that sociability is crucial for promoting well-being. This underscores the emphasis placed in the existing literature on the social value attribute of public spaces, which distinguishes them from other types of urban spaces (7, 75, 76). From this perspective, community public spaces play a critical role in urban development, not only in terms of their physical layout within the urban environment but also in the positive experiences that people derive from their use of these spaces (52). When a space functions as a "social space," its design must move beyond the mere transformation of the objective physical environment and consider environmental studies, behavior, psychology, and sociology to ensure that people have a positive social experience in the built environment (77). This underscores the importance of community public spaces as shared communication spaces for public life (47). As Arendt (78) argues, the shared nature of these spaces is an essential attribute of public life and is key to consolidating and maintaining community consciousness. Thirdly, configuration analysis has revealed that the three configurations associated with high well-being can be distinguished by differences in their social function. The activity-based configuration requires sufficient activity venues and environmental quality. The acquaintance-based configurations emphasize high sociability but ignore the physical form quality of the space and distinguish their primary users based on accessibility. Fourthly, asymmetric analysis reveals that five configurations produce low well-being. Among the five condition variables, lack of activity quality and sociability are the main conditions that make it difficult for community cafes to improve residents' well-being.

6.1. Theoretical contribution

This study integrates five key factors from public space theory and interaction & space theory, comprising a total of 11 variables, to investigate the impact of community cafes, as typical community public spaces, on residents' well-being. Previous studies have focused on limited factors, and the internal mechanism of the synergistic influence of the comprehensive elements of the five factors remains unclear. Additionally, few studies have proposed evaluation indicators for community-scale public spaces. Therefore, this study enriches the evaluation dimension of community public space, and conducts a deep analysis of the influence of factor configuration on residents' well-being. Based on the literature review and exploratory factor analysis, this study establishes a relatively comprehensive theoretical framework and explores the complex concurrent causal relationship between community cafes and residents' well-being, which is beneficial in revealing the black box of this causal relationship and providing specific theoretical support for the construction practice of community public space. In addition, this study also demonstrates the complex configuration relationship among influencing factors, suggesting that researchers and practitioners should not only focus on single critical conditions but also consider the configuration effect among different conditions. Moreover, through the QCA method, this study demonstrates a causal asymmetry of the impact, indicating that the paths to high and non-high well-being are not entirely opposite. The negative reasons cannot be analyzed simply by opposing the influence paths of high well-being.

6.2. Practical enlightenment

6.2.1. Strengthen the social attribute of community public space

This study supports the importance of the social aspects of community public space. It warns the community construction industry, which has recently overemphasized physical spatial attributes while ignoring social attributes. Scholars generally believe that the social significance of the built environment is as important as the apparent meaning of spatial intention, and its social value for public space is even more in line with the connotation of "public"

(37, 48, 50). From a semiotic perspective, the built environment reflects the cultural characteristics of society, and its meaning changes as social values change (79). The environmental significance of community public space lies in building the cultural identity of the community, especially because of its social orientation. Communities are not only the most minor functional division in an urban environment, but they are also widely regarded as the more important basic units of actual and potential solidarity and social cohesion. With the geographical construction of neighborhoods and a range of possible expectations, the community has been endowed with community-like expectations for security and connection, which has become a complex spatial form integrating identity, use, and action (80).

As one of the earliest scholars who introduced the term "public space" into urban research, Jacob (35) believes that public space is critical in promoting good social interaction in community building. The value of public space lies in the social understanding and integration brought by its inclusiveness and diversity, which is an important source to enhance residents' well-being. Scholars generally believe that social interaction in public spaces is a vital link to maintaining social relations at different levels. It serves as a balance and supplement to the private sphere (29, 73, 81–83).In fact, different communities based on geographical background have gradually evolved different social characteristics, which may lead to systematic community differences in residents' well-being (84). Under the background of rapid urbanization, the connection between neighborhood and community has cracked, leading to various "community questions" (85). This demonstrates the principle that must be addressed in community building: returning to the concept of community, treating the community as viable units of identity and action, and paying attention to the community's sociality and intimacy. Community public space is a critical breaking point in the modern high-density and high-privacy housing development trend.

6.2.2. Clarify the social orientation of community public space

According to configuration analysis, this study suggests that the community public space should flexibly choose the mode of activity-based or acquaintance-based according to the type of activity, spatial scale, and geographical location. This also demonstrates that the space environment can express and transmit meaning through various elements, leading to the difference in human behavior (77). Activity-based public space confirms the significance of space in shaping people's behavior, emphasized by the theory of communication space (52). It also illustrates the role of complex space in promoting social interaction (53). This reveals that community public space with good social attributes needs to stimulate residents' spontaneous and social activities through specific physical space elements. The acquaintance-based community public space more obviously reflects the different attitudes of different groups toward the community interpersonal network. According to Relph (86), different people can give meaning to space through life experiences, and the key to transforming space into place is a sense of belonging. This sense of belonging comes not only from the experience triggered by the physical form of space, but also from the human network built based on space. The main users of this kind pay attention to smaller, closer, and more frequent interpersonal networks. They tend to have more spatially proximate and robust neighbor networks (87). Therefore, it is easier to form tight but selective social ties (88). This type of social tie implies the integration of social cohesion and positive social control over public space, which is called collective efficiency and helps to reduce unsafe factors such as disorder and crime, giving people a good psychological experience (89).

6.2.3. Avoid extremes and improve the conditions of community public space according to the actual situation

Since the reasons affecting residents' well-being are asymmetric, the causes of non-high well-being cannot be reversed according to the reasons of high well-being, demonstrating that the opposites of configurations 1,2, and 3 cannot be considered as lessons to inhibit residents' well-being. Similarly, we cannot assume that improving the factors of configurations 4, 5, 6,7, and 8 will improve the residents' well-being. The development of community public space needs to combine the actual situation and comprehensively consider various antecedent conditions.

7. Conclusion and research limitation

This study aims to investigate the complex configuration paths of community cafes to enhance residents' well-being. Therefore, the fuzzy set qualitative comparative analysis (fsQCA) method was adopted to analyze 20 typical cases in Shanghai, China, as samples. The condition variables were selected from 12 factors identified in the literature and reduced to 11 factors and five dimensions through exploratory factor analysis. The outcome variable is subjective well-being. This study constructs a theoretical framework that explains how community cafes influence residents' well-being through activity quality, psychological cognition, physical quality, physical accessibility, and sociability. The results indicate that the impact has significant configuration differences, among which the sociability condition is particularly important. The current data highlight the importance of clarifying community public space's social orientation according to spatial conditions.

This study appears to be one of the first attempts to examine the configurations of community-scaled public space's effect on residents' well-being. The insights gained from this study may be of assistance to community-building research and practice. However, it is important to note that the study has some limitations, including limited sample size and coverage. Furthermore, the investigation focuses on exploring the relationship between condition variables and the outcome variable, and it does not analyze the influencing factors of condition variables in detail. Future research could further explore larger-scaled community public space samples and delve deeper into the condition variables with greater granularity.

Data availability statement

The original contributions presented in the study are included in the article/Supplementary material, further inquiries can be directed to the corresponding author.

Ethics statement

Ethical review and approval was not required for the study on human participants in accordance with the local legislation and institutional requirements.

Author contributions

YL led the overall study. MZ and TS jointly completed the research plan and manuscript writing. ZM was also responsible for data collection and analysis. All authors read, contributed to the research design, and approved the final manuscript.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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Supplementary material

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