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Multi-scale urban built environment and human health

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Multi-scale urban built environment and human health

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Editorial: Multi-scale urban built environment and human health

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KEYWORDS

multi-scale analysis, built environment (BE), settlement, public health, big data

Editorial on the Research Topic
Multi-scale urban built environment and human health

1 Introduction

Urbanization not only reshape where people live and how move, but also reshape the patterns of public health. The contributions in this Research Topic show that the built environment (BE) exerts health effects across scales, from housing quality and street-level greenness to neighborhood services and citywide mobility systems. Collectively, they move beyond single-exposure, single-scale perspectives toward scale-aware, pathway-specific, and context-sensitive understandings of how place affects health. Based on the submitted manuscripts, we can observe three insights that matter in shaping health issues: (1) measurement refers to exposure definitions, spatial and temporal scales, and interpretability choices that influence inferences; (2) social pathways refers to community attachment, cohesion, and affordability that shape mental and cardiometabolic outcomes alongside physical features; and (3) policy levers exist at multiple levels, i.e., parcel, street, neighborhood, and city, enabling coordinated, equity-centered action that captures co-benefits while managing trade-offs.

2 The multi-scale imperative

Understanding the health impacts of urban environments requires moving beyond single-scale analyses. The BE factors operate simultaneously across multiple spatial scales, e.g., dwelling unit, neighborhood, district, and metropolitan region. Each scale presents distinct exposure pathways and intervention opportunities. The contributions in this Research Topic demonstrate that scale matters profoundly, as a fundamental determinant of how environmental factors translate into health outcomes.

Three works exemplify this multi-scale approach through innovative methodologies. Peng et al. employ machine learning to uncover non-linear threshold effects of BE characteristics on weekend metro ridership in Shanghai, revealing that land use mixture, distance to CBD, and transit connectivity operate through distinct spatial ranges with specific optimal thresholds. The findings challenge linear assumptions pervading transportation-health research, showing that maximum ridership occurs when land use entropy remains below 0.7 and bus line density reaches 35 routes. Similarly, to match cooling service provision with resident needs, Song et al. develop a supply-demand framework to evaluate park cold island effects across neighborhoods, integrating remote sensing data with Thiessen polygon analysis. The finding reveals that 40% units exhibit supply-demand mismatches, concentrated in areas with complex building environments and poor landscape connectivity. Besides, He et al. investigate the relationship between housing quality and tenant mental health across seven urban villages in Shenzhen, as demonstrates how community-level attachment mediates between dwelling conditions and psychological wellbeing, and illustrates how individual, household, and neighborhood scales interact to shape health outcomes.

3 Bridging environmental metrics and health pathways

A common theme across these works is the imperative to elucidate the behavioral, social, and physiological pathways linking environments to health. Several works employ structural equation modeling approaches to unpack sophisticated mediation mechanisms. For instance, Zuo et al. examine how urban green space influences older adults" mental health through relative deprivation, physical activity, and social trust. The findings reveal that green space coverage reduces perceived relative deprivation and promotes physical activity, which in turn enhance mental health. It suggests that environmental equity and behavioral activation represent more proximate pathways than social cohesion for this population. Feng and Zheng's study toward Nanjing older adults uncovers significant gender differences in how BE affects subjective wellbeing, with community-level factors explaining 33.68% of variance for female vs. 28.50% for male. Household structure operates through gendered divisions of domestic labor and culturally-specific norms around filial piety, demonstrating how socio-cultural mechanisms intersect with physical environments. Gu et al. trace the pathways from BE through health behaviors to hypertension risk, revealing that clinic density, supermarket proliferation, and road network characteristics influence disease risk by shaping residents' walking time, physical activity duration, and fruit/vegetable consumption. This work exemplifies how BE features cascade through multiple behavioral mediators to affect cardiometabolic outcomes.

4 Vulnerable populations and environmental justice

Several other works investigate how BE impacts vary across population subgroups by age, gender, socioeconomic status, and migrant status, raising critical environmental justice concerns. The concentration of investigating older adults reflects both demographic imperatives and recognition that elderly populations experience heightened environmental sensitivity due to declining physical function and constrained activity spaces. Feng and Zheng document that older women's wellbeing responds more strongly to BE quality than men's, likely reflecting their greater domestic responsibilities, more localized activity patterns, and differential physiological sensitivities. This finding challenges gender-blind planning approaches and calls for designing environments attuned to gender needs. Meanwhile, He et al.'s study on urban village tenants and migrants highlights how informal housing serves as the primary shelter for low-income groups excluded from formal housing markets. Despite substandard conditions, these settlements foster community attachment that buffers mental health impacts, suggesting that social belonging may partially compensate for physical environmental deficits. Gu et al. note that older urban residents in areas undergoing renewal face compounded vulnerabilities, such as aging infrastructure, limited healthcare access, and economic precarity converge to elevate hypertension risk. The result shows these social determinants operate alongside and interact with BE exposures, underscoring the need for integrated interventions addressing both physical infrastructure and social services. Collectively, these findings demonstrate that environmental justice requires attending not only to distribution of resources (parks, transit, services) but also to how environmental effects vary by social position and how cumulative disadvantages multiply health risks.

5 From linear assumptions to non-linear realities

A methodological contribution throughout this Research Topic is the application of non-linear modeling techniques, which helps to capture threshold effects, diminishing returns, and interaction effects often obscured by conventional linear regression. For instance, Peng et al. adopt the GBDT model and SHAP value, which reveal that most BE variables exhibit non-monotonic relationships with metro usage, with effective ranges beyond which additional environmental improvements yield minimal behavioral change. Similarly, Song et al. document that cold island supply exhibits an inverted-U relationship with BE intensity, and it shows that moderate densification enhances cooling services, whereas excessive development degrades environmental quality despite increased green space investment. Gu et al. find that higher road network density increases hypertension risk by extending walking time and reducing fruit/vegetable consumption, which counter to the assumption that walkability universally benefits health. The non-linear reality demands nuanced, context-sensitive design that balances competing objectives (e.g., density for transit ridership vs. greenness for thermal comfort) and recognizes that more is not always better. These findings have profound planning implications. Rather than maximizing single environmental attributes, planners should calibrate interventions to optimal ranges while considering interactive and context-dependent effects.

6 Future directions

While the collections in this Research Topic advances the understanding of multi-scale environment-health relationships, several priorities remain for further research. First, most studies employ the cross-sectional design, which has limitation for the causal inference. It's helpful to employ the longitudinal and quasi-experimental designs that track environmental changes and health trajectories. Second, integrating GPS mobility data to activity-space exposure assessments could better capture dynamic environmental exposures beyond residential neighborhoods, particularly for working-age populations. Third, integrating objective environmental measures with subjective perceptions would illuminate how individual differences in environmental experience mediate health effects. Fourth, climate change may introduce compounding stressors, such as heat extremes, flood risks, and air pollution, as calls for conducting research on multi-hazard exposures and adaptation strategies. Finally, participatory approaches engaging communities in defining environmental priorities and co-designing interventions could ensure research translates to contextually appropriate, equitable solutions.

7 Conclusion

It's necessary to remind the importance of integrating multi-scale thinking, attention to behavioral and social pathways, commitment to environmental justice, and acknowledgment of non-linear complexities when creating health-promoting cities. As urbanization continues reshaping human habitats worldwide, evidence-based urban planning informed by rigorous environment-health research becomes ever more essential. We hope the collections in this Research Topic inspires scholars, practitioners, and policymakers to advance approaches that foster healthier, more equitable, and more sustainable urban futures for urban residents.

Author contributions

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Relationship between urban green space and mental health in older adults: mediating role of relative deprivation, physical activity, and social trust

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Introduction: The importance of improving older adults' mental health is increasing worldwide with the rapid development of the aging process. Green space is an important part of the urban built environment, demonstrates a deep connection with the mental health of older adults, and its internal mechanisms have been widely studied. This study analyzed the influence of urban green spaces on the mental health of older adults via three factors: relative deprivation, physical activity, and social trust.

Methods: Based on the 2018 China Labor Dynamics Survey, a multi-level structural equation model was used to explore the mediating roles of relative deprivation, physical activity, social trust in urban green spaces, and the mental health of older adults.

Results: Urban green space was positively correlated with the mental health of older adults. Relative deprivation and physical activities played a mediating role between urban green space and the mental health of older adults.

Discussion: An increase in urban green spaces can help increase the number of older adults obtaining green space resources, and help them maintain good mental health. Secondly, older adults with a relatively homogeneous environment have more equal opportunities to obtain urban green space resources, which helps to reduce the comparison of older adults in access to green space resources and reduce the adverse impact of relative deprivation on their mental health. Additionally, increasing urban green spaces can encourage older adults to engage in physical activities and improve their mental health. Finally, we suggest improving the accessibility, fairness, and quality of green spaces, paying attention to the psychological needs of older adults, encouraging older adults to engage in physical activities in green spaces, and taking various measures to enhance the positive role of green space on the mental health of older adults.

KEYWORDS

urban green space, older adults, mental health, relative deprivation, China

1 Introduction

Population aging has become an irreversible trend in global population development. According to the World Social Report 2023, the number of people worldwide aged 65 years and over is expected to more than double by the middle of this century (1). China's population is gradually aging, and its older adult population is expected to account for ~25% of the total population by 2030; this increase is expected to be more evident in adults aged 80 years and older (2). In the context of urbanization with a large population gathering, the negative factors of the urban environment seriously affect the mental health of older adults. Research has shown that nearly two-fifths of older adults in China report subclinical levels of depression (3). Factors such as physical function, psychological distress, mental illness, and nursing relationships affect older adults' mental health (4–6). Considering the immense challenges brought about by aging, promoting healthy aging has become a countermeasure for China and the world to deal with the aging problem (7). The World Health Organization's definition of health refers not only to physical health, but also to a state of mental and social fulfillment. China's "14th Five-Year Plan for Healthy Aging" report highlighted that comprehensive and systematic intervention measures should be taken to better meet the health needs of older adults and build a healthy and livable urban and community environment, to improve the health level of older adults (7). As a scarce resource, urban green spaces play an important role in reducing the negative impacts of cities and improving the mental health of older adults (8). Therefore, understanding the influence mechanism of urban green spaces on the mental health of older adults is of great significance in building a healthy and livable city and promoting the development of healthy aging in China.

Mental health is the cornerstone of high-quality old-age care for older adults, and its influencing factors have been widely discussed by the academic community. Green spaces are an important factor affecting the mental health of older adults in urban environments through various biological, psychological, and social channels (9). Biologically, green space can reduce older adults' harmful environmental exposure by improving the urban environment, providing a livable urban environment, and improving older adults' mental health (10–13). Psychologically, attention recovery and stress reduction theories also suggest that green spaces can promote the mental health of older adults by reducing their psychological stress and improving negative emotions (14, 15). Socially, green spaces provide an open activity space for older adults, which helps them perform social interactions and physical activities to improve their mental health (16).

At the individual level of older adults, scholars have widely considered the role of the degree of deprivation of older adults on the relationship between green spaces and mental health. Among them, the relationship between absolute deprivation (that is, objective economic status) and green space has attracted the attention of most studies, such as the impact of socioeconomic status on accessibility (17) and fairness (18) of urban green spaces environment. Individuals with different degrees of absolute deprivation have different access to green space resources and, consequently, experience varied health benefits of green spaces (19). However, absolute deprivation pertains to measuring health inequality due to a gap in objective economic income; it is impossible to determine the relative income of different individuals in the group and the different effects on health brought about by this comparison (20). This perception of one being deprived of something compared with other individuals is called relative deprivation (21). Relative deprivation theory hypothesizes that various forms of socioeconomic comparisons lead to negative mental and physical health outcomes (22, 23). Moreover, most studies support the negative impact of relative deprivation on mental health. Relative deprivation has a greater negative impact on the health of older adults (24). Simultaneously, relative deprivation also affects physical activity, social trust, social cohesion, and other factors (14, 16, 25). Most studies support the link between relative deprivation and mental health as well as the link between urban greening and mental health. However, few studies have explored the relationship between relative deprivation and mental health in green spaces.

Research on the relationship between urban green spaces and older adults' mental health has gradually increased. However, more attention has been paid to the relationship between absolute deprivation and mental health, while ignoring the mediating role of individual physiological, psychological, and social factors, such as relative deprivation, physical activity, and social trust. Moreover, current studies have not sufficiently considered the impact path of these three factors on older adults' mental health. Therefore, using data from the 2018 China Labor Force Dynamics Survey and employing structural equation modeling (SEM), this study explored the mediating roles of relative deprivation, physical activity, and social trust in the relationship between green spaces and mental health in older adults, and proposed a theoretical framework to provide strategies for realizing healthy aging and building an aging-friendly and livable urban.

2 Literature review

2.1 Urban green space and mental health of older adults

The Third International Conference on Mental Health highlighted that mental health not only involves the absence of mental illness and good social adaptability, but also refers to the ideal personality and full development of spiritual potential, and the best mental state under certain objective conditions. Mental health levels are commonly assessed using several classic scales, including the General Health Questionnaire (26), Short Warwick Edinburgh Mental Health Scale (27), and EuroQol Five Dimensions Questionnaire (28). Roberts et al. (29) believe that people's mental health is influenced by three dimensions: physiological, psychological, and social factors. Physiologically, gender, education level, marital status, and other factors will affect the mental health of older adults (30–33). Psychologically, individuals who feel relatively deprived experience negative emotions, such as depression or stress, that may negatively impact mental health (34, 35). In the social dimension, social participation, social support, and relationships with family members are related to older adults' mental health status (36, 37).

As the most important settlement of people at present, the impact of urban construction and the social environment on people's mental health has been widely studied in academic circles, particularly the relationship between urban green spaces and mental health. Previous studies have shown that green spaces can reduce the negative impact of the urban environment on physical and mental health in various bio-psychosocial ways and can improve the mental health of residents (9). In terms of biological functioning, green spaces can affect air quality through particle deposition, dispersion, and modification, and reduce the negative impact of air pollution on residents' health and wellbeing (10). It also can adjust the urban climate, relieve the heat island effect, and reduce noise pollution, thereby promoting people's physical and mental health (11–13). By contrast, the psychological pathway mainly improves residents' mental health by reducing life pressure and arousing positive emotions. The attention recovery theory states that the interaction between residents and the surrounding green spaces can attract people's attention, mentally free up residents from daily troubles and problems, reduce pressure on residents, and improve their mental health (15). Meanwhile, the stress reduction theory states that the natural environment, as a restorative environment, can provide residents with opportunities to appreciate the natural landscape, generate positive emotions, and overcome negative thoughts, thus enhancing their ability to cope with stress and their mental health state (14). Studies have shown that older adults living in parks exhibit improved physical health, mood, and attention (38). The more green space visible, the lower the level of negative emotions people have (39). Moreover, green space is associated with the prevention of depression in older adults (40). From the social pathway, social participation and interaction are crucial for the relationship between green spaces and residents' mental health. First, residents living in natural environments can enhance their prosocial decisions and actions (such as cooperation, generosity, and trust), reduce antisocial behaviors (such as aggression and crime), and achieve good social health, which contributes to the maintenance of their psychological wellbeing (41). Second, neighborhood streetscape greening can indirectly affect the mental health of residents by promoting neighborhood attachment and community participation (14). There are also positive links between green Spaces, physical activity, and mental health. Liu et al. used SEM to study green space and walking behavior, stress, social cohesion, satisfaction with green space, and other factors. The results showed that most urban green spaces provided relatively safe and attractive outdoor physical activity spaces for people, which could attract people to engage in physical activities, stimulate the human body to produce natural feel-good hormones, and then improve mental health (42). In addition, green spaces help reduce the likelihood of depression. Studies have shown that physical activity, stress, and neighborhood social cohesion fully mediate the negative association between residential green space exposure and depression (43). Therefore, we propose the following hypothesis:

Hypothesis 1: Green spaces directly impact older adults' mental health.

2.2 Deprivation, green space, and mental health of older adults

Deprivation is a basic sociological concept that refers to a state of unsatisfied needs (44), and has two main divisions. On the one hand, objective economic deprivation, namely absolute deprivation, mainly refers to a situation in which some people's most basic life needs are not satisfied because of unfair treatment (45). On the other hand, it is the state of an individual's unsatisfied psychological needs, that is, relative deprivation. Specifically, it refers to the subjective perception of being deprived of one's interests by other groups when an individual is compared with other individuals with higher status and better living conditions around them, and the resulting feeling of a gap, anger, dissatisfaction, and other emotions brought about by such comparison (21). Social injustice is an important cause of relative deprivation (46).

Research on the role of deprivation in the relationship between green spaces and health has focused primarily on absolute deprivation. In the relationship between green space and absolute deprivation, the research results show that the urban green space resources available to individuals or groups are different due to different objective socio-economic status (47). In terms of green space accessibility, communities with higher degrees of absolute deprivation are further away from green spaces (48). Green space accessibility is more advantageous for residents in wealthier communities than in disadvantaged communities (49). Even if poor areas have equally accessible green spaces, the quality of their green spaces is relatively low (50). In terms of green space availability, low socio-economic status, and minority groups also have poor availability and quality of green spaces (51). Therefore, influenced by the relationship between absolute deprivation and green space, the health benefits of green spaces may be distributed unevenly among groups or communities with different socioeconomic statuses (19). Wang and Lan's (52) study showed that the accessibility and quality of park green space in socially disadvantaged communities are lower, health outcomes are poorer, and residents' access to park green space is associated with health outcomes. The health benefits of green spaces appear to be stronger for residents living in socioeconomic-advantaged neighborhoods than for residents in socioeconomic-disadvantaged neighborhoods (53). This inequality can be better explained by the theory of social causality: an individual's position in the social structure determines their level of health. Compared with people of higher absolute deprivation, those with lower absolute deprivation are more likely to have access to adequate material supplies, superior working conditions, and health services, and to have good physical and mental health (54, 55). Similarly, they are more likely to reap the health benefits of green spaces.

However, absolute deprivation can only study health inequality from the perspective of economic income gap; it is impossible to determine the different effects of comparison on health brought about by the relative income of various individuals in a group (20). The relative deprivation hypothesis explains the relationship between health inequality and income. It argues that inequality manifests through various forms of socioeconomic comparison (especially income inequality). These comparisons undermine social cohesion, social capital, trust, and wellbeing, ultimately leading to negative psychological and physical outcomes (22, 23). Theoretically, relative deprivation can affect health through two pathways. In the material pathway, relative deprivation limits individuals' access to things that represent a social standard of living, thereby adversely affecting their health. In the psychological pathway, inequality exacerbates negative emotions experienced by relatively poor people, leading to adverse health conditions (22). Numerous studies have shown that relative deprivation is detrimental to mental health. First, relative deprivation damages health-related quality of life, which is not conducive to the physical and mental health of residents (56). Simultaneously, relative deprivation significantly increases the risk of suicide in people over the age of 25 years (35). For the mental health of older adults, relative deprivation also has an important impact. Higher relative deprivation can damage the cognitive function and mental health of older adults. The negative effects are more pronounced on adults over 80 years of age and those living in urban areas than on middle-aged people (24). Liu et al. have also shown that increasing relative deprivation has a negative impact on the physical and mental health of older adults. The study also showed that older adults were more affected by relative deprivation than middle-aged people (57).

Additionally, relative deprivation is associated with physical activity and social trust. In terms of physical activity, relative deprivation was associated with lower physical activity. Studies have shown that the negative effects of relative deprivation may drive individuals to engage in unhealthy behaviors, including reduced physical activity and unbalanced eating habits (16). In studies of relative deprivation and obesity, it has also been shown that relative deprivation is associated with skipping breakfast, less physical activity, fewer healthy food choices, and a lower likelihood of dieting to lose weight (58). In terms of social trust, social psychology believes that people who feel relatively deprived may expand their psychological distance and distrust toward many members of society (59). Studies have shown that people of lower relative social status may feel distrust because they are unable to achieve the same status as people of higher relative status (60).

Generally, multiple empirical studies have shown that urban green spaces affect mental health through various pathways including physical activity and social trust (44, 61, 62). However, few studies have explored the role of relative deprivation in the relationship between green spaces and mental health. Relative deprivation, as an important factor affecting mental health, is associated with both physical activity and social trust. In addition, SEM provide a maximum-likelihood estimation of the entire system in a hypothesized model and enable the assessment of variables with the data (63). It allows for complex, multidimensional, and more precise analysis of empirical data taking into account different aspects of the examined reality and abstract concepts or theoretical constructs (64). As a multivariate data analysis tool, SEM is an important analytical means in mental health-related studies. For instance, Liu et al. (14) used the multilevel SEM model to study the relationship between natural outdoor environment and mental health, and Dzhambov et al. (65) also used SEM to study the relationship between residential perception of green space and residents' mental health. Therefore, in the internal influence mechanism of green space and the mental health of older adults, this study considered the indirect influence of relative deprivation, physical activity, and social trust. SEM was used to study the mediation effect, and the following hypotheses were put forward:

- **Hypothesis 2:** Relative deprivation, physical activity, and social trust play mediating roles in the relationship between green spaces and mental health of older adults.
- **Hypothesis 3:** Green spaces are related to physical activity and social trust through relative deprivation, which indirectly affects older adults' mental health.

3 Research design

3.1 Study area and population

Data were obtained from the 2018 China Labor Dynamics Survey (CLDS), a large-scale, nationally representative tracking survey of labor force dynamics designed and implemented by the Center for Social Science Research at Sun Yat-sen University. The 2018 CLDS contains data collected from 28 provinces in China, excluding Hong Kong, Macao, Taiwan, Tibet, Hainan, and Xinjiang. The database covers comprehensive data on 368 communities, 13,501 households, and 16,537 individuals in the labor force. The 2018 CLDS adopted a multi-stage, multi-level probability sampling method proportional to the size of the labor force, which minimizes sampling errors and ensures the randomness and scientific nature of sample selection. The present study drew on existing research (66), and defined older adults as individuals aged 60 years or older. We collected 2,465 valid samples from 119 Chinese cities.

3.2. Measurement of variables

3.2.1. Mental health

The Center for Epidemiologic Studies Depression Scale was used to assess mental health. It contains 20 items used to assess depressive symptoms (67), scored on a four-point reverse scale (1 = almost always, or 5–7 days per week; 2 = often, or 3–4 days per week; 3 = rarely, or 1–2 days per week; and 4 = almost never, or $<$1 day per week). The total score ranges from 20 to 80, with higher scores indicating improvement in older adults' mental health from the previous week. Cronbach's α of the mental health subscale was 0.946, indicating the reliability of the research questionnaire.

3.2.2. Green spaces

Drawing on existing studies that have used the proportion of green space to measure urban green space (68), this study employed the green space coverage rates of built-up regions as indicators to quantify urban green space. The green space coverage rate of built-up areas refers to the proportion of urban built-up areas covered by greenery to the total built-up area, which was obtained from the 2018 China Urban Statistical Yearbook (69). Owing to the random processing of the community in the questionnaire, this study could not identify the community of each respondent,

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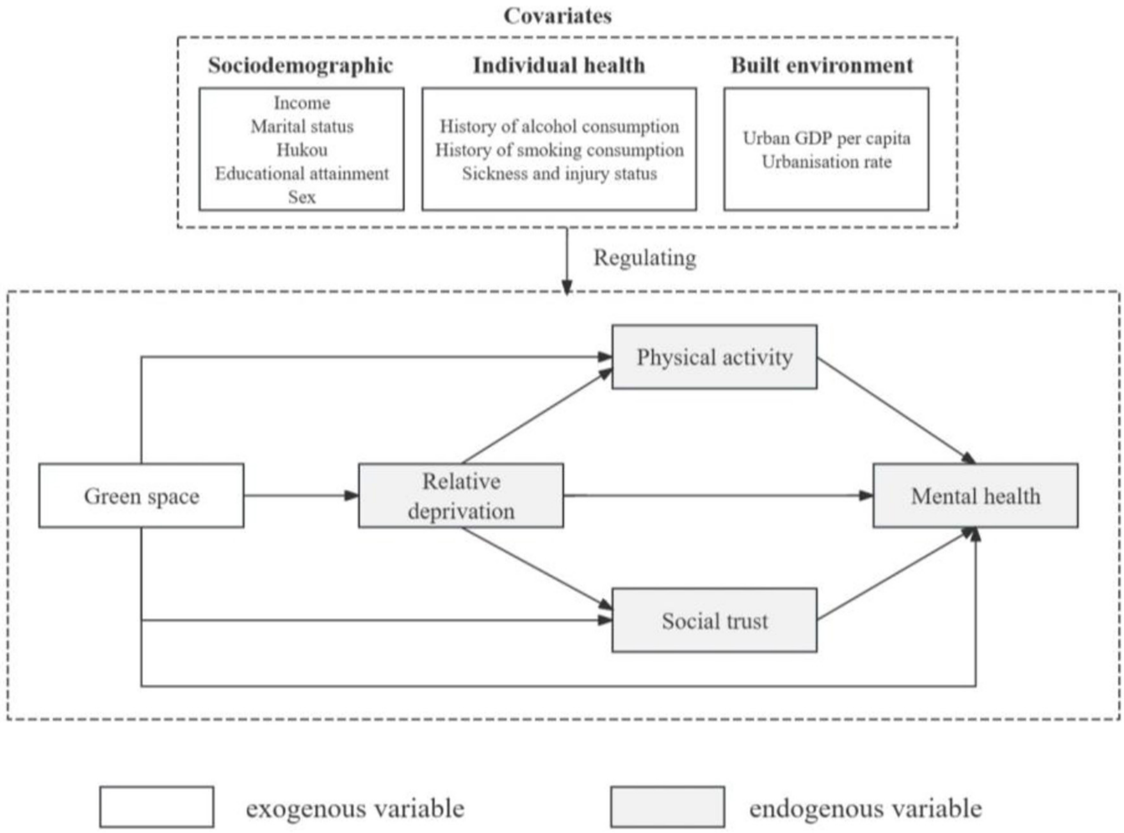

FIGURE 1
Theoretical framework for the SEM construction.

only the city information related to each respondent. Therefore, we could not study the accessibility of green spaces. This study assigned corresponding values to the respondents according to the green space coverage rate of each city.

3.2.3. Relative deprivation

This study used the MacArthur scale to measure relative deprivation (70). Participants were asked to indicate their position in a self-defined society on a picture of an upright ladder with 10 rungs—with a score of "1" representing the bottom rung and a score of "10" representing the top rung. Relative deprivation was measured using the question, "Where do you currently see yourself in the hierarchy?" Higher scores indicate lower perceived relative deprivation.

3.2.4. Social interaction

Drawing on the existing research literature, this study assessed the potential relationship between green space and mental health along social and behavioral dimensions (68). In the social dimension, social trust was evaluated through the following questions from the 2018 CLDS: "What is your level of trust in the following categories of people?" The categories included family members, relatives and friends, neighbors, classmates, fellow students, strangers, people who work or do things together, businesspeople who come into contact while buying things, and those who have religious beliefs. The trustworthiness score for social trust was determined using a five-point Likert scale (1 = not at all trustworthy; 5 = completely trustworthy). Total scores range from 9 to 45, with higher scores indicating a higher level of social trust in all types of people. Cronbach's α for social trust was 0.733, indicating that the questionnaire had good reliability. In the behavioral dimension, this study measured respondents' physical activity through the question, "Have you performed regular exercise in the last month?" and assigned values of 1 and 0, depending on whether the respondents answered yes or no, respectively.

3.2.5. Covariates

This study adjusted for covariates of older adults' sociodemographic and individual health characteristics, and built environment (71). For individual-level covariates, this study included gender (binary variable: male vs. female), marital status (binary variable: not single vs. single), annual personal income (continuous variable), hukou (binary variable: local vs. non-local; i.e., whether the place of domicile was the same as their place of residence), and education (binary variable: educated vs. uneducated). For covariates of individual health characteristics, this study included illness and injury status (binary variable: no sickness or injury in the last 2 weeks vs. sickness and injury within the last 2 weeks), history of alcohol consumption (binary variable: no history of alcohol consumption vs. history of alcohol consumption), and history of smoking (binary variable: no history of smoking vs. history of smoking). Considering that the mental health of older adults may be affected by chronic diseases, as the 2018 CLDS does not have questions related to chronic diseases, the illness and injury status of older adults can be substituted for this question to some extent (8). For covariates of built environment, this study uses urban GDP per capita (continuous variable; i.e., gross urban product divided by total population) and urbanization rate (continuous variable; i.e., proportion of urban permanent population to the total permanent population), with data for the built environment taken from the 2018 China Statistical Yearbook (69).

3.3. Statistical analysis

This study used SEM to examine the links between urban green spaces, latent media, and mental health. Notably, SEM can measure the total, direct, and indirect effects of one variable (e.g., urban green space) on another (e.g., mental health), allowing for the exploration of potential mechanisms behind the relationship between urban green space and mental health (72). In the SEM, chain mediation models were tested. Mental health was considered a continuous variable in the baseline model. Physical activity intensity was considered a binary variable. Relative deprivation and social trust were considered continuous variables. An analysis of this set of covariates was performed. The green space, sociodemographic, built environment, and individual health characteristics were set as exogenous variables. Relative deprivation, physical activity, social trust, and mental health were set as endogenous variables (Figure 1).

Because the variables estimated in this paper were observed variables rather than latent variables, the SEM without latent variables constructed in this paper can be expressed as follows:

$$y = By + \Gamma x + \delta \tag{1}$$

where y refers to the $N_Y \times 1$ vector of endogenous variables, x refers to the $N_X \times 1$ vector of exogenous variables, B is the $N_Y \times N_X$ matrix of coefficients representing the direct effects of endogenous variables on other endogenous variables, Γ is the $N_Y \times N_X$ matrix of coefficients representing the direct effects of exogenous variables on endogenous variables, and δ is the $N_Y \times 1$ vector of errors in the equation.

Additionally, this study considered existing research to determine the fit parameters for SEM (73), which tested the proposed models. The following model fit parameter criteria were used: the chi-square to degrees of freedom ratio (CMIN/DF) ≤5; root mean square error of approximation (RMSEA) ≤0.08; goodness-of-fit index (GFI) ≥0.90; normed fit index (NFI) ≥0.90; incremental fit index (IFI) ≥0.90; Tucker-Lewis index (TLI) ≥0.90; and comparative fit index (CFI) ≥0.90. SPSS Amos 26 was used for multi-level SEM, and STATA version 13.1 was used for basic pre-analysis data cleaning.

TABLE 1 Statistics of variables.

Variables	Assignments	Total ($N = 2,465$)
Dependent variables		
Mental health [mean (SD)]	Continuous variables (20–80)	71.73 (9.89)
Independent variable		
Green [mean (SD)]	Continuous variables	41.01 (3.60)
Mediators		
Relative deprivation [mean (SD)]	Continuous variables (1–10)	4.50 (1.77)
Social trust [mean (SD)]	Continuous variables (9–45)	30.78 (4.12)
Physical activity [*N* (%)]	1 = regular exercise for the last month	677 (27.5%)
	0 = no regular exercise for the last month	1,788 (72.5%)
Covariates		
Annual personal income [mean (SD)]	Continuous variables	16,752.10 (18,911.34)
Marital status [*N* (%)]	1 = non-single	2,223 (90.2%)
	0 = single	242 (9.8%)
Hukou [*N* (%)]	1 = local	2,357 (95.6%)
	0 = non-local	108 (4.4%)
Educational attainment [*N* (%)]	1 = educated	1,741 (70.6%)
	0 = uneducated	724 (29.4%)
Sex [*N* (%)]	1 = male	1,304 (52.9%)
	0 = female	1,161 (47.1%)
Sickness and injury status [*N* (%)]	1 = no sickness or injury within the last 2 weeks	2,096 (85.0%)
	0 = sickness and injury within the last 2 weeks	369 (15.0%)
History of alcohol consumption [*N* (%)]	1 = no history of alcohol consumption	1,881 (76.3%)
	0 = history of alcohol consumption	584 (23.7%)
History of smoking consumption [*N* (%)]	1 = no history of smoking consumption	806 (32.7%)
	0 = history of smoking consumption	1,659 (67.3%)

4 Results

4.1. Descriptive statistics

Table 1 presents the descriptive statistics for all the variables. The mean score of mental health was 71.73 (SD ±9.89), which was much higher than the cutoff (i.e., 2/3 of the total score of 80), revealing that the participants exhibited good mental health. The mean levels of relative deprivation and social trust were 4.50 (SD ±1.77) and 30.78 (SD ±4.12), respectively. Notably, the mean value of relative deprivation is less than half of the total relative deprivation score, indicating that older adults perceive themselves to be in a vulnerable position in society. Regarding physical activity, 72.5% of the older adults did not exercise regularly in the previous month, constituting the majority of the total sample and indicating a lack of physical activity among older adults. Regarding the control variables, 70.6% of the participants were educated, 90.2% were not single, 95.6% were local, 52.9% were male, 85% had no illness or injury in the preceding 2 weeks, 76.3% had no history of alcohol consumption, and 32.7% had no history of smoking. The mean annual income of older adults was 16,752.10 yuan (SD ± 18,911.34).

4.2. Structural equation analysis

4.2.1. Analysis and fit of the model

SEM model was used to validate the conceptual framework (Figure 2). The fitness indicators of the model are as follows: CMIN/DF = 2.473, RMSEA = 0.025, GFI = 0.984, NFI = 0.969, IFI = 0.982, TLI = 0.969, and CFI = 0.981. The model passes the test for each indicator, as outlined in Section 3.3.

4.2.2. Associations between green space, mediators, and mental health

The SEM model results are shown in Figure 3. Urban green space was significantly and positively associated with the mental health of older adults ($\beta = 0.035$, $p < 0.1$), indicating that an increase in urban green space favors the level of mental health of older adults. Therefore, Hypotheses 1 was supported. In the association between urban green space and mediating variables, urban green space was positively associated with both relative deprivation ($\beta = 0.055$, $p < 0.05$) and physical activity ($\beta = 0.031$, $p < 0.1$). The results reveal that an increase in urban green space allows more older adults to enjoy the benefits of green space resources in order to reduce the relative deprivation. In addition, the increase in green spaces provides more open space for older adults to engage in more physical activities. By contrast, there was no statistical relationship between urban green space and social trust ($\beta = -0.007$, $p > 0.1$). This suggests that an increase in urban green space does not directly increase social trust among older adults. Regarding the interrelationships of the three mediating variables, relative deprivation was positively associated with both increased physical activity ($\beta = 0.136$, $p < 0.01$) and social trust ($\beta = 0.111$, $p < 0.01$) among older adults. This suggests that lower relative deprivation among older adults increase their willingness to be physically active and social trusting. Regarding the relationship between the three mediating variables and mental health, older adults with lower relative deprivation were more likely to report higher levels of mental health ($\beta = 0.218$, $p < 0.01$). A decrease in relative deprivation suggests that older adults' perceived social status has risen, which to a certain extent enhances their psychological feelings of self-confidence, self-esteem, and pleasure, which is conducive to their psychological wellbeing. Older adults who engaged in regular physical activity were more likely to report higher levels of mental health ($\beta = 0.046$, $p < 0.05$). Additionally, older adults with higher levels of interpersonal trust in society were likely to have higher levels of mental health ($\beta = 0.093$, $p < 0.01$).

Table 2 presents the direct, indirect, and overall effects of urban green spaces and covariates on mental health. The overall effect of urban green spaces on mental health was statistically significant. The relationship between urban green spaces and mental health was mediated by relative deprivation and physical activity with indirect effect coefficients of 0.011 ($p < 0.05$) and 0.002 ($p < 0.1$), respectively. There is insufficient evidence in this study that social trust mediates the relationship between urban green spaces and mental health ($\beta = -0.001$, $p > 0.1$). Therefore, Hypotheses 2 was partially supported. This result reveals the role of urban green spaces in influencing mental health, mainly by reducing relative deprivation and promoting physical activity in older adults, thus improving mental health. In addition, urban green spaces can influence the level of mental health of older adults by influencing the feeling of relative deprivation, which in turn affects physical activity and social trust, with indirect effect coefficients of 0.001 ($p < 0.05$) and 0.001 ($p < 0.05$), respectively. Therefore, Hypotheses 3 was supported. These results reveal that a sense of relative deprivation plays an important mediating role between urban green spaces and mental health, which may, in turn, affect mental health through social interactions and other pathways.

5 Discussion

5.1 Green spaces and mental health

The results of this study showed that older adults with more green spaces in their living environments exhibited better mental health than those with less green spaces. This finding is consistent with those of most existing evidence (74, 75). Natural landscapes within green spaces can provide a rich sensory experience that helps residents relieve stress, generate positive attitudes, and relieve negative emotions. This study takes urban green space coverage as a quantitative index, and the results also prove that urban green space coverage is related to the mental health of older adults. A possible explanation is the relationship between green space and urban environmental improvement. The improvement of urban greening coverage is beneficial to reducing air pollution in urban (76). Many studies have proved that air pollution in urban is one of the important causes of damage to the mental health of older adults (77–80), including the increased risk of depression (78), the occurrence of sleep disorders (80), and the decline of cognitive function (79). Moreover, older adults who exhibit reduced abilities due to physical or cognitive decline may be highly sensitive to changes in environmental factors (81). Such that urban green spaces may have better direct benefits for the mental health of older adults compared to residents of other age groups (82). It shows that the improvement of urban green space coverage helps maintain a good psychological state.

Land measurements may influence the association between green spaces and mental health in older adults. This study used the coverage rate of green space in the urban built environment as an indicator to quantify urban green space, while other relevant indicators of urban green space, such as type, quality, and subjective perception, were missing (83). For example, Wang et al. (84)

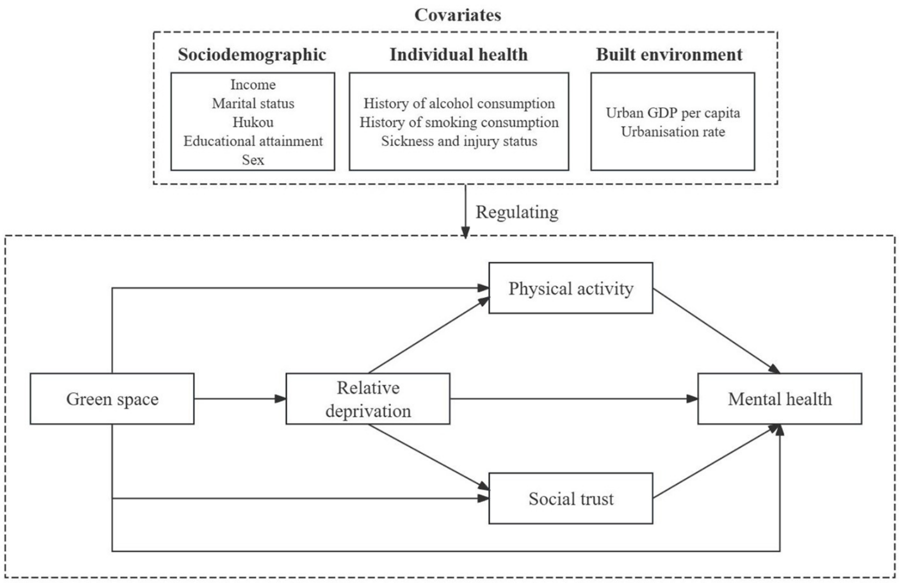

FIGURE 2
Conceptual framework.

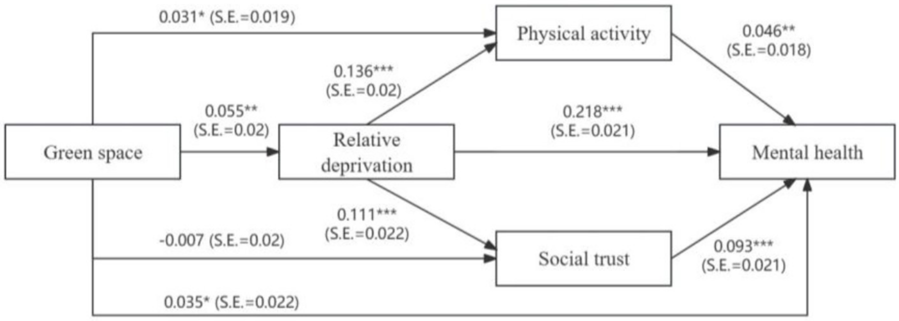

FIGURE 3
The model was adjusted for all covariates shown in Table 1. All the coefficients are standardized regression coefficients. $*p < 0.1$, $**p < 0.05$, $***p < 0.01$.

evaluated the quality of green space with respect to accessibility, maintenance, change, naturalness, color, clear arrangement, shelter, presence of garbage, safety, and overall impression, and found that abundant green space is correlated with enhanced mental health. Regarding subjective perception, previous studies have shown that green spaces directly impact older adults' mental health through the perception of bodily organs, wherein streetscape greenery can directly affect older adults' mental health through their visual system (14).

5.2 Potential associations between green spaces and mental health

The relationship between green spaces and older adults' mental health is influenced by many complex and potential factors. Studies have shown that green spaces mediate older adults' mental health through relative deprivation. With the increase of green space, older adults' sense of relative deprivation was weakened, which indirectly improved their mental health status. Relative deprivation means that individuals or groups realize that they are in a disadvantageous position through comparison and think that they deserve better treatment, which leads to anger, resentment, anxiety and other negative emotions (85), and has adverse impact on mental health (86). For older adults, relative deprivation is associated with depression and low cognitive function (87). The existing evidence has shown that relative deprivation affects older adults more than middle-aged people (24, 57). So far, in the research on green space and mental health, academic circles have paid more attention to the differences caused by absolute deprivation, but less research on the role played by relative deprivation. Therefore, we innovatively consider the mediating role of relative deprivation in studying the relationship between green space and mental health in older adults. According to social comparison theory, individuals interacting with others with similar social status can help alleviate mental

TABLE 2 The direct effect, indirect effect and total effect of green space and covariates on mental health.

	Direct effect Coef. (SE)	Indirect effect Coef. (SE)	Total effect Coef. (SE)
Green space → mental health	0.035* (SE = 0.022)	0.014** (SE = 0.006)	0.049** (SE = 0.022)
Green space → relative deprivation → mental health		0.011** (SE = 0.005)	
Green space → physical activity → mental health		0.002* (SE = 0.001)	
Green space → social trust → mental health		−0.001 (SE = 0.002)	
Green space → relative deprivation → physical activity → mental health		0.001** (SE = 0.001)	
Green space → relative deprivation → social trust → mental health		0.001** (SE = 0.001)	
Covariates			
Annual personal income → mental health	0.016 (SE = 0.019)		
Marital status → mental health	0.006 (SE = 0.019)		
Hukou → mental health	−0.007 (SE = 0.016)		
Educational attainment → mental health	0.046** (SE = 0.022)		
Sex → mental health	0.100*** (SE = 0.025)		
Sickness and injury status → mental health	0.158*** (SE = 0.022)		
History of alcohol consumption → mental health	−0.001 (SE = 0.020)		
History of smoking consumption → mental health	0.037 (SE = 0.023)		
Urban GDP per capita → mental health	0.179*** (SE = 0.032)		
Urbanization rate → mental health	−0.067** (SE = 0.035)		

Coef., coefficient; SE, standard error.
*p < 0.1.
**p < 0.05.
***p < 0.01.
The model was adjusted for all covariates shown in this Table. All the coefficients are standardized regression coefficients.

stress and cognitive inconsistency (88, 89). As an important public resource, urban green space is affected by the degree of absolute deprivation, and individuals with lower absolute deprivation can get more green space resources (47–50). As a result, individuals with different socio-economic status have differences in acquiring green space resources. The improvement of green space coverage can help improve the accessibility of green space and alleviate environmental inequality (90). Therefore, the increase in urban green space may help to narrow the difference in green space resources accessed between relatively low-status older adults and relatively high-status older adults. The contrast between the green resources subjectively available to older adults and those available to the surrounding groups may be even less obvious. Thus, it is helpful to reduce the comparison of older adults in terms of access to green space resources, relieve the pressure on older adults and their dissatisfaction with social inequity, and promote improvement in the mental health level of older adults. Earlier empirical studies have indicated that in the social environment of smaller comparison, individuals with lower status may face less obvious contrast, bear less psychological pressure, and have better mental health status (91). At the same time, in the research on the relationship between green space and wellbeing, it is also shown that relative deprivation partially mediates the relationship between green space and wellbeing (92). Wellbeing is closely related to mental health. This study confirms these early findings to some extent.

Secondly, this study also found that physical activity played an important role in the relationship between green spaces and mental health among older adults. This is consistent with the conclusions of most current studies (43, 93). Urban green spaces are the primary sites for physical exercise and activity. They provide open, healthy, and active outdoor spaces for adults, which helps enhance their physical activity abilities (94). Physical activity is important for older adults to remain healthy. Studies have shown that regular physical exercise in green spaces can greatly reduce health risks associated with cardiovascular diseases, respiratory diseases, hypertension, paralysis, diabetes, and other chronic diseases (38). Simultaneously, higher levels of physical activity are significantly associated with lower rates of mental illness, and appropriate physical activity can help reduce the risk of depression and anxiety in older adults (95), improve memory function (96), and alleviate cognitive impairment (97). Therefore, improving urban green space coverage can help improve older adults' physical activity and reduce the risk of chronic diseases and mental illness, thus improving older adults' mental health. Further, this study hypothesized that urban green spaces enhance the social trust of older adults and are thus associated with their mental health; however, the results showed that there was no significant mediating effect between social trust and green spaces and older adults' mental health. The current research mainly discusses the relationship between trust and green spaces based on trust-related indicators. For example, interpersonal trust in social capital plays a mediating role in alleviating loneliness in older adults through green space (98). But the role of social trust indicators in the relationship between green space and mental health has been less explored. More from the social cohesion, social capital, and other aspects to explore the relationship. The benefits of green spaces for older adults should be further explored (8, 14, 98, 99).

Considering the interwoven relationship between potential intermediaries, this study suggests that urban green spaces indirectly benefit older adults' mental health through relative deprivation (physical activity) and relative deprivation (with social trust). Both pathways were consistent with the expected results. The improvement of green spaces can help reduce the negative impact of relative deprivation on older adults and encourage them to carry out physical activities, thus improving mental health. There was a positive correlation between relative deprivation and physical activities. On the one hand, deprived people are less likely to be physically active than privileged people (100). On the other hand, relative deprivation disrupts the ability of older adults to age successfully and reduces healthy behaviors in older adults, including physical activity (16). The psychological pathway that intensifies social comparison is associated with individual physical activity (58). As for green space—relative deprivation—social trust—mental health pathway, relative deprivation is associated with relevant indicators of social trust. First, lower subjective social status predicts higher perceptions of relative deprivation, which in turn predicts higher interpersonal distrust (101). Individuals with lower subjective status tend to believe that they have less access to resources, and the perception of limited resources can be a threat to interpersonal communication and contribute to mistrust (102). Second, social trust is an important factor affecting emotional health; social trust can help reduce the risk of depression among older adults (103). Higher levels of social trust contribute to higher life goals and self-realization in older adults. Additionally, a high level of mental health among older adults depends on a high level of social trust and support (99). Therefore, a possible explanation is that green spaces can improve older adults' sense of trust in society by reducing the negative impact of relative deprivation on interpersonal relationships, thus affecting their mental health.

This study has some limitations. First, the data selected for this study were cross-sectional. In the statistical collection of cross-sectional data, there may be missing variables or unobservable differences between individuals. Second, owing to data limitations, this study did not consider attributes such as accessibility, quality, type, and subjective perception of green spaces. Although the coverage rate of green space is also an important indicator of urban green space, the lack of other green space attributes affects the final results of the study to some extent. Simultaneously, limited by the original data of the study sample, only a single indicator was selected to measure relative deprivation. Although relative deprivation can be explained to a certain extent, the ideal state of multidimensional measurement has not been reached, which may affect the accuracy of the results. More complex tests will be required in future studies and analyses.

6 Conclusion

This study employed SEM model, using statistics from the nationally representative 2018 CLDS database, to examine the relationship between urban green space rates and older adults' mental health in Chinese urban settings, with a particular focus on the multiple mediating roles of relative deprivation, physical activity, and social trust. The SEM results indicated that urban green spaces were positively associated with older adults' mental health. This suggests that having more greenery in built-up urban areas can improve older adults' mental health. The results of the mediation analysis showed that green spaces can enhance the sense of relative deprivation and physical activity, which, in turn, affects older adults' mental health. There was no evidence that social trust directly mediates the relationship between green spaces and mental health. Further, relative deprivation can mediate the effect of green spaces on mental health by promoting physical activity, social trust, and ultimately, mental health among older adults.

The results of this study are of great significance for promoting the construction of healthy living cities and ensuring healthy aging in China. First, green space can improve the mental health of older adults. The government should implement scientific urban environmental intervention measures to enhance the construction of green space in the urban. Secondly, from the perspective of the role of relative deprivation in the connection between green space and the mental health of older adults, it is very important to promote the environmental equity of urban green space. In the long-term development of the urban, the use of urban planning means to build more fair, safe and comfortable urban public green space and narrow the difference of green space resources obtained by older adults with different social and economic status plays an important role in improving the mental health level of older adults. But in the short term, it is not realistic to increase the green space in the urban. Therefore, other ways are recommended to make the health benefits of green space better reach older adults. Emphasis should be placed on improving the quality of existing green Spaces, especially those in poorer urban environments, taking into account the actual needs of older adults to use green Spaces, such as building sound barrier-free facilities and eliminating unnecessary height differences. At the same time, the government or all sectors of society can make use of urban green Spaces to carry out social activities for older adults, encourage older adults to engage in physical exercise and social interaction in green Spaces, and increase the opportunities for older adults to contact the natural environment in their daily lives. For example, gardening activities for older adults are carried out in urban public green Spaces to provide an interesting and enjoyable gardening experience for older adults. To increase older adults' contact with natural landscapes, plants and sounds, in order to reduce the generation of negative emotions and improve their mental health (104). In addition, according to our research results, physical activities in green areas are conducive to the maintenance of good mental health of older adults, and activities such as aerobics, dancing and walking can be organized in green spaces for older adults. Moreover, social interaction in green Spaces contributes to positive psychological changes. Carrying out social activities for older adults in green space, such as literary performances and chess games, is conducive to increasing the social interaction opportunities of older adults, promoting the improvement of older adults' sense of social trust, and reducing the negative mental health status of older adults. Finally, the good quality of urban green space and the development of older adults' activities cannot be separated from a sound green space operation, maintenance and management system. Effective management of urban green space plays an important role in promoting the long-term benefit of green space to the mental health of older adults.

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

WZ: Conceptualization, Data curation, Formal analysis, Methodology, Writing – original draft. BC: Conceptualization, Data curation, Methodology, Writing – original draft. XF: Conceptualization, Formal analysis, Resources, Writing – original draft. XZ: Resources, Supervision, Writing – original draft, Funding acquisition.

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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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References

1. Leaving No One behind in an Ageing World; Vereinte Nationen, Ed., World Social Report. New York, NY: United Nations (2023). ISBN 978-92-1-130458-9.

2. National Bureau of Statistics Main Data of the Seventh National Population Census. Available at: https://www.stats.gov.cn/english/PressRelease/202105/t20210510_1817185.html (accessed May 19, 2024).

3. Lei X, Sun X, Strauss J, Zhang P, Zhao Y. Depressive symptoms and ses among the mid-aged and elderly in China: evidence from the China health and retirement longitudinal study national baseline. *Soc Sci Med.* (2014) 120:224–32. doi: 10.1016/j.socscimed.2014.09.028

4. McGee P, Tuokko H, Maccourt P, Donnelly M. Factors affecting the mental health of older adults in rural and urban communities: an exploration. *Can J Commun Ment Health.* (2004) 23:117–26. doi: 10.7870/cjcmh-2004-0018

5. Cicek B, Sahin H, Erkal S. Factors affecting the risk of self neglect and loneliness level of the older adults: a case study from Turkey. *Educ Gerontol.* (2024) 50:62–75. doi: 10.1080/03601277.2023.2219956

6. Han A-R, Park S-A, Ahn B-E. Reduced stress and improved physical functional ability in elderly with mental health problems following a horticultural therapy program. *Complement Ther Med.* (2018) 38:19–23. doi: 10.1016/j.ctim.2018.03.011

7. National Health Commission. *The 14th Five-Year Plan for Healthy Ageing*. Beijing: National Health Commission.

8. Zheng Y, Cheng B, Dong L, Zheng T, Wu R. The moderating effect of social participation on the relationship between urban green space and the mental health of older adults: a case study in China. *Land.* (2024) 13:317. doi: 10.3390/land13030317

9. Liu Y, Xiao T, Wu W. Can Multiple pathways link urban residential greenspace to subjective well-being among middle-aged and older Chinese adults? *Landsc Urban Plan.* (2022) 223:104405. doi: 10.1016/j.landurbplan.2022.104405

10. Diener A, Mudu P. How can vegetation protect us from air pollution? A critical review on green spaces' mitigation abilities for air-borne particles from a public health perspective-with implications for urban planning. *Sci Total Environ.* (2021) 796:148605. doi: 10.1016/j.scitotenv.2021.148605

11. Na H. The Effect of urban green-space on relieving the urban heat island effect in Beijing, China. *Acad J Environ Earth Sci.* (2023) 5:25–41. doi: 10.25236/AJEE.2023.050804

12. Xu C, Han B, Lu F, Wu T. Assessing the traffic noise reduction effect of roadside green space using LiDAR point cloud data in Shenzhen, China. *Forests.* (2022) 13:765. doi: 10.3390/f13050765

13. Markevych I, Schoierer J, Hartig T, Chudnovsky A, Hystad P, Dzhambov AM, et al. Greenspace to health: theoretical and methodological guidance. *Environ Res.* (2017) 158:301–17. doi: 10.1016/j.envres.2017.06.028

14. Liu Y, Wang R, Lu Y, Li Z, Chen H, Cao M, et al. Natural outdoor environment, neighbourhood social cohesion and mental health: using multilevel structural equation modelling, streetscape and remote-sensing metrics. *Urban For Urban Green.* (2020) 48:126576. doi: 10.1016/j.ufug.2019.126576

15. Kaplan R, and Kaplan, S. *The Experience of Nature: A Psychological Perspective.* Cambridge: Cambridge University Press (1989). ISBN 0-521-34939-7.

16. Zheng X, Leng J, Ma H, Hu P. Physical "lying flat": the negative effect of personal relative deprivation on health-promoting lifestyles. *J Affect Disord.* (2024) 349:414–9. doi: 10.1016/j.jad.2024.01.006

17. Yang Z, Fang H, Wei G, Mo J, Gao X, Zhang S, et al. An assessment of urban park accessibility using multi-source data in Hefei, China: a social equity perspective. *Land Degrad Dev.* (2024) 35:3627–41. doi: 10.1002/ldr.5156

18. Patiño JE. Analyzing long-term availability of urban green space by socioeconomic status in Medellin, Colombia, using open data and tools. *IEEE.* (2020) 87–92. doi: 10.1109/LAGIRS48042.2020.9165672

19. Aerts R, Nemery B, Bauwelinck M, Trabelsi S, Deboosere P, Van Nieuwenhuyse A, et al. Residential green space, air pollution, socioeconomic deprivation and cardiovascular medication sales in Belgium: a nationwide ecological study. *Sci Total Environ.* (2020) 712:136426. doi: 10.1016/j.scitotenv.2019.136426

20. Deaton A. Health, inequality, and economic development. *J Econ Lit.* (2003) 41:113–58. doi: 10.1257/jel.41.1.113

21. Mummendey A, Kessler T, Klink A, Mielke R. Strategies to cope with negative social identity: predictions by social identity theory and relative deprivation theory. *J Pers Soc Psychol.* (1999) 76:229. doi: 10.1037//0022-3514.76.2.229

22. Wilkinson RG. *Unhealthy Societies: The Afflictions of Inequality*. New York, NY: Routledge (2002). ISBN 0-203-42168-X.

23. Walker I, Smith HJ. *Relative Deprivation: Specification, Development, and Integration*. Cambridge: Cambridge University Press (2002). ISBN 0-521-80132-X.

24. Lyu S, Sun J. How does personal relative deprivation affect mental health among the older adults in China? Evidence from panel data analysis. *J Affect Disord.* (2020) 277:612–9. doi: 10.1016/j.jad.2020.08.084

25. Chiao C, Weng L-J, Botticello AL. Social participation reduces depressive symptoms among older adults: an 18-year longitudinal analysis in Taiwan. *BMC Public Health.* (2011) 11:1–9. doi: 10.1186/1471-2458-11-292

26. Goldberg DP, Hillier VFA. Scaled version of the general health questionnaire. *Psychol Med.* (1979) 9:139–45. doi: 10.1017/S0033291700021644

27. Tennant R, Hiller L, Fishwick R, Platt S, Joseph S, Weich S, et al. The Warwick-Edinburgh Mental Well-Being Scale (WEMWBS): development and UK validation. *Health Qual Life Outcomes.* (2007) 5:1–13. doi: 10.1186/1477-7525-5-63

28. Group TE. EuroQol-a new facility for the measurement of health-related quality of life. *Health Policy.* (1990) 16:199–208. doi: 10.1016/0168-8510(90)90421-9

29. Roberts BL, Dunkle R, Haug M. Physical, psychological, and social resources as moderators of the relationship of stress to mental health of the very old. *J Gerontol.* (1994) 49:S35–43. doi: 10.1093/geronj/49.1.S35

30. Baune BT, Suslow T, Arolt V, Berger K. The relationship between psychological dimensions of depressive symptoms and cognitive functioning in the elderly–the MEMO-study. *J Psychiatr Res.* (2007) 41:247–54. doi: 10.1016/j.jpsychires.2006.06.004

31. Sheikholeslami F, Reza Masouleh S, Khodadadi N, Yazdani MA. Loneliness and general health of elderly. *J Holist Nurs Midwifery.* (2011) 21:28–34.

32. Chou K-L, Chi I. Comparison between elderly Chinese living alone and those living with others. *J Gerontol Soc Work.* (2000) 33:51–66. doi: 10.1300/J083v33n04_05

33. Gallego F, Larroulet C, Palomer L, Repetto A, Verdugo D. Socioeconomic inequalities in self-perceived oral health among adults in Chile. *Int J Equity Health.* (2017) 16:1–13. doi: 10.1186/s12939-017-0519-9

34. Kuo C-T, Chiang T. The association between relative deprivation and self-rated health, depressive symptoms, and smoking behavior in Taiwan. *Soc Sci Med.* (2013) 89:39–44. doi: 10.1016/j.socscimed.2013.04.015

35. Pak T-Y, Choung Y. Relative deprivation and suicide risk in South Korea. *Soc Sci Med.* (2020) 247:112815. doi: 10.1016/j.socscimed.2020.112815

36. Chen J, Zeng Y, Fang Y. Effects of social participation patterns and living arrangement on mental health of chinese older adults: a latent class analysis. *Front Public Health.* (2022) 10:915541. doi: 10.3389/fpubh.2022.915541

37. Iizuka G, Tsuji T, Ide K, Watanabe R, Kondo K. Does social participation foster social support among the older population in Japan? A three-year follow-up study from the japan gerontological evaluation study. *SSM-Popul Health.* (2023) 22:101410. doi: 10.1016/j.ssmph.2023.101410

38. Ali MJ, Rahaman M, Hossain SI. Urban green spaces for elderly human health: a planning model for healthy city living. *Land Use Policy.* (2022) 114:105970. doi: 10.1016/j.landusepol.2021.105970

39. Wang R, Browning MHEM, Qin X, He J, Wu W, Yao Y, et al. Visible green space predicts emotion: evidence from social media and street view data. *Appl Geogr.* (2022) 148:102803. doi: 10.1016/j.apgeog.2022.102803

40. Helbich M, Yao Y, Liu Y, Zhang J, Liu P, Wang R, et al. Using deep learning to examine street view green and blue spaces and their associations with geriatric depression in Beijing, China. *Environ Int.* (2019) 126:107–17. doi: 10.1016/j.envint.2019.02.013

41. Arbuthnott KD. Nature exposure and social health: prosocial behavior, social cohesion, and effect pathways. *J Environ Psychol.* (2023) 90:102109. doi: 10.1016/j.jenvp.2023.102109

42. Liu Y, Wang R, Grekousis G, Liu Y, Yuan Y, Li Z. Neighbourhood greenness and mental wellbeing in Guangzhou, China: what are the pathways? *Landsc Urban Plan.* (2019) 190:103602. doi: 10.1016/j.landurbplan.2019.103602

43. Liu Y, Wang R, Xiao Y, Huang B, Chen H, Li Z, et al. Exploring the linkage between greenness exposure and depression among chinese people: mediating roles of physical activity, stress and social cohesion and moderating role of urbanicity. *Health Place.* (2019) 58:102168. doi: 10.1016/j.healthplace.2019.102168

44. Akpinar A, Barbosa-Leiker C, Brooks KR. Does green space matter? Exploring relationships between green space type and health indicators. *Urban For Urban Green.* (2016) 20:407–18. doi: 10.1016/j.ufug.2016.10.013

45. Li Q. *Sociological Theory of "Deprivation" and the Problem of Peasant Workers in China*. Academics (2004), p. 7–22. doi: 10.3969/j.issn.1002-1698.2004.04.001

46. Xiong M, Ye Y. The concept, measurement, influencing factors and effects of relative deprivation. *Adv Psychol Sci.* (2016) 24:438. doi: 10.3724/SP.J.1042.2016.00438

47. Schüle SA, Hilz LK, Dreger S, Bolte G. Social inequalities in environmental resources of green and blue spaces: a review of evidence in the WHO European Region. *Int J Environ Res Public Health.* (2019) 16:1216. doi: 10.3390/ijerph16071216

48. Xiao Y, Wang Z, Li Z, Tang Z. An assessment of urban park access in shanghai–implications for the social equity in Urban China. *Landsc Urban Plan.* (2017) 157:383–93. doi: 10.1016/j.landurbplan.2016.08.007

49. Chen Y. Which communities have better accessibility to green space? An investigation into environmental inequality using big data. *Landsc Urban Plann.* (2020) 204:103919. doi: 10.1016/j.landurbplan.2020.103919

50. Rigolon A. Parks and young people: an environmental justice study of park proximity, acreage, and quality in Denver, Colorado. *Landsc Urban Plan.* (2017) 165:73–83. doi: 10.1016/j.landurbplan.2017.05.007

51. Rigolon AA. Complex landscape of inequity in access to urban parks: a literature review. *Landsc Urban Plan.* (2016) 153:160–9. doi: 10.1016/j.landurbplan.2016.05.017

52. Wang Q, Lan Z. Park green green spaces, public health and social inequalities: understanding the interrelationships for policy implications. *Land Use Pol.* (2019) 83:66–74. doi: 10.1016/j.landusepol.2019.01.026

53. Hong A, Martinez L, Patino JE, Duque JC, Rahimi K. Neighbourhood green space and health disparities in the global south: evidence from Cali, Colombia. *Health Place.* (2021) 72:102690. doi: 10.1016/j.healthplace.2021.102690

54. Mills C. The psychiatrization of poverty: rethinking the mental health–poverty nexus. *Soc Personal Psychol Compass.* (2015) 9:213–22. doi: 10.1111/spc3.12168

55. Feinstein JS. The relationship between socioeconomic status and health: a review of the literature. *Milbank Q.* (1993) 71:279–322. doi: 10.2307/3350401

56. Caner A, Yigit YC. Relative deprivation and its association with health indicators: lower inequality may not improve health. *SSM-Popul Health.* (2019) 7:100381. doi: 10.1016/j.ssmph.2019.100381

57. Liu C, Yi F. Relative deprivation and health revisited: new evidence from middle-aged and older adults in rural China. *China Econ Rev.* (2023) 79:101948. doi: 10.1016/j.chieco.2023.101948

58. Elgar FJ, Xie A, Pförtner T-K, White J, Pickett KE. Relative deprivation and risk factors for obesity in canadian adolescents. *Soc Sci Med.* (2016) 152:111–8. doi: 10.1016/j.socscimed.2016.01.039

59. Hu A. On the relationship between subjective inequality and generalized trust. *Res Soc Stratif Mobil.* (2017) 49:11–9. doi: 10.1016/j.rssm.2017.03.003

60. Fischer JAV, Torgler B. The effect of relative income position on social capital. *Econ Bull.* (2006) 26:1–20. doi: 10.1111/j.1439-054X.2006.00097.x

61. Vegaraju A, Amiri S. Urban green and blue spaces and general and mental health among older adults in washington state: analysis of BRFSS data between 2011-2019. *Health Place.* (2024) 85:103148. doi: 10.1016/j.healthplace.2023.103148

62. Cardinali M, Beenackers MA, Fleury-Bahi G, Bodénan P, Petrova MT, van Timmeren A, et al. Examining green space characteristics for social cohesion and mental health outcomes: a sensitivity analysis in four European Cities. *Urban For Urban Green.* (2024) 93:128230. doi: 10.1016/j.ufug.2024.128230

63. Jöreskog KG, Sörbom D. Recent developments in structural equation modeling. *J Mark Res.* (1982) 19:404–16. doi: 10.1177/002224378201900402

64. Tarka P. An overview of structural equation modeling: its beginnings, historical development, usefulness and controversies in the social sciences. *Qual Quant.* (2018) 52:313–54. doi: 10.1007/s11135-017-0469-8

65. Dzhambov AM, Markevych I, Hartig T, Tilov B, Arabadzhiev Z, Stoyanov D, et al. Multiple pathways link urban green- and bluespace to mental health in young adults. *Environ Res.* (2018) 166:223–33. doi: 10.1016/j.envres.2018.06.004

66. Woo J, Yu R, Cheung K, Lai E. How much money is enough? Poverty and health in older people. *J Nutr Health Aging.* (2020) 24:1111–5. doi: 10.1007/s12603-020-1444-y

67. Radloff LS. The CES-D scale: a self-report depression scale for research in the general population. *Appl Psychol Meas.* (1977) 1:385–401. doi: 10.1177/014662167700100306

68. Helbich M, Klein N, Roberts H, Hagedoorn P, Groenewegen PP. More green space is related to less antidepressant prescription rates in the Netherlands: a Bayesian geoadditive quantile regression approach. *Environ Res.* (2018) 166:290–7. doi: 10.1016/j.envres.2018.06.010

69. Urban Socio-Economic Survey Division, National Bureau of Statistics 2018 China Urban Statistical Yearbook. (2019). ISBN 978-7-5037-8770-6.

70. Adler NE, Epel ES, Castellazzo G, Ickovics JR. Relationship of subjective and objective social status with psychological and physiological

functioning: preliminary data in healthy, White Women. *Health Psychol.* (2000) 19:586. doi: 10.1037//0278-6133.19.6.586

71. Guo Y, Liu Y, Lu S, Chan OF, Chui CHK, Lum TYS, et al. Objective and perceived built environment, sense of community, and mental wellbeing in older adults in hong kong: a multilevel structural equation study. *Landsc Urban Plan.* (2021) 209:104058. doi: 10.1016/j.landurbplan.2021.104058

72. Ullman JB, Bentler PM. Structural equation modeling. In: *Handbook of Psychology*, 2nd Edn. Hoboken, NJ: John Wiley & Sons, Inc (2012), p. 2. doi: 10.1002/9781118133880.hop202023

73. Hu L, Bentler PM. Cutoff criteria for fit indexes in covariance structure analysis: conventional criteria versus new alternatives. *Struct Equ Model Multidiscip J.* (1999) 6:1–55. doi: 10.1080/10705519909540118

74. Van Herzele A, De Vries S. Linking green space to health: a comparative study of two urban neighbourhoods in Ghent, Belgium. *Popul Environ.* (2012) 34:171–93. doi: 10.1007/s11111-011-0153-1

75. Grigoletto A, Toselli S, Zijlema W, Marquez S, Triguero-Mas M, Gidlow C, et al. Restoration in mental health after visiting urban green spaces, who is most affected? Comparison between good/poor mental health in four European Cities. *Environ Res.* (2023) 223:115397. doi: 10.1016/j.envres.2023.115397

76. Qiu L, Liu F, Zhang X, Gao T. Difference of airborne particulate matter concentration in urban space with different green coverage rates in Baoji, China. *Int J Environ Res Public Health.* (2019) 16:1465. doi: 10.3390/ijerph16081465

77. Zhou Y, Liu J. Air Pollution and mental health of older adults in China. *Sustainability.* (2020) 12:950. doi: 10.3390/su12030950

78. Pun VC, Manjourides J, Suh H. Association of ambient air pollution with depressive and anxiety symptoms in older adults: results from the NSHAP study. *Environ Health Perspect.* (2017) 125:342–8. doi: 10.1289/EHP494

79. Lo Y-TC, Lu Y-C, Chang Y-H, Kao S, Huang H-B. Air pollution exposure and cognitive function in taiwanese older adults: a repeated measurement study. *Int J Environ Res Public Health.* (2019) 16:2976. doi: 10.3390/ijerph16162976

80. Tang M, Li D, Liew Z, Wei F, Wang J, Jin M, et al. The association of short-term effects of air pollution and sleep disorders among elderly residents in China. *Sci Total Environ.* (2020) 708:134846. doi: 10.1016/j.scitotenv.2019.134846

81. Lawton F, Blackledge G. Melphalan in epithelial ovarian cancer: speed of clinical response as a predictor of activity. *J Obstet Gynaecol.* (1986) 7:135–8. doi: 10.3109/01443618609112297

82. Aliyas Z. Physical, mental, and physiological health benefits of green and blue outdoor spaces among elderly people. *Int J Environ Health Res.* (2021) 31:703–14. doi: 10.1080/09603123.2019.1681379

83. Park H, Brown CD, Pearson ALA. Systematic review of audit tools for evaluating the quality of green spaces in mental health research. *Health and Place.* (2024) 86:103185. doi: 10.1016/j.healthplace.2024.103185

84. Wang R, Feng Z, Pearce J, Zhou S, Zhang L, Liu Y, et al. Dynamic greenspace exposure and residents' mental health in Guangzhou, China: from over-head to eye-level perspective, from quantity to quality. *Landsc Urban Plan.* (2021) 215:104230. doi: 10.1016/j.landurbplan.2021.104230

85. Smith HJ, Pettigrew TF, Pippin GM, Bialosiewicz S. Relative deprivation: a theoretical and meta-analytic review. *Pers Soc Psychol Rev.* (2012) 16:203–32. doi: 10.1177/1088868311430825

86. Beshai S, Mishra S, Meadows TJS, Parmar P, Huang V. Minding the gap: subjective relative deprivation and depressive symptoms. *Soc Sci Med.* (2017) 173:18–25. doi: 10.1016/j.socscimed.2016.11.021

87. Hofbauer LM, Rodriguez FS. Association of social deprivation with cognitive status and decline in older adults. *Int J Geriatr Psychiatry.* (2021) 36:1085–94. doi: 10.1002/gps.5555

88. Schieman S, Pearlin LI. Neighborhood disadvantage, social comparisons, and the subjective assessment of ambient problems among older adults. *Soc Psychol Q.* (2006) 69:253–69. doi: 10.1177/019027250606900303

89. Young M, Wheaton B. The impact of neighborhood composition on work-family conflict and distress. *J Health Soc Behav.* (2013) 54:481–97. doi: 10.1177/0022146513504761

90. Huang S, Wang C, Deng M, Chen Y. Coupling coordination between park green space (PGS) and socioeconomic deprivation (SED) in high-density city based on multi-scale: from environmental justice perspective. *Land.* (2022) 12:82. doi: 10.3390/land12010082

91. Yang XY, Hu A, Schieman S. Relative deprivation in context: how contextual status homogeneity shapes the relationship between disadvantaged social status and health. *Soc Sci Res.* (2019) 81:157–69. doi: 10.1016/j.ssresearch.2019.03.011

92. He G, He L, Zhang B, Ge T, Chen Y. The greener, the happier? The effects of greenspace on residents' happiness in contemporary Urban China. *J Community Psychol.* (2022) 50:2808–28. doi: 10.1002/jcop.22798

93. Dadvand P, Bartoll X, Basagana X, Dalmau-Bueno A, Martinez D, Ambros A, et al. Green spaces and general health: roles of mental health status, social support, and physical activity. *Environ Int.* (2016) 91:161–7. doi: 10.1016/j.envint.2016.02.029

94. Petersen E, Schoen G, Liedtke G, Zech A. Relevance of urban green space for physical activity and health-related quality of life in older adults. *Qual Ageing Older Adults.* (2018) 19:158–66. doi: 10.1108/QAOA-01-2018-0002

95. Rahmati M, Lee S, Yon DK, Lee SW, Udeh R, McEvoy M, et al. Physical activity and prevention of mental health complications: an umbrella review. *Neurosci Biobehav Rev.* (2024) 106:105641. doi: 10.1016/j.neubiorev.2024.105641

96. Lino-González AL, Téllez-Alanís B, Carrillo-Mora P, Palacios-Hernández B, Hernández-Galván A, Durand-Rivera A, et al. Physical activity, mental health, support networks, lifestyle, and memory in older adults during the COVID-19 pandemic. *Neurol Perspect.* (2024) 4:100146. doi: 10.1016/j.neurop.2024.100146

97. Qi C, Wang X, Li D, Ding H, Shen J, Jiao Y, et al. of Physical function and physical activity on cognitive function in the elderly. *Glob Transit.* (2024) 6:85–92. doi: 10.1016/j.glt.2024.02.002

98. Su Y, Zhang X, Xuan Y. Linking neighborhood green spaces to loneliness among elderly residents—a path analysis of social capital. *Cities.* (2024) 149:104952. doi: 10.1016/j.cities.2024.104952

99. Gao Y, Wu J. Aging in place in rural Northeast China: a mixed methods examination of the influence of social capital on mental well-being in middle and late adulthood. *Front Public Health.* (2024) 11:1261132. doi: 10.3389/fpubh.2023.1261132

100. Farrell L, Hollingsworth B, Propper C, Shields MA. The socioeconomic gradient in physical inactivity: evidence from one million adults in England. *Soc Sci Med.* (2014) 123:55–63. doi: 10.1016/j.socscimed.2014.10.039

101. Yu G, Zhao F, Wang H, Li S. Subjective social class and distrust among chinese college students: the mediating roles of relative deprivation and belief in a just world. *Curr Psychol.* (2020) 39:2221–30. doi: 10.1007/s12144-018-9908-5

102. Yang T-C, Matthews SA, Shoff C. Individual health care system distrust and neighborhood social environment: how are they jointly associated with self-rated health? *J Urban Health.* (2011) 88:945–58. doi: 10.1007/s11524-011-9561-x

103. Wu TL, Hall BJ, Canham SL, Lam AIF. The association between social capital and depression among chinese older adults living in public housing. *J Nerv Ment Dis.* (2016) 204:764–9. doi: 10.1097/NMD.0000000000000561

104. Chan HY, Ho RC-M, Mahendran R, Ng KS, Tam WW-S, Rawtaer I, et al. Effects of horticultural therapy on elderly' health: protocol of a randomized controlled trial. *BMC Geriatr.* (2017) 17:192. doi: 10.1186/s12877-017-0588-z

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Gender differences in the subjective wellbeing of the older adults and the determinant factors: a case study of Nanjing

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Objective: This paper aims to examine the gendered differences in the subjective wellbeing of older adults and underlying determinant factors which contribute to these differences in China where the unique social and cultural systems, the consequent concept of filial piety and the perceptions towards different living arrangements in later life provide an excellent laboratory for studying the topic.

Methods: Hierarchical linear models are employed to analyze the impacts of household structure and built environment on the subjective wellbeing of older adults based on a survey conducted in Nanjing in 2021.

Results: There are significant gender differences in the subjective wellbeing of older adults, with older women reporting higher levels of subjective wellbeing (4.95 vs.4.69). Gender differences also exist in how the built environment affects the subjective wellbeing of older adults, with a greater impact on older adult women (33.68% vs. 28.50%). Household structure impacts the subjective wellbeing of older adults through the division of housework and the company of family members.

Conclusion: There are three major mechanisms through which gender affects the subjective wellbeing of older adults, including structural mechanisms, socio-cultural mechanisms, and physiological mechanisms. Targeted environmental interventions and urban planning policies are recommended to promote the subjective wellbeing of older adults.

KEYWORDS

subjective wellbeing, older adults, gender differences, built environment, household structure

1 Introduction

Subjective wellbeing (SWB) is an important indicator for measuring the mental health of older adults (1, 2). It is also a critical criterion for assessing "healthy aging". In the era that the whole world is experiencing fast aging, enhancing the SWB of older adults is crucial for improving their mental health and constructing an age-friendly society. The rapid increase in both the proportion and absolute number of older adults in China will have a series of impacts on the entire society (3, 4). The huge gender differences in life expectancy between men and women have resulted in an imbalanced population proportion of older men and women, suggesting that public policies aimed at enhancing the wellbeing and health status of older adults need to account more for gender differences (5, 6).

In recent decades, gender inequality in SWB has been a hot topic of research. There are also many studies that have examined the factors influencing the SWB of older adults (7, 8). Yet, studies focusing on gender differences in the SWB of older adults and the determinant factors are relatively scarce. There are only few exceptions that scholars have explored the impacts of leisure activities participation (9, 10), social involvement (9, 11), intergenerational support (12), and learning behaviors (13) of older adults on the gender differences in SWB. Other factors, including the built environment and household structure, are rarely examined. Previous research has indicated that built environment and household structure are significant factors for the SWB of older adults (14–16), and it seems that they influence the wellbeing of the old men and old women differently. However, to the best of our knowledge, there are still no studies that have comprehensively examined how built environment and household structure are associated with SWB and particularly how these associations vary with gender.

Due to substantial differences in social systems, cultural norms, gender roles and the built environments (17–20), gender differences in SWB among older adults and the determinants might differ across countries (21–23). China's unique social and cultural systems, the consequent concept of filial piety and the perceptions toward different patterns of older adult care and living arrangements in later life as well as the distinctive built environments have resulted in different understandings and preferences regarding SWB from their counterparts in other countries. These differences cast doubt on the applicability of empirical research results and policy recommendations based on cases abroad. In other words, China's distinctive context provides an excellent laboratory for exploring gender differences in the SWB of older adults and can offer a unique perspective to examine the determinant factors of SWB. Therefore, research on gender differences in SWB among older adults in Chinese society and its determinants are important for deepening academic understanding of SWB, as well as for formulating targeted intervention policies to enhance the wellbeing of older adults.

To bridge the above academic gap, this paper attempts to answer the following questions: Are there gender differences in the SWB among older adults people in China? How do household structure and the built environment affect the gendered SWB perception among older adults? To answer these questions, this paper employs a hierarchical linear model to analyze the gender differences in the impacts of built environment and household structure on the subjective wellbeing of older adults based on a survey of the quality of life of older adults in Nanjing.

The reminder of the paper is structured as follows: Section 2 reviews the relevant literature on gender differences in SWB among older adults. Section 3 starts with an overview of the data, measures of the variables and the methods used. In Section 4, we turn our attention to an analysis of our dataset and a number of regression models. Section 5 delves into the discussion of the analysis results, shedding light on the mechanisms of the gender differences in SWB. Finally, conclusions are drawn in Section 6.

2 Literature review

The differences between SWB of men and women has received increasing attention in the academic communities of gerontology, psychology, and health geography (17, 18, 24). Nonetheless, these studies have not reached consistent results, with some studies found that the level of SWB of women is higher than that of men and others found the reverse (25–27). There are also studies that find no significant gender differences in SWB (28, 29). Moreover, gender differences in SWB may vary with age, i.e., the increase in age may have different effects on the SWB between men and women (30).

Relatively few studies have been dedicated to the gender differences in SWB of the old people. According to existing studies, there are interactions between gender, age and wellbeing (30, 31), suggesting a complex picture of gender differences in SWB of older adults. A metal-analysis by Pinquart and Sorensen (32) concluded that the relationship between gender and wellbeing tends to reverse as age increases, and older women reports markedly lower SWB than men. However, those studies focusing on this issue have mostly stemmed from western contexts. Less attention has been paid to the situation of China, resulting in incomplete understandings of the gender differences in the wellbeing of the older adults.

With respect to the factors that contribute to the gendered differences in SWB, there are even fewer studies focusing on this topic with only few exceptions. Li et al. (11) and Zhang et al. (10) found that social activities were more beneficial to SWB for males than for females. Regarding intergenerational support, the financial support offered by the offspring plays a much more crucial role in SWB for older women than for older men, while caregiving support matters more to men than to women (12). With respect to learning behaviors, Shi et al. (13) concluded that the positive impact of learning behaviors on subjective wellbeing of older women was more pronounced compared to older men. Due to declines in physical function and cognitive capacity (33), older adults' daily activity spaces shrink, making them highly reliant on the built environment at the community level (34, 35). In other words, the built environment at the community level tend to play a much more vital part in improving older adults SWB (16, 36) than other population sections. Moreover, women are reported to be more sensitive to the local environment for physiological differences (37). Regarding household structure, previous studies have shown that it can affect the wellbeing of older adults through domestic roles (9, 38) and the consequent division of household responsibilities (21, 39), emotional bonds (40, 41) and social appraisal of the eldercare model (42, 43), yet whether it impacts the old men and old women in the same way and to the same extent remains unexplored.

At present, aging-in-place remains the mainstream eldercare model in China, meaning that both the built environment at the community level and household structure are important factors affecting the SWB of older adults. It is therefore necessary to explicitly investigate how and why the effects of these factors on senior's happiness vary with gender. Base on previous studies, the gender-differentiated effect of built environment and household structure on senior's subjective wellbeing might be attributed not only to physiological differences between men and women, but also to the gender disparities, socio-cultural norms, the division of household labor and thus the differing needs of living environments, etc. For example, in China, women generally take on much more household responsibilities than men (44, 45), and this gendered divisions of household labor continue into late life (39, 46). The household responsibilities not only directly affect older adults wellbeing, but also make them perceive the surrounding built environment differently (47). However, only a few studies have examined the gender differences in older adults wellbeing and its determinants, the underlying mechanisms still remains to be fully explored.

Therefore, in this study we will address the above research gap by exploring the gender differences in the SWB among the old males and females in China and investigating the gender-differentiated effects of built environment and household structure. Our study seeks to provide a complete picture of the gender differences in SWB and its determinants in China while also advance the theoretical discussions in happiness studies.

3 Materials and methods

3.1 Study area and data

Mega-cities in China are the areas where the senior population concentrated (48), and therefore are the ideal places for studying academic issues related to aging society. Nanjing, located in the eastern coast region of China, is not only the capital city of Jiangsu Province and an important central city in Eastern China, but also the sub-center of the Yangtze River Delta Mega-City Regions. In 2015, the population of Nanjing was ~8.23 million. The people who are aged 65 and above accounted for 10.69% of the total population, indicating that Nanjing has entered an aging society (49). By the end of 2021, the population of Nanjing had reached about 9.42 million, with the amount of older adults who are 65 years and above rising to a percentage of 14.49%. According to the national statistics, the percentage of older adults people and the speed of aging in Nanjing is quite typical among the Mega-cities in developed area in China and therefore be selected as the study area.

We analyzed the connections between the built environment and the SWB of older adults based on a survey called "The quality of life of older adults in Nanjing", which was conducted between September and November 2021. Actually, we had conducted almost the same survey in the same selected communities in 2015. The newly conducted survey is the continuation of that research. The survey was also funded by a national grant. It was designed to investigate how the built environment influences the quality of life of older adults. The questionnaire includes the socio-economic attributes of older adults (including age, income, marital status and household structure, etc.), involvements of household responsibilities, their daily travel-activity information and subjective wellbeing.

We utilized a stratified sampling approach for the survey execution. Initially, we examined various communities across the entire metropolitan region of Nanjing, noting the diverse characteristics of their built environment. Informed by this assessment, we identified and chose representative communities. Subsequently, we performed random sampling of the senior population within these selected areas. Employing such informed stratification reduced the variance inside each strata compared to the total population variance, therefore producing better strata efficiency than systematic sampling or random sampling methods (50, 51). For our study, a total of 12 communities were chosen to typify the diversity in built environment, considering both location and the internal and external conditions of the communities (Figure 1; Table 1). In each community, we drew a random sample of about 50 senior respondents that we either encountered in their communities or surveyed at their homes. In total, we collected data from 640 individuals. The final, valid sample includes 617 respondents, and the percent of the valid sample is 96%. Before examining the interrelations among household structure, built environment, and the subjective wellbeing of older adults, we first tested the validity and reliability of the data with SPSS 25. The P-value of the Bartlett's test was <0.05, the Kaiser-Meyer-Olkin (KMO) score was 0.786, and Cronbach's alpha value was 0.755, suggesting that the survey questionnaire has good validity and reliability.

3.2 Research framework and methods

As shown in Figure 2, this paper will analyze the gender differences in SWB among older adults and to detect the different impacts of built environment at the community level and household structure at the individual level. To realize this research aim, Hierarchical Linear Model (HLM) is employed and other socio-economic characteristics of older adults is controlled including age, education attainment and income level. Additionally, two factors with particular Chinese characteristics (hukou status and communist party membership) are selected in the article.

HLM is useful for understanding the relationships in hierarchical data structures. Data are collected on random samples of older adults nested within each community. In this application, it might be appropriate to adjust for covariates at both the individual-level (age, gender, education attainment, income level, hukou status, communist party membership and household structure) and at the community-level (built environments). The model begins with a fixed slope, random intercepts model, expressed as:

$$\begin{aligned} First\ level: y_{ij} = \beta_{0j} + \beta_{1j} gender_{ij} + \beta_{2j} household_{ij} \\ + \beta_{kj} individual_{ij} + e_{ij} \end{aligned} \quad (1)$$

$$Second\ level: \beta_{0j} = \gamma_{00} + \gamma_{01} environment_j + \mu_{0j} \quad (2)$$

Here (Equation 1), y_{ij} represents the subjective wellbeing of older adults, that is, the subjective wellbeing of the i individual in the j community. The first level is the individual-level equation; β_{0j} is the community-level intercept, representing the average subjective wellbeing of older adults at the community level; $gender_{ij}$ denotes the gender of older adults, $household_{ij}$ indicates their household structure, and $individual_{ij}$ represents other individual demographic and socio-economic attributes, with e_{ij} being the individual-level random error. The second level (Equation 2) is the community-level equation; γ_{00} is the mean of β_{0j}, that is, the overall average score of older adults subjective wellbeing, $environment_j$ is the built environment indicator at the community level, and μ_{0j} is the community-level random error.

The implicit assumption of the above model is that the effects of community-level built environment on the relationship between individual-level variables and subjective

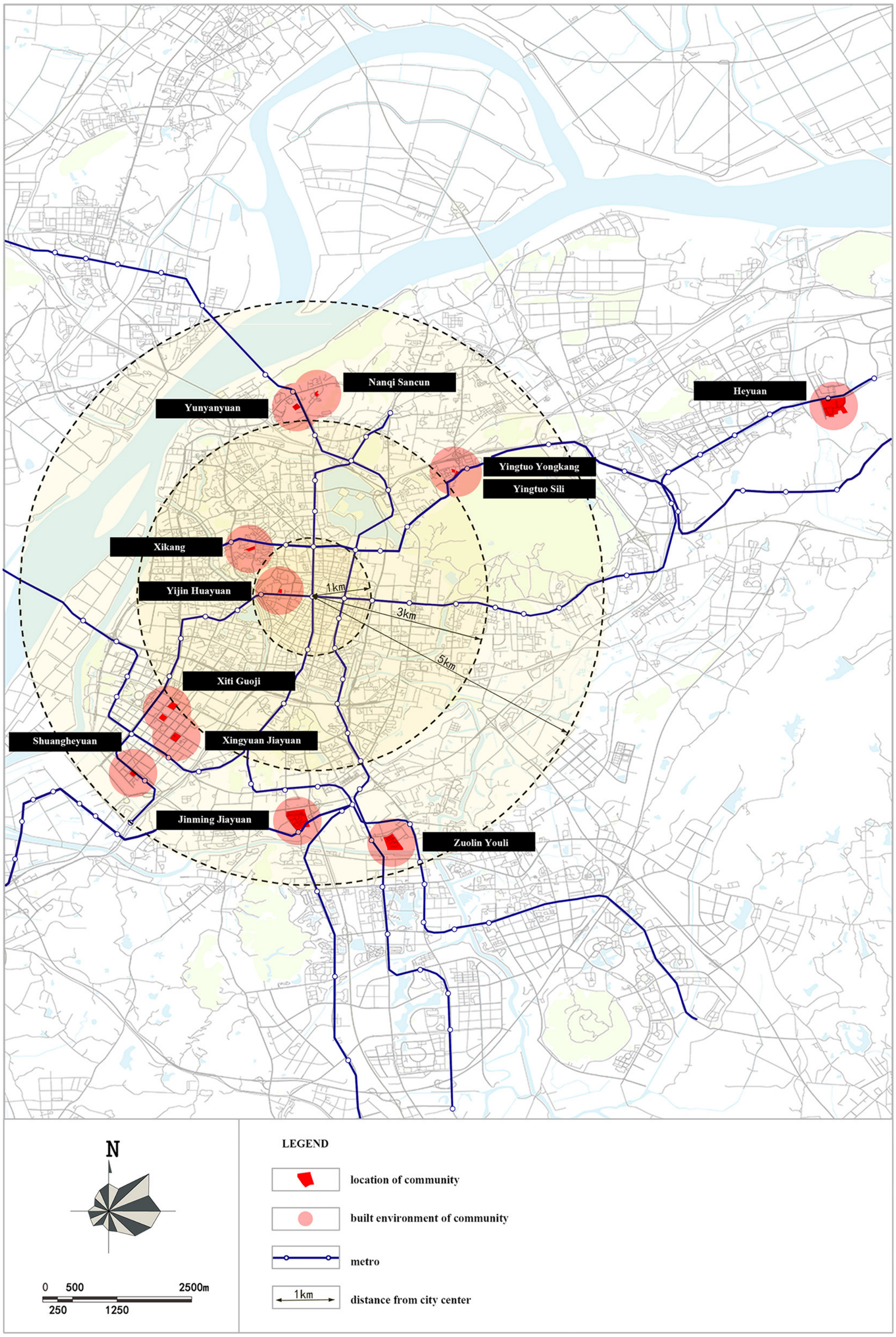

FIGURE 1
The location of 12 typical communities.

wellbeing is constant. However, the impact of gender on the subjective wellbeing of older adults may vary with the built environments. Therefore, we construct a random slope, random intercepts model to analyze how built environments affect the relationship between gender and subjective wellbeing of older adults (Equations 3, 4). This involves interacting

TABLE 1 Profile of the samples.

Attributes	Categories	Proportion (%)	Mean/SD
Socio-economic attributes			
Gender	Male (=ref.)	39.61	
	Female	60.39	
Age	60–65 (=ref.)	33.06	
	66–70	34.21	
	Older than 71	32.73	
Education attainment	Illiteracy (=ref.)	9.17	
	Primary school	13.09	
	Middle school	33.72	
	High school or technical secondary school	25.37	
	Junior college, undergraduate and above	18.65	
Income (RMB per month)	0 (=ref.)	3.60	
	<1,000	7.20	
	1,001–3,000	44.19	
	3,001–5,000	27.17	
	More than 5,001	17.84	
Hukou status	Local people	67.43	
	Non-local people (=ref.)	32.57	
Communist party membership	Yes	22.09	
	No (=ref.)	77.91	
Household structures	Single	8.02	
	Couple	32.08	
	Living with daughter	9.00	
	Living with daughter-in-law (=ref.)	6.71	
	Living with daughter and grandchildren	9.82	
	Living with daughter-in-law and grandchildren	21.11	
	Others	13.26	
Built environments			
Population density	Population per unit area of community (10,000/km²)		2.04/1.20
Land use mix	The extent to which facilities are evenly distributed within the 500-meter buffer zone around the community		0.55/0.11
Accessibility of open space	Straight-line distance from the community to the nearest open space (m)		1,404.26/593.28
Accessibility of kindergarten	Number of kindergartens within 1,000 meters of the community		7.36/5.09
Accessibility of public transport	Number of metro stations within 1,000 meters of the community		1.09/0.76

gender with the built environment variables, keeping the second level unchanged, while the first level model is expressed as:

$$First\ level: y_{ij} = \beta_{0j} + \beta_{1j}gender_{ij} + \beta_{2j}household_{ij} + \beta_{kj}individual_{ij} + e_{ij} \tag{3}$$

$$Second\ level: \beta_{1j} = r_{10} + r_{11}community_j + \mu_{1j} \tag{4}$$

3.3 Measures

In this study, SWB is measured using the widely utilized and readily available Satisfaction With Life Scale (SWLS) (52). The five SWLS statements are: "In most ways, my life is close to my ideal," "I am satisfied with my life," "So far, I have achieved the important things I want in life," "The conditions of my life are excellent" and "If I could live my life over again, I would change almost nothing" (Table 2). The questionnaire

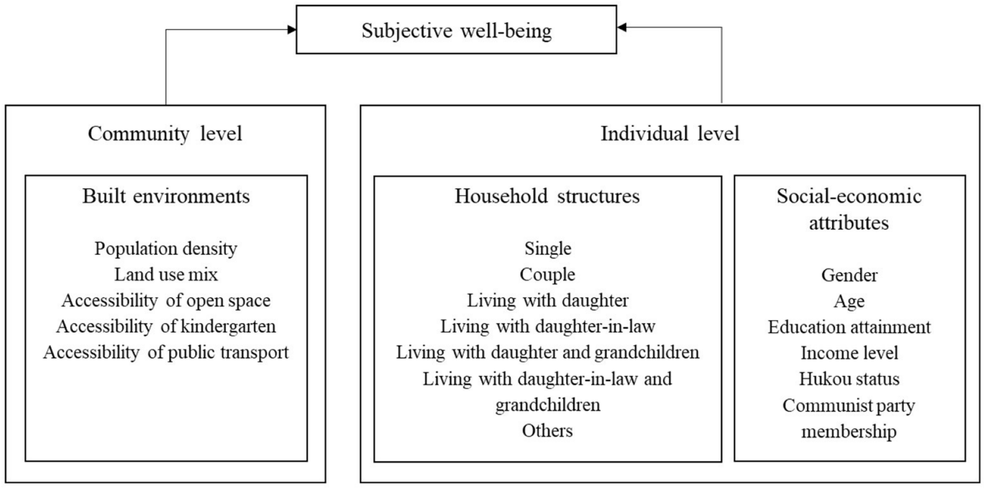

FIGURE 2
The research framework of HLM.

TABLE 2 Measurement of subjective wellbeing indicators.

	Questions	Mean/standard deviation	Minimum	Maximum
SWLS	In most ways, my life is close to my ideal	2.66/0.63	1	5
	I am satisfied with my life	2.71/0.57	1	5
	The conditions of my life are excellent	2.56/0.73	1	5
	So far, I have achieved the important things I want in life	2.46/0.81	1	5
	If I could live my life over again, I would change almost nothing	2.68/0.61	1	5

records respondents' answers using a Five Point Likert Scale, where 1–5 points represent "strongly disagree," "disagree," "neutral," "agree," and "strongly agree," respectively. Principal Component Analysis (PCA) is then conducted to obtain the dependent variable of subjective wellbeing (continuous variable) used in the final model. The Kaiser-Meyer-Olkin (KMO) value is 0.908, and the P-value of Bartlett's test is <0.01, indicating that PCA is an appropriate method.

Based on the "5Ds" of the built environment (53) and considering data availability, this paper developed five built environment variables: population density, land use mix, accessibility of open space, accessibility of kindergarten and accessibility of public transport. Population density is calculated as the ratio of population and area of the community in Nanjing. Land use mix simultaneously accounts for the variety and prevalence of different functions in the area. Following Ewing and Cervero (53), we calculated an entropy index:

$$S = -\sum_{j} \frac{[P_{jk} \times \ln(P_{jk})]}{\ln(J)}$$

In this equation, S refers to land use mix (entropy); j is the type of land use ($j = 1, 2, \ldots, J$); k is the community ($k = 1, 2, \ldots, K$); P_{jk} is the proportion of land use j within the community. The entropy ranges from 0 (homogeneity-only one type of land use) to 1 (heterogeneity-shares of uses evenly distributed over all land use categories). We include six land use types with highest relevance for residents' daily activities: residential, commercial, public, industrial, offices and research sites, and parks and recreational use. Accessibility of open space is calculated by the straight-line distance to the nearest green square. Accessibility of kindergarten/public transport is calculated by the number of kindergartens/metro stations within a straight-line distance of 1 kilometer from the center of the community, respectively.

Household structure is an important factor affecting the subjective wellbeing of older adults. In contrast to the west, Chinese society places a high priority on aging-in-place, and there are still a substantial portion of Chinese seniors living together with their married children. Sons bear main responsibility for taking care of their parents, while daughters need to care for her husband's parents as a daughter-in-law after marriage. Existing research also found that there are great differences between living with daughter and living with daughter-in-law on the subjective wellbeing of older adults (54). In the light of the above reasons, this paper categorizes household structure into seven types namely "Living alone," "Living with spouse," "Living with daughter-in-law," "Living with daughter," "Living with daughter-in-law and grandchildren," "Living with daughter and grandchildren," and "Others." The analytical results of the paper show that different types of household structures tend to have significant different

TABLE 3 Gender differences in SWB.

Subjective wellbeing	Mean	Standard deviation
Male	4.69***	1.03
Female	4.95***	0.93

***$p < 0.01$.

consequences in shaping the level of senior's SWB, indicating the validity of our classification.

4 Results

4.1 Gender differences in SWB of older adults

As shown in Table 3, there are differences in SWB between older adult men and women, with women having a higher average level than men (4.95 vs. 4.69). Mann-Whitney U-test shows that the difference in subjective wellbeing between older adult men and women is significant ($P < 0.01$). Additionally, the larger standard deviation suggests that the distribution of SWB score among older adult men is more polarized, whereas the distribution among older adult women is relatively steady. There might be several reasons accounting for the gendered discrepancies in SWB. Firstly, women and men may have different expectations regarding aging and contentment. This could shape their self-reported feelings of wellbeing, with women perhaps having more adaptable or realistic expectations compared to men. Secondly, in China women are often seen as being more resilient and better at maintaining social networks. They are more likely to express their feelings and seek help when facing emotional difficulties, which can contribute to emotional support and satisfaction in later life. Men, on the other hand, may have traditionally derived much of their identity and satisfaction from their professional roles, and retirement could disrupt this source of fulfillment. The polarization among men could reflect a reluctance to seek help or discuss emotional issues, resulting in more extreme levels of reported SWB or dissatisfaction. Thirdly, family and living arrangements might also contribute to the discrepancies: older adult women may benefit more from household structures that provide emotional and practical support; men might experience more loneliness if widowed, as they may be less likely to maintain extensive social networks outside of marriage. In other words, these gender discrepancies in SWB among older adults likely stem from a complex interplay of social-cultural, physiological-psychological, and economic factors. Therefore, in next subsection, we adopted multilevel regression models to detect the underlying factors.

4.2 Determinant factors of the gendered differences in SWB of older adults

This paper adopted hierarchical linear regression models to analyze the gender differences in subjective wellbeing and their influencing factors using software of Stata 15.0 and SPSS 25. Before modeling, multicollinearity diagnostics is performed, yielding a Variance Inflation Factor (VIF) <5, indicating no multicollinearity among the independent variables. To test the applicability of the multilevel model, an empty model is constructed to examine whether there are intra-class differences among the samples. Results show that the inter-class variance for the empty model is 0.3029, and the intra-class correlation coefficient (ICC) value is 0.3172, meaning that community differences account for 31.72% of the total variance in senior's subjective wellbeing and the explanatory power of the multilevel model is significantly higher than that of single-level models (55). Then the hierarchical linear regression models are conducted and the results are shown in Table 4. It can be observed that the overall effect of gender on senior's SWB is significantly validated (Model 2 and Model 3), with older adult women having notably higher levels of subjective wellbeing than men, indicating that even after controlled for other variables, gender differences in SWB of older adults still exist.

4.2.1 The impact of the built environments on SWB

Model 1 is the model that adds the built environment variables into the empty model. In this model, the between-group variance decreases to 0.0443, and the ICC drops to 6.37%, indicating that the selected built environment variables can effectively explain the heterogeneities of SWB at the community level among older adults. In other words, the differences of SWB at the community level are largely due to variations in the built environment.

Specifically, population density is significantly negatively correlated with the SWB of older adults ($\beta = -0.3239$, $p < 0.01$). Existing studies indicate that SWB is inverted U-shaped in population density (50, 51). That is, SWB level tends to increase with population density, reaches the peak, and then decreases while the population density increase. Studies based on Western cases often find a positive correlation between population density and SWB (56–58), for the reason that the population densities there are generally low, reflecting the first half of the inverted "U". In our case, the population densities of the communities are all very high. The results here actually reflect another half of the inverted "U"-the negative relationship between population density and SWB. Land use mix is significantly positively correlated with SWB ($\beta = -0.3239$, $P < 0.01$), consistent with the literature (59, 60). The reason could be that mixed land use can provide convenient living conditions for older adults and the proximity of destinations promotes social interaction, thereby improving their psychological health.

Regarding the accessibility of the open space, the result shows that the further away from open space, the higher the subjective wellbeing of older adults ($\beta = 0.0004$, $P < 0.05$), which contradicts with existing research (61, 62). On the one hand, open spaces provide good conditions for exercise and recreation, facilitating physical and social activity involvements, thus increasing SWB of older adults. On the other hand, in China older adult people, especially women, often gather in open space to dance with loud background music. Being closer means being more susceptible to the noisy and crowded living conditions, potentially lowering their SWB. The two pathways have contradicted effects on SWB and the negative influence of proximity to open space dominate the overall results.

TABLE 4 Hierarchical linear model of subjective wellbeing of older adults.

Independent variables	Empty model		Model 1		Model 2		Model 3	
	Coefficient	S.E.	Coefficient	S.E.	Coefficient	S.E.	Coefficient	S.E.
Household structures (living with daughter-in-law = ref.)								
Single					−0.3055*	0.1729	−0.2989*	0.1727
Couple					−0.2080	0.1408	−0.2236	0.1404
Living with daughter					−0.2129	0.1652	−0.2278	0.1648
Living with daughter and grandchildren					−0.3279**	0.1654	−0.2676*	0.1447
Living with daughter-in-law and grandchildren					−0.2826*	0.1453	−0.3200*	0.1649
Others					−0.1313	0.1559	−0.1323	0.1553
Social-economic attributes								
Gender (Male = ref.)					0.2356***	0.0748	0.2355***	0.0746
Age (60–65 = ref.)								
66–70					0.1497*	0.0872	0.1361	0.0874
Older than 71					0.0292	0.0876	0.0277	0.0874
Education attainment (Illiteracy = ref.)								
Primary school					0.2392*	0.1431	0.2218	0.1429
Middle school					0.2708**	0.1285	0.2630**	0.1281
High school or technical secondary school					0.2066	0.1388	0.2151	0.1384
Junior college, undergraduate and above					0.2031	0.1578	0.1933	0.1575
Income level (0 = ref.)								
<1,000					−0.0982	0.2099	−0.1194	0.2101
1,001–3,000					−0.1213	0.1843	−0.1288	0.1837
3,001–5,000					−0.0983	0.1950	−0.0804	0.1944
More than 5,001					−0.0398	0.2076	−0.0507	0.2074
Hukou status (non-local people = ref.)					0.0795	0.0847	0.0801	0.0848
Communist party membership (no = ref.)					−0.0055	0.0907	−0.0118	0.0907
Built environments								
Population density			−0.3239***	0.0958	−0.3119***	0.0957	−0.2047*	0.9305
Land use mix			5.2960***	0.8247	5.1335***	0.8213	5.1482***	0.9305
Accessibility of open space			0.0004**	0.0001	0.0004**	0.0001	0.0003*	0.0002
Accessibility of kindergarten			0.0861***	0.0253	0.0805***	0.0252	0.0557*	0.0288
Accessibility of public transport			−0.2733***	0.0937	−0.2578***	0.0936	−0.3146***	0.1055
Female × population density							−0.1628*	0.0976
Female × accessibility of kindergarten							0.0412*	0.0246
Intercept	−0.0009	0.1622	−0.0012	0.0690	−0.1552	0.2443	−0.1420	0.2431
Between-group variance	0.3029	0.1289	0.0443	0.0233	0.0436	0.0231	0.0407	0.0220
Within-group variance	0.6521	0.3768	0.6521***	0.0377	0.6204***	0.0359	0.6144	0.0355
ICC (%)	31.72%		6.37%		6.57%		6.21%	

*$p < 0.1$, **$p < 0.05$, ***$p < 0.01$. ICC = between-group variance/(between-group variance + within-group variance).

Accessibility to kindergartens is found to be positively correlated with SWB (β = 0.0861, $P < 0.01$), perhaps because having more kindergartens within walking distance makes it more convenient for older adults to drop off and pick up children, thus positively affecting their level of SWB. Regarding accessibility to metro stations, the more subway stations around the community, the lower the SWB level of older adults. Like population density, previous research has shown that accessibility to subway stations could have both positive and negative impacts on subjective wellbeing (56, 63). In this paper, the negative effect may be because that communities closer to subway stations typically have higher building densities, more shops, and larger traffic flows, and therefore lead to a decline in SWB of older adults.

In order to examine whether built environments have different impacts on the SWB of older adult men and women, we conducted regression analyses separately for older adult females and males (model results are not presented here due to limited space). Results indicate that community-level variables can explain 28.50% of the total variance in SWB for older adult men and 33.68% for older adult women. All built environment variables had significant impacts ($P < 0.01$) on the SWB of older adult women, while population density had no significant effects on men's SWB. Compared to older adult men, there are greater differences in SWB at the community level and the built environments exert more prominent impacts on SWB of older adult women.

To further explore how specific attribute of built environments impact SWB of older adult men and women, we established interactions between the built environment variables and gender to investigate the moderating role, as shown in Model 3. Results show that there are gender differences in the impacts of the built environments on the wellbeing of older adults: the coefficient for the interaction between women and population density is negative and significant at the 10% level, indicating that as population density increases the SWB of older adult women reduces more than that of men. Moreover, the interaction between women and accessibility to kindergartens is positive and significant at the 10% level, suggesting that accessibility to these facilities has a more pronounced effect on enhancing the wellbeing of older adult women compared to men.

4.2.2 The impact of household structure on SWB

Model 2 incorporates seven types of household structure at the individual level and controls for socio-demographic variables. In the model, living with daughter-in-law is taken as reference group. The levels of SWB among older people in different household structures rank from high to low as follows: living with daughter-in-law, others, living with spouse, living with daughter, living with daughter-in-law and grandchildren (β = −0.2826, $P < 0.1$), living alone (β = −0.3055, $P < 0.1$), living with daughter and grandchildren (β = −0.3279, $P < 0.05$). Pairwise compared, older people living with daughter-in-law have high SWB than those living with daughter-in-law and grandchildren, and older people living with daughter are more satisfied with their life than those living with daughter and grandchildren. It seems that the presents of the grandchildren tend to reduce the SWB level of older adults. This might be related to more household tasks allocated to older adults when there are grandchildren in the family. Living with daughter or living with daughter-in-law also influences old people's SWB. When pairwise compared, older people living with daughter-in-law have high SWB than those living with daughter, and older people living with daughter-in-law and grandchildren are more satisfied with their life than those living with daughter and grandchildren. China is a country with a robust tradition of extended family and patriarchal and patrilocal living arrangements. This tradition is ascribed to Confucian doctrines that emphasize children's filial obligations to their parents, particularly those of sons. To live with sons are considered successful aging and therefore positively associated with wellbeing. Obviously, household structure is an important factor influencing older adults' SWB.

We also conducted regression analyses separately for older adult females and males to investigate whether household structures have different impacts on the SWB of older adult men and women (model results are not presented here due to limited space). Results show that the presences of grandchildren seem reduced the SWB of the older adult men more substantially than that of the older adult women. The reason could be that old men have to share the additional housework stemming from the existence of the grandchildren.

5 Discussion

The above analyses show that there are indeed significant gender differences in SWB of older adults: older adult women have higher levels of SWB than older adult men. Built environment and household structure are found to be important factors affecting SWB of older adults, and their influences are also gendered. In the following, we proposed three mechanisms that can explain these empirical results.

5.1 Structural mechanisms

The structural mechanism refers to discrepancies between old men and women in resource acquisition, education attainment, opportunities of employment and social-economic status in the society. Existing research indicates that SWB of older adults varies with the degree of gender inequality and people's attitudes toward gender equality in the society (20): the more positive the attitude toward gender equality and the smaller the gender inequality, the smaller the gender difference in subjective wellbeing (20, 64). The old women of our respondents are of the cohorts who have spent most of their lives in a relatively disadvantaged society. Compared with old men, they generally have lower expectations of SWB (17). However, in recent decades, women's social and economic conditions have greatly improved. Gender inequality in China has significantly decreased. The advantages of men in resource acquisition, employment opportunities, and social status have sharply declined. The above changes may be the reason why the SWB of older adult women has significantly improved and exceeded that of older adult men (30). Another structural change in later life is that the dominant person in the family often reverses from men to women. While men traditionally hold dominance, their economic advantage diminishes as they enter retirement.

Moreover, older adult men become increasingly reliant on older adult female caregivers for their daily needs, which in turn elevates the status of women within the household. The changing roles in the family narrows the gender-related gaps to some extent and enhance the SWB of older adult women.

5.2 Socio-cultural mechanisms

The socio-cultural mechanism pertains to the manner in which gender roles and norms, as shaped by social and cultural forces, give rise to disparities in subjective wellbeing among older adults. Gender roles refer to the social and behavioral norms that are widely considered to be socially appropriate for individuals of a specific sex within a specific culture (65). These roles dictate how men and women should behave, dress, speak, interact, and fulfill their duties in society based on their gender. There are at least two pathways through which gender roles influence the subjective wellbeing of older adults. Firstly, gender roles could influence the division of household works between men and women and consequently impact their subject wellbeing. In the Chinese traditional norms, men tend to provide economic support, while women bear more responsibility for caring for the family and raising children (9, 38, 66). As shown in Table 5, older adult women tend to share considerably more household chores compared with older adult men in the same household type. Meanwhile, the household burdens carried by older adult women are not changed along with household types as dramatically as those carried by the older adult men. It can be understood that older adult women, accustomed to this labor burden, are not significantly affected by changes in housework due to changes in household structure. Nevertheless, changes in the type and intensity of housework tend to significantly affect the happiness of older adult men. This explains the model result those older adult men living with a daughter-in-law and grandchildren have a significantly lower level of happiness compared to those living with daughter-in-law, while there is no significant change for older adult women.

Moreover, gender differences in the division of household tasks lead to differing demands for the built environments and facilities. Since women mainly take on the responsibility of caring for the family and raising children, they rely more on the surrounding built environment (67) and consequently the built environment has more significant impacts on the subjective wellbeing of older adult women. This also explains why population density and accessibility to kindergartens demonstrates a greater impact on their wellbeing in the model.

Secondly, the socio-cultural norms could change the level of wellbeing of older adults by influencing their preference and attitudes toward different patterns of older adult care and living arrangements in later life. Chinese society emphasizes cohabitation and mutual support between generations (5, 42), and living with adult children, especially sons, is often seen as a necessary prerequisite for older adult people to obtain intergenerational support and ensure happiness in later life. Hence, most older adult people tend to live with adult children, especially sons (68), and believe that cohabiting with children can yield a higher social evaluation and is considered a "successful" pattern to aging (43).

TABLE 5 The proportion of older adults participating in housework in different household structures.

Housework	Gender	Single	Couple	Daughter	Daughter-in-law	Daughter and grandchildren	Daughter-in-law and grandchildren	Others	Total
Sharing housework	Male	53.8%*	84.4%*	75.0%*	86.7%*	81.0%*	88.9%*	74.1%*	81.8%*
	Female	94.4%	95.0%	89.7%	92.3%	100.0%	96.0%	92.6%	94.6%
Laundering, cleaning, cooking	Male	85.7%	86.4%	75.0%	84.6%	94.1%	81.3%	95.0%	85.9%
	Female	100.0%	98.9%	94.3%	100.0%	94.9%	91.7%	98.0%	96.6%
Taking care of children	Male	0.0%***	18.5%***	41.7%***	53.8%***	76.5%***	70.8%***	50.0%***	42.4%***
	Female	5.9%***	20.0%***	31.4%***	37.5%***	84.6%***	76.4%***	38.0%***	42.4%***
Sending and picking up children	Male	0.0%***	12.3%***	33.3%***	38.5%***	47.1%***	41.7%***	20.0%***	25.8%***
	Female	2.9%***	14.7%***	20.0%***	16.7%***	53.8%***	45.8%***	22.0%***	26.1%***
Daily shopping	Male	42.9%	60.5%	58.3%	61.5%	76.5%	54.2%	50.0%	58.6%
	Female	70.6%*	74.7%*	68.6%*	50.0%*	87.2%*	84.7%*	72.0%*	75.1%*

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

This may explain why the subjective wellbeing of older adults living with daughter-in-law are higher than those living with daughter, and those living with daughter-in-law and grandchildren are much happier than those living with daughter and grandchildren when pairwise compared. Overall, socio-cultural mechanism, especially the concept of filial piety and the division of household tasks, are important pathways through which household structure and the built environment have significant gender differences in their impacts on the wellbeing of older adults.

5.3 Physiological mechanisms

Previous studies suggest that differences in the physiological factors such as hormonal and genetic structures between men and women may directly lead to variations in subjective wellbeing between the sexes (69, 70). Due to these differences, women tend to pay more attention to self-expression, intimacy and support compared to men (71). They also have the tendency toward altruism and find that closeness to family and helping others have a more significant positive impact on their subjective wellbeing (40, 41). Therefore, there is a significant increase in levels of happiness for older adults women living with daughters-in-law as compared to those living with spouses. The positive effects of fulfilling emotional needs even surpass the negative impacts caused by an increased burden of household chores. On the other hand, as they age, individuals experience a decline in physical and perceptual abilities, and their daily activity spaces gradually shrink (55, 72). Comparison to older adult men, older adult women have an even smaller ranges of activities and are more dependent on the built environment at the community scale (72, 73), making them more susceptible to its influences (73). The model results of this paper suggest that the built environment at the community level has a more pronounced impact on the wellbeing of older adult women, which also echoes the findings of existing research (55, 73).

6 Conclusions

Subjective wellbeing serves as a vital metric for evaluating the psychological health of senior citizens. Notable disparities in life expectancy and subject wellbeing between men and women highlight the necessity for gender-sensitive public policies that aim to uplift the wellbeing and health of the aging population. Based on a survey of the quality of life of older adults in Nanjing, this study finds significant gender differences in the subjective wellbeing of older adults. Built environment and household structures are found to exert markedly different influences on the happiness of older men and women. Structural mechanisms, socio-cultural mechanisms, and physiological mechanisms are the three main factors contributing to these gender differences. China's unique built environment, social and cultural background profoundly affect the cognition, preferences, and behavior patterns of older adults, thus resulting in their differences in perceptions of wellbeing and the underlying mechanisms from those in the West. This paper reveals the patterns and mechanisms of the gender differences in senior's wellbeing in the Chinese context, and also, to some extent, enriches the empirical research and theories related to subjective wellbeing.

The results can provide references in formulating policies to create age-friendly community and enhance the health and welfare of older adults for both sexes. Firstly, the high-density built environment in China is quite different from that in West, and the excessive population density has a negative impact on the happiness of older adults, especially on older women. Therefore, policies should not only focus on the provisions of various facilities but also on using measures such as constructing green belts and regulating behavioral norms for some activities especially Square Dance to reduce negative impacts of high density. Moreover, given the significant gender differences in the impacts of the built environment on older adults' SWB, it is essential to consider these differences in the patterns of daily behavior and the consequent facility needs between men and women. Environmental interventions, such as increasing land-use diversity and accessibility of related facilities should be implemented to reduce the burden of domestic labor and to facilitate independent life for older adults, especially older women.

It is important to note that the household structure we studied is the reflection of domestic labor, family comfort and other factors affecting the older adults' SWB. However, living apart does not necessarily prevent children from providing financial and emotional support to older adults. In addition, regarding the variables of the built environment, our study solely focuses on the impact of the objective built environment on SWB and ignores the subjective built environment. In the future more sophisticated survey will be conducted to explore the impacts of both the objective and subjective built environments on senior's subjective wellbeing.

Data availability statement

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

Author contributions

JF: Conceptualization, Data curation, Funding acquisition, Methodology, Supervision, Validation, Writing – review & editing. MZ: Conceptualization, Formal analysis, Software, Writing – original draft, Writing – review & editing.

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References

1. Diener E, Oishi S, Lucas RE. Personality, culture, and subjective well-being: emotional and cognitive evaluations of life. *Annu Rev Psychol.* (2003) 54:403–25. doi: 10.1146/annurev.psych.54.101601.145056

2. Xing Z. A review of research on measurement of subjective well-being. *J Psychol Sci.* (2002) 336–8+42. doi: 10.16719/j.cnki.1671-6981.2002.03.022

3. Du P, Li L. Long-term trends projection of China's population aging in the new era. *J Renmin Univ. China.* (2021) 35:96–109. doi: 10.3969/j.issn.1000-5420.2021.01.010

4. Mu G, Zhang T. The development trend of population aging in China and its strategic response. *J Central China Normal Univ.* (2011) 50:29–36. doi: 10.3969/j.issn.1000-2456.2011.05.005

5. Yang H, Hagedorn A, Zhu H, Chen H. Mental health and well-being in older women in China: implications from the Andersen model. *BMC Geriatr.* (2020) 20:254. doi: 10.1186/s12877-020-01639-z

6. Camargos M, Machado C, Rodrigues R. Sex differences in healthy life expectancy from self-perceived assessments of health in the City of São Paulo, Brazil. *Ageing Soc.* (2008) 28:35–48. doi: 10.1017/S0144686X07006277

7. Liu R, Gong Y. The subjective well-being of the elderly and its influential factors. *Chinese J Clin Psychol.* (2000) 8:73–8. doi: 10.16128/j.cnki.1005-3611.2000.02.003

8. Xu J. Research on subjective well-being of the elderly and its influencing factors. *Chin J Gerontol.* (2009) 29:3241–3. doi: 10.3969/j.issn.1005-9202.2009.24.036

9. Dury S, Stas L, Switsers L, Duppen D, Domènech-Abella J, Dierckx E, et al. Gender-related differences in the relationship between social and activity participation and health and subjective well-being in later life. *Soc. Sci. Med. (1982).* (2021) 270:113668. doi: 10.1016/j.socscimed.2020.113668

10. Zhang W, Feng Q, Lacanienta J, Zhen Z. Leisure participation and subjective well-being: exploring gender differences among elderly in Shanghai, China. *Arch Gerontol Geriatr.* (2017) 69:45–54. doi: 10.1016/j.archger.2016.11.010

11. Li YP, Lin SI, Chen CH. Gender differences in the relationship of social activity and quality of life in community-dwelling Taiwanese elders. *J Women Aging.* (2011) 23:305–20. doi: 10.1080/08952841.2011.611052

12. He L. *The Influence of Intergenerational Relationship on Subjective Well-Being of the Elderly: From the Perspective of Intergenerational Support and the Quality of Intergenerational Relationship*. Beijing: University of Chinese Academy of Social Sciences (2022).

13. Shi X, Li Y, Sun L, Yu Y, Zhou S. Gender differences in the subjective well-being of older adult learners in China. *Front Psychol.* (2022) 13:1043420. doi: 10.3389/fpsyg.2022.1043420

14. Liu Y, Dijst M, Geertman S. The subjective well-being of older adults in Shanghai: the role of residential environment and individual resources. *Urban Stud.* (2017) 54:1692–714. doi: 10.1177/0042098016630512

15. Chen G. *The Impact of Family Structure on the Mental Health of the Elderly*. Wuhan: Zhongnan University of Economics and Law (2019).

16. Zhou S, Peng Y, Liu L, Lin R, Zhang C. The impact of built environment on well-being of older adults under different geographic contexts. *Geogr Res.* (2019) 38:1625–39. doi: 10.11821/dlyj020180292

17. Batz C, Tay L. Gender differences in subjective well-being. In: Diener E, Oishi S, Tay L, editors. *Handbook of Well-being.* Salt Lake City, UT: DEF Publishers (2017). p. 358–72.

18. Kiely KM, Brady B, Byles J. Gender, mental health and ageing. *Maturitas.* (2019) 129:76–84. doi: 10.1016/j.maturitas.2019.09.004

19. Qiu Y, Liu Y, Liu Y, Li Z. Exploring the linkage between the neighborhood environment and mental health in Guangzhou, China. *Int J Environ Res Public Health.* (2019) 16:3206. doi: 10.3390/ijerph16173206

20. Tesch-Roemer C, Motel-Klingebiel A, Tomasik M. Gender differences in subjective well-being: comparing societies with respect to gender equality. *Soc Indic Res.* (2008) 85:329–49. doi: 10.1007/s11205-007-9133-3

21. Sara C. Health and well-being in late life: gender differences worldwide. *Front Med.* (2019) 218:21. doi: 10.3389/fmed.2019.0021

22. Chung Y, Cho YH. Gender difference in quality of life after controlling for related factors among Korean young-old and old-old elderly. *J Agric Med Community Health.* (2014) 39:176–86. doi: 10.5393/JAMCH.2014.39.3.176

23. Okabayashi H, Hougham G. Gender differences of social interactions and their effects on subjective well-being among Japanese elders. *Aging Mental Health.* (2013) 18:788997. doi: 10.1080/13607863.2013.788997

24. Li J, Tian L, Ouyang W. Exploring the relationship between neighborhood-built environment and elderly health: a research based on heterogeneity of age and gender groups in Beijing. *Front Public Health.* (2022) 10:882361. doi: 10.3389/fpubh.2022.882361

25. González-Carrasco M, Casas F, Malo S, Viñas F, Dinisman T. Changes with age in subjective well-being through the adolescent years: Differences by gender. *J Happiness Stud.* (2017) 18:63–88. doi: 10.1007/s10902-016-9717-1

26. Graham C, Chattopadhyay S. Gender and well-being around the world. *Int J Happ Dev.* (2013) 1:212–32. doi: 10.1504/IJHD.2013.055648

27. Stevenson B, Wolfers J. The paradox of declining female happiness. *Am Econ J.* (2009) 1:190–225. doi: 10.3386/w14969

28. Kahneman D, Krueger AB. Developments in the measurement of subjective well-being. *J Econ Perspect.* (2006) 20:3–24. doi: 10.1257/089533006776526030

29. Okun MA, George LK. Physician- and self-ratings of health, neuroticism and subjective well-being among men and women. *Pers Individ Dif.* (1984) 5:533–9. doi: 10.1016/0191-8869(84)90027-8

30. Ronald I. Gender, aging, and subjective well-being. *Int J Comp Sociol.* (2002) 43:391–408. doi: 10.1177/002071520204300309

31. Zheng Z, Chen H, Yang L. Transfer of promotion effects on elderly health with age: from physical environment to interpersonal environment and social participation. *Int J Environ Res Public Health.* (2019) 16:2794. doi: 10.3390/ijerph16152794

32. Pinquart M, Sörensen S. Gender differences in self-concept and psychological well-being in old age: a meta-analysis. *J Gerontol.* (2001) 56:P195–213. doi: 10.1093/geronb/56.4.P195

33. Yen IH, Michael YL, Perdue L. Neighborhood environment in studies of health of older adults: a systematic review. *Am J Prev Med.* (2009) 37:455–63. doi: 10.1016/j.amepre.2009.06.022

34. Clarke P, Nieuwenhuijsen ER. Environments for healthy ageing: a critical review. *Maturitas.* (2009) 64:14–9. doi: 10.1016/j.maturitas.2009.07.011

35. Wang D. An analysis of the evolution and hotspots of the research on built environment and elderly health. *Popul Soc.* (2022) 38:30–40. doi: 10.14132/j.2095-7963.2022.02.003

36. Yue Y, Yang D, Xu D. How built environments affect urban older adults' mental health: contrasting perspective of observation and perception. *Mod Urban Res.* (2022) 6–14. doi: 10.3969/j.issn.1009-6000.2022.01.002

37. Mohai P. Gender differences in the perception of most important environmental problems. *Race Gender Class.* (1997) 5, 153–69.

38. Cunningham M. Gender in cohabitation and marriage the influence of gender ideology on housework allocation over the life course. *J Fam Iss.* (2005) 26:1037–61. doi: 10.1177/0192513X0427 3592

39. Zhang W, Feng Q, Liu L, Zhen Z. Social engagement and health: Findings from the 2013 survey of the Shanghai elderly life and opinion. *Int J Aging Hum Dev.* (2015) 80:332–56. doi: 10.1177/0091415015603173

40. Beutel AM, Marini MM. Gender and values. *Am Sociol Rev.* (1995) 60:436–48. doi: 10.2307/2096423

41. Crossley A, Langdridge D. Perceived sources of happiness: a network analysis. *J Happ Stud.* (2005) 6:107–35. doi: 10.1007/s10902-005-1755-z

42. Liu S, Zhang W, Wu LH, Wu B. Contributory behaviors and life satisfaction among Chinese older adults: exploring variations by gender and living arrangements. *Soc Sci Med (1982).* (2019) 229:70–8. doi: 10.1016/j.socscimed.2018.06.015

43. Zhan HJ. Willingness and expectations: intergenerational differences in attitudes toward filial responsibility in China. *Marriage Fam Rev.* (2004) 36:175–200. doi: 10.1300/J002v36n01_08

44. Hubers C, Schwanen T, Dijst M. Coordinating everyday life in the netherlands: a holistic quantitative approach to the analysis of ICT-related and other work-life balance strategies. *Geografiska Annaler.* (2011) 93:57–80. doi: 10.1111/j.1468-0467.2011.00361.x

45. Wang D, Li J. A model of household time allocation taking into consideration of hiring domestic helpers. *Transport Res Part B Methodol.* (2009) 43:204–16. doi: 10.1016/j.trb.2008.05.004

46. Zhang W, Chai Y. Theories and confirmed model of urban resident's travel demand: considering intra-household interaction. *Acta Geogr Sin.* (2008) 63:1246–56.

47. Molinari C, Ahern M, Hendryx M. The relationship of community quality to the health of women and men. *Soc Sci Med (1982).* (1998) 47:1113–20. doi: 10.1016/S0277-9536(98)00114-2

48. Yu T. Spatial characters of population aging in Chinese big cities. *Planners.* (2015) 31:95–100. doi: 10.3969/j.issn.1006-0022.2015.12.016

49. Cheng X, Wang D, Dai R. Research on the status quo, influence and countermeasures of aging in Nanjing. *Stat Manag.* (2017) 82–4. doi: 10.16722/j.issn.1674-537X.2017.03.028

50. Lin J, Sun B. Impact of built environment on urban residents' subjective well-being: evidence from the China labor-force dynamics survey. *Urban Stud.* (2017) 24:69–75.

51. Cao X. How does neighborhood design affect life satisfaction? Evidence from twin cities. *Travel Behav Soc.* (2016) 5:68–76. doi: 10.1016/j.tbs.2015.07.001

52. Diener E, Emmons RA, Larsen RJ, Griffin S. The satisfaction with life scale. *J Person Assess.* (1985) 49:71–5. doi: 10.1207/s15327752jpa4901_13

53. Ewing R, Cervero R. Travel and the built environment. *J Am Plann Assoc.* (2010) 76:265–94. doi: 10.1080/01944361003766766

54. Feng J. Mobility and quality of life of the elderly in urban China: the role of household structure. In: Wang DG, He SJ, editors. *Mobility, Sociability and Well-Being of Urban Living.* Vol 6. Berlin Heidelberg: Springer (2016). p. 111–26.

55. Gu Z, Chai Y. Change of mobility of urban elderly and effects on their daily life: a narrative analysis of the life of a retired couple living in an urban community. *Progr Geogr.* (2015) 34:1617–27. doi: 10.18306/dlkxjz.2015.12.010

56. Yin C. *Influence of the Urban Built Environment on Residents' Health and Its Pathways: Evidence From Shanghai*. Shanghai: East China Normal University (2020).

57. Frank LD, Iroz-Elardo N, MacLeod KE, Hong A. Pathways from built environment to health: a conceptual framework linking behavior and exposure-based impacts. *J Transport & Health.* (2019) 12:319–35. doi: 10.1016/j.jth.2018.11.008

58. Mouratidis K. Compact city, urban sprawl, and subjective well-being. *Cities.* (2019) 92:261–72. doi: 10.1016/j.cities.2019.04.013

59. Han S. Social capital and subjective happiness: which contexts matter? *J Happ Stud.* (2014) 16:241–55. doi: 10.1007/s10902-014-9506-7

60. Pfeiffer D, Cloutier S. Planning for happy neighborhoods. *J Am Plann Assoc.* (2016) 82:1–13. doi: 10.1080/01944363.2016.1166347

61. Loukaitou-Sideris A, levy-storms L, Chen L, Brozen M. Parks for an aging population: needs and preferences of low-income seniors in Los Angeles. *J Am Plann Assoc.* (2016) 82:1–16. doi: 10.1080/01944363.2016.1163238

62. Wells N, Laquatra J. Why green housing and green neighborhoods are important to the health and well-being of older adults. *Generations.* (2008) 33:50–7. doi: 10.1016/j.exger.2009.10.008

63. Hirsch JA, DeVries DN, Brauer M, Frank LD, Winters M. Impact of new rapid transit on physical activity: a meta-analysis. *Prev Med Rep.* (2018) 10:184–90. doi: 10.1016/j.pmedr.2018.03.008

64. Jorm A, Ryan S. Cross-national and historical differences in subjective well-being. *Int J Epidemiol.* (2014) 43:330–40. doi: 10.1093/ije/dyt188

65. Lei X. *A Study of Gender Theory From Multi Perspectives*. Wuhan: Huazhong University of Science and Technology (2008).

66. Zhang J, Han J, Liu P-W, Zhao Y. Trends in the gender earnings differential in urban China, 1988-2004. *Ind Labor Relat Rev.* (2008) 61:224–43. doi: 10.1177/001979390806100205

67. Stafford M, Cummins S, Macintyre S, Ellaway A, Marmot M. Gender differences in the associations between health and neighbourhood environment. *Soc Sci Med (1982).* (2005) 60:1681–92. doi: 10.1016/j.socscimed.2004.08.028

68. Bian F, Logan JR, Bian Y. Integenerational relations in urban China: proximity, contact, and help to parents. *Demography.* (1998) 35:115–24. doi: 10.2307/3004031

69. Hyde JS, Mezulis A, Abramson LY. The ABCs of depression: integrating affective, biological, and cognitive models to explain the emergence of the gender difference in depression. *Psychol Rev.* (2008) 115:291–313. doi: 10.1037/0033-295X.115.2.291

70. McRae K, Ochsner KN, Mauss IB, Gabrieli JJD, Gross JJ. Gender differences in emotion regulation: An fMRI study of cognitive reappraisal. *Group Process Intergr Relat.* (2008) 11:143–62. doi: 10.1177/1368430207088035

71. Rubin Z, Shenker S. Friendship, proximity, and self-disclosure. *J Person.* (1978) 46:1–22. doi: 10.1111/j.1467-6494.1978.tb00599.x

72. Pettersson P, Schmöcker J-D. Active ageing in developing countries? – Trip generation and tour complexity of older people in Metro Manila. *J Transport Geogr.* (2010) 18:613–23. doi: 10.1016/j.jtrangeo.2010.03.015

73. Wu Z, Wang Z, Zhang F, Song Y, Wang H, Gao L. The impact of urban built environment on the health of the elderly: model validation mediated by physical activity. *China Sport Sci Technol.* (2019) 55:41–9. doi: 10.16470/j.csst.2019142

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Hypertension risk pathways in urban built environment: the case of Yuhui District, Bengbu City, China

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Introduction: The rapid development of urbanization has brought about changes in residents' living environment and behavior, leading to health challenges such as hypertension. An improvement in the built-up environment in the community could contribute to the construction of a healthy city, promote the active life of the residents, and prevent and relieve hypertension. However, there is little research on the relationship between the built environment of the community and hypertension. This cross-sectional study aims to evaluate the relationship between communities' built environment, health behavior, and hypertension grade of residents in Yuhui District of Bengbu City.

Methods: This study is based on data from the 2022 Health Survey of Residents in 21 communities. To investigate the impact of the community's built environment on residents' hypertension and the underlying mechanisms, regression and structural equation modeling were employed.

Results and discussion: The results show that the built environment of urban communities has a significant impact on the residents' hypertension. The presence of high densities of supermarkets, convenience stores, parks and plazas, but low densities of clinics and hospitals, has been identified as a significant risk factor for the development of high blood pressure among the residents. Nevertheless, the adoption of healthy behaviors, including regular walking, physical activity, and a diet rich in fruit and vegetables, can play an important role in reducing the risk of hypertension. The findings of this study show that enhancements to the built environment in urban neighborhoods could contribute to a reduction in the prevalence of hypertension among residents. Furthermore, the implementation of efficacious health interventions in urban settings would facilitate the alteration of residents' health behaviors and enhance their overall health status.

KEYWORDS

built environment, hypertension, health behavior, impact path, mediating effects

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1 Introduction

Rapid urbanization is the major factor affecting urban public health. One notable consequence of urbanization is the marked increase in the incidence of hypertension. In some Asian countries, cardiovascular diseases have become the leading cause of mortality (1) and, in some developing countries, urban populations are more likely to suffer from diseases such as hypertension than rural populations (2). Pedestrian-friendly environments characterized by high densities, mixed-use functions, and accessible road networks have a significant inhibitory effect on reducing hypertension among the population in Europe and the United States. In China, community environments that are multi-functional, in addition featuring a dense road network, ample health facilities, and healthy food, are also helpful in reducing the incidence of hypertension (3). Related studies have shown that the urban built environment may influence the regulation of blood pressure among people (4). The prevalence of high population density in residential areas may impose constraints on the manner in which individuals engage in leisure activity (5). Concurrently, a reduction in public activity space and green open space *per capita* may result in increased psychological stress for residents, which increases the risk of hypertension. It is evident that atmospheric pollution (6) and noise pollution (7) contribute significantly to hypertension. This is particularly the case in developing countries, where the majority of roads are designed with the primary objective of facilitating the movement of motor vehicles, rather than providing safe and accessible routes for pedestrians. Consequently, the high-density road network has an adverse effect on the blood pressure of the population (8). Clinics and hospitals provide residents with more opportunities for blood pressure measurement and health education, giving them the possibility to prevent hypertension in advance (9). The proliferation of high-density supermarkets and convenience stores carry the potential of diminishing the availability of nutritious food items, such as fruits and vegetables. Conversely, this situation results in an increased intake of high-energy foods in the residents' daily diets. Consequently, such a diet increases the likelihood of residents developing high blood pressure (10). Park plazas, being green open spaces and public activity spaces that promote people's health, have been shown to be effective in reducing the risk of hypertension in a number of studies (11).

The hypertensive population (defined as residents with blood pressure levels higher than 120/80 mmHg) exceeds 20% in the Yuhui District in Bengbu City. In this area, the aging population is also approaching 30%. It is a compact community with an array of public facilities and is significantly distinct from other areas. Consequently, in order to examine the relationship between the built environment and health, and to elucidate the impact of the built environment on the health of the residents, Yuhui District in Bengbu City was selected as a representative case study. It has been demonstrated that the construction of compact neighborhoods enhances the accessibility of fitness venues. It is more likely to facilitate greater levels of physical activity among the residents (12) and mitigate the risk of hypertension. As such, effective spatial planning can reduce the risk of hypertension of the residents. Nevertheless, the number of studies examining the influence of the built environment on health pathways remains limited. Prior research has concentrated on the impact of residents' travel and dietary habits on the risk of hypertension (13). The proximity of residents' homes to their places of work has been demonstrated to reduce the frequency of car travel on a daily basis. This, in turn, has been shown to lead to an increase in the use of healthier modes of travel, such as walking and cycling. Consequently, these habits have a beneficial impact on the residents' capacity to maintain optimal blood pressure levels. Residents living in neighborhoods with low availability of healthy foods are prone to consuming cheap but unhealthy food in nearby fast food restaurants, which can increase the risk of hypertension (14).

The majority of current research on the urban built environment and hypertension among residents is conducted at the macro-scale, with studies focusing on the county level (15), the provincial level (16), and the downtown areas of large cities (17). There is a paucity of research at smaller scales, such as the community level, and the impact of issues such as aging and older urban areas has been relatively neglected. Furthermore, the impact of individual health status and poor lifestyle choices is overlooked. Therefore, this study employs the Yuhui District in Bengbu City as a case study to examine the influence of the built environment on the residents' hypertension and the communities' associated behavioral patterns. Furthermore, this article presents recommendations regarding the configuration of urban spatial structure. It is hoped that the recommendations provided will enhance the efficacy of active health intervention in urban areas, reduce the risk of hypertension and other diseases, and improve the overall health of the residents.

2 Materials and methods

2.1 Overview of the study area

Bengbu, located in the northeast of Anhui Province, is an important city in the middle and lower reaches of Huaihe River; it's also the central city in northern Anhui. The study area is 21 plots in 3 neighbourhoods in Yuhui District, Bengbu City, involving three communities: Chaoyang Street, Daqing Street, and Diaoyutai Street. According to the survey conducted in 2020, the permanent population of the study area was 120,000, and the aging population nearly account for 30%, making it a severely aging area. Concurrently, 20% of the population is afflicted with hypertension. The blood pressure levels of these individuals exceed the generally accepted norm (120/80 mmHg). This poses a significant risk of cardiovascular diseases among the population. Therefore, this area is selected as the research unit.

2.2 Data sources

The data on residents' hypertension come from the survey of daily activities and health status of Bengbu residents carried out by the research group in 2022. Random household questionnaires were distributed among the 21 communities in Yuhui District and their response gathered. The survey staff received training and passed an examination. The questionnaire was reviewed by the ethics committee of Bengbu Medical College and was given to the residents only after obtaining their informed consent. The questionnaire includes personal basic information (gender, age, marital status, educational background, monthly income), daily behavior (daily walking time, physical exercise time, frequency of eating fruits and vegetables), health status (height, weight, medical expenses of the year) and bad habits (smoking and drinking). All questionnaires were subjected to a comprehensive review. A questionnaire was deemed invalid if more than 15% of the options selected by the respondent failed to provide a coherent representation of their views on the matter in question. A total of 2,539 questionnaires were distributed, and 2,412 were returned as valid, representing a 95% response rate. The blood pressure of the respondents was measured on the spot and the hypertension grade was calculated (18). In accordance with the recommendations of a medical practitioner from Bengbu Medical College, the subject group underwent blood pressure assessments between 8 and 10 a.m. on the same day. The blood pressure measurements were taken for a minimum of 5 min per individual. A minimum of two blood pressure readings were recorded for each measurement, with an interval of one to 2 min between readings. The average of the two readings was then calculated. The device utilized for the measurement of blood pressure was an Omron U702 sphygmomanometer. In accordance with the standards set forth by the World Health Organization, normal adult blood pressure is defined as 120 mmHg systolic and 80 mmHg diastolic. A diagnosis of hypertension was made if the subject exhibited a systolic blood pressure of ≥140 mmHg and/or a diastolic blood pressure of ≥90 mmHg on two separate occasions.

The data of the Built Environment Index derive from the data of the Seventh Population Census of China in Bengbu City and the point of interest (POI) data of various facilities were collected from the map website. The "Seventh Population Census of China" refers to the national census conducted by China in 2020, and POI refers to the point data in the electronic map on the Internet, which basically consists of four attributes, namely, name, address, coordinates, and category. The 500-meter distance represents the daily 10-min walking distance for residents, with a 500-meter buffer zone encompassing the road network and POI density ranges (19).

2.3 Research framework

This article employs a statistical analysis of data pertaining to the relationship between the community's built environment and hypertension among the residents. Furthermore, a multiple regression model was employed to ascertain the significance of the impact of the community's built environment on hypertension and to investigate the manner in which the built environment influences hypertension levels through health behavior pathways. Finally, the improvement strategies are suggested. The theoretical analysis model is shown in Figure 1.

2.4 Data analysis

2.4.1 Multiple regression model

In this article, the statistical control method (20) is selected for analysis. The hypertension level is usually influenced by many factors such as personal economic, social attributes, and built environment. Individual health status (including height, weight, and current year's medical costs) and poor lifestyle habits (such as smoking and alcohol consumption) represent significant external factors influencing population health. It is therefore essential to incorporate these variables into the model and to evaluate the robustness of the regression results. The model is represented as follows:

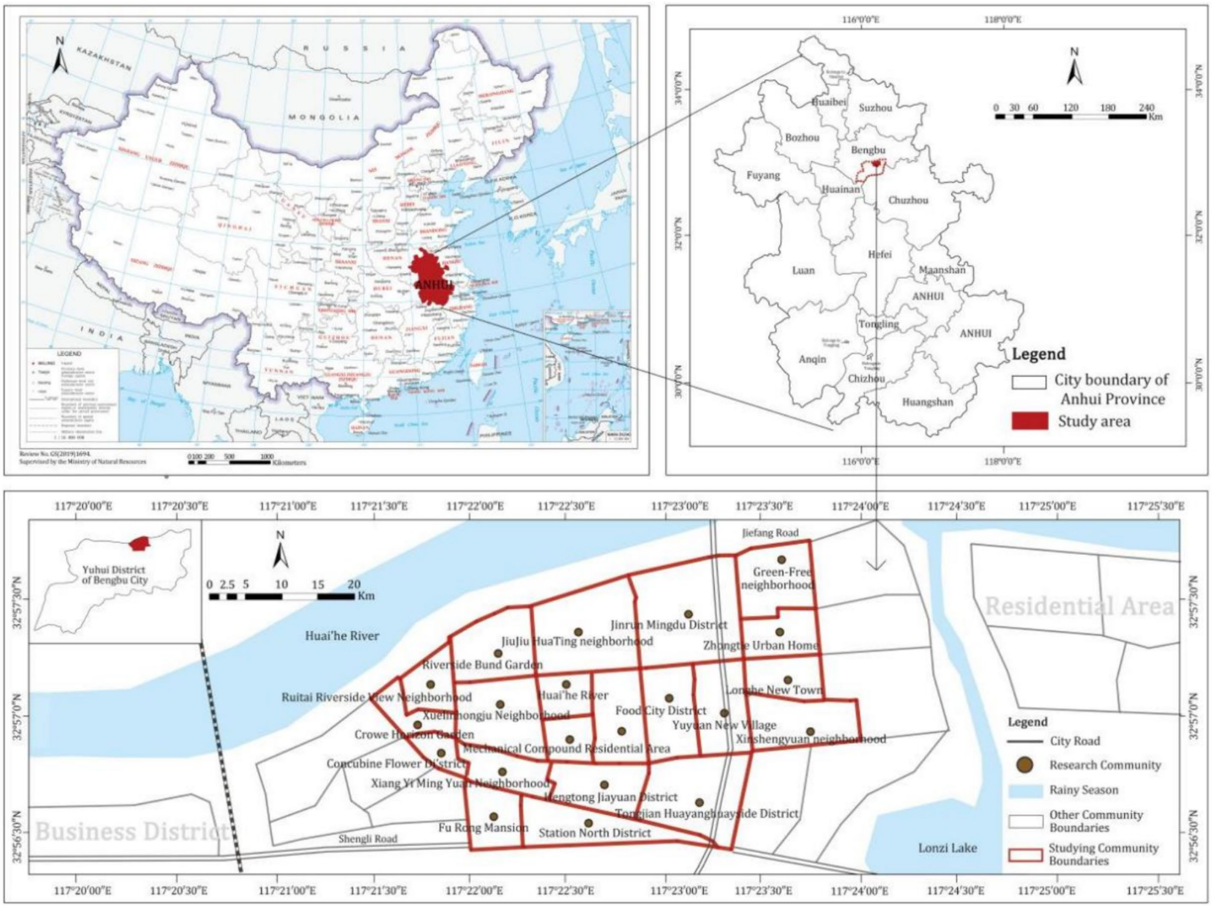

FIGURE 1
Distribution of the scope of investigation.

$$H_{it} = \alpha + \beta_{BE} BE_{it} + \beta_S SES_{it} + \beta_S HC_{it} + \beta_S UNH_{it} + \varepsilon \quad (1)$$

where H_{it} is the hypertension rank status of individual *i* living in community *t*. BE is the matrix of the community's built environment variables of the study individual (the core variable of this study). SES is the matrix of socioeconomic attributes variables of the study individual (the control variable of this study). HC and UNH are the health status and bad habits, respectively, and α and ε are the constant and error terms of the regression model, respectively (Equation 1). In order to control for the effects of individual health status and adverse behavior, the model setting of previous studies (21) was employed. Subsequently, the hypothesis that the relationship between the built environment and the grade of hypertension remains statistically significant will be tested. This will enable us to ascertain whether the effects of hypertension are attributable to individual health status and poor behavior (22) (Figure 2).

2.4.2 Mediation effect test

Figure 3 shows the relationship between the built environment, health behavior, and risk of hypertension. The total effect of the built environment on the risk of hypertension as calculated from the model H_{it} is shown in Figures 3A,C. Given that the built environment exerts a partial influence on hypertension classification through the promotion of health-related behaviors, the total effect, designated as c, is classified into three distinct categories: a, b, and c'. In this context, a and b represent the effects of the total effect c through the health behavior pathway, while c' denotes the effect of the other pathways. On the basis of Figure 3B, a structural equation model diagram of multiple mediators was formed (Figure 3C), and health behaviors were classified into three aspects: walking time, exercise time, and amount of fruits and vegetables consumed. The bias-corrected non-parametric percentile Bootstrap method was also used to test whether mediating effects a1b1, a2b2, and a3b3 were present in c.

2.4.3 Handling of nested data structures

Model 1 incorporates a range of variables, including socioeconomic attributes and health status, which are measured on an individual scale. However, the community-built environment indicators are consistent for all the residents within the same community, and the respondents are not independent individuals. It was thus necessary to ascertain whether the community-built environment indicators exerted an influence on the regression model. Therefore, the null model of the multilevel model was constructed to test.

$$H_{\text{it}} = \alpha_{00} + \mu_{0t} + \varepsilon_{it} \quad (2)$$

where α_{00} denotes the total mean of the hypertension classes in the sample, μ_{0t} denotes the random effect of the community, and ε is the error term. The intra-group correlation coefficient (ICC) was obtained

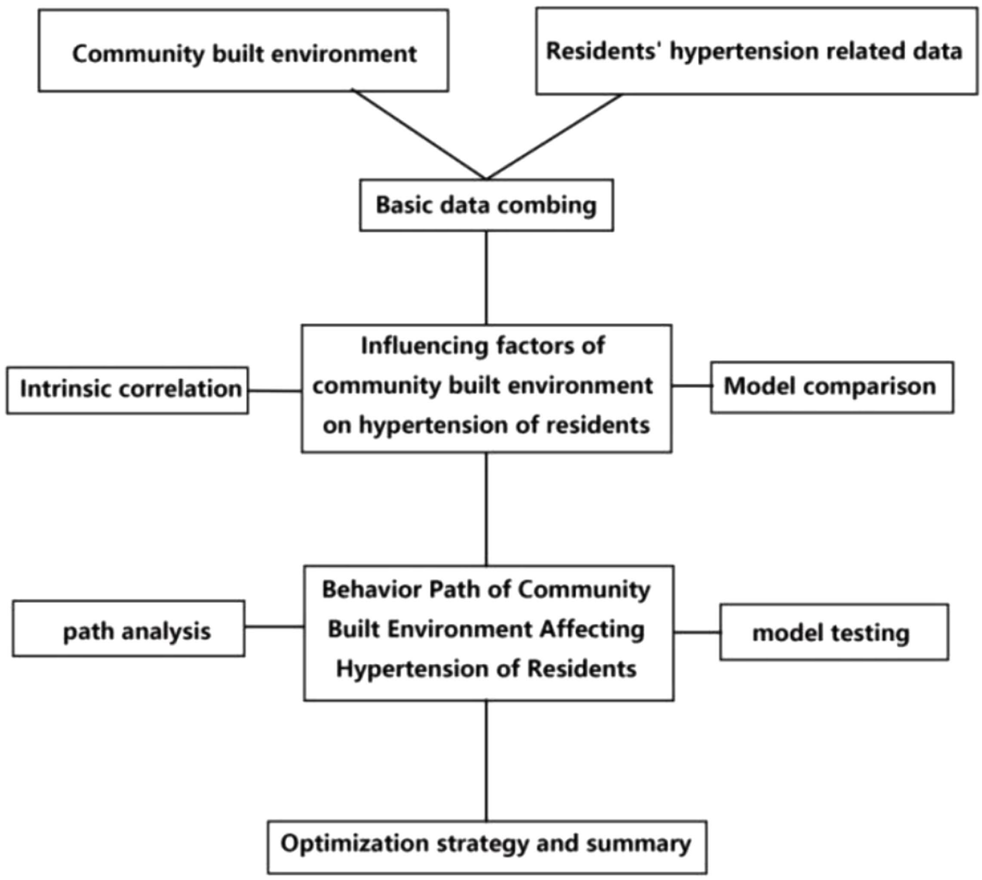

FIGURE 2
The influence of urban community's built environment on residents' hypertension and its path research framework.

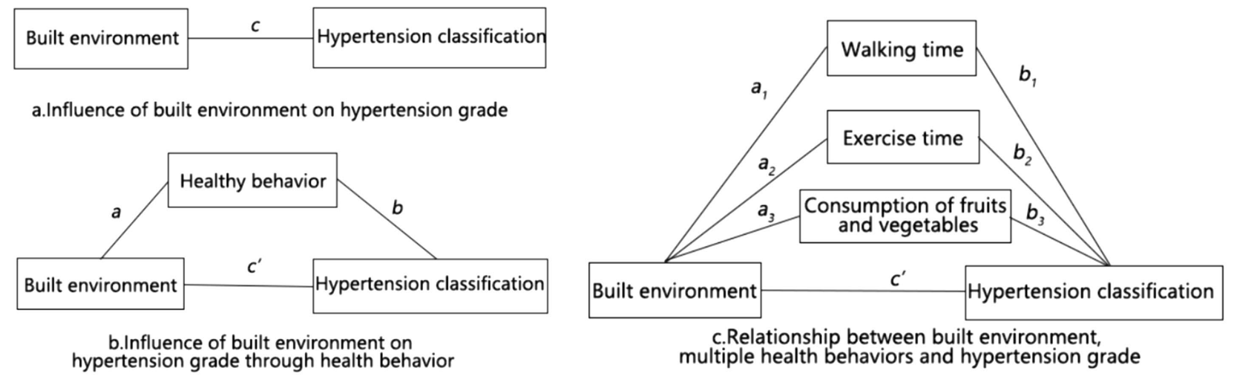

FIGURE 3
Relationship between the built environment, health behavior, and hypertension grade.

by finding the variance on both sides of it, and if ICC < 0. 06, it indicates that the difference between groups is not significant (23) and can still be tested using model 1.

3 Results

3.1 Effect of urban built environment on hypertension of the population

As shown in Table 1, the overall regression of Model IV was statistically significant ($R^2 = 0.118$, $F = 143.99$). In terms of model test indicators, the R^2 value of Model III (0. 118) was higher than that of Models I (0. 077) and II (0. 108), and it can be assumed that the model with the inclusion of individual health status and bad habits was more effective (Table 1). Therefore, the subsequent study was conducted based on Model IV. Among the community's built environment factors, population density ($\beta = 0.014$), road network density ($\beta = 0.02$), and supermarkets and convenience stores ($\beta = 0.033$) positively predicted residents' hypertension levels ($p < 0.05$), indicating that some of the built environment factors positively affected residents' hypertension levels, while park square ($\beta = 0.244$*) and other built environment factors were less significantly associated with hypertension levels. Among the economic and social attributes of residents, age ($\beta = 0.013$**) and marital status ($\beta = 0.117$*) had a greater effect on hypertension levels, while gender ($\beta = 0.073$) had a less effect on hypertension levels. In conclusion, regression analyses were employed to elucidate elements of the built environment, including neighborhood density, population density, and road density, as well as elements of personal attributes, such as residents' gender and age. Furthermore, the analysis revealed that residents' self-assessed health status and health behaviors exert a significant influence on hypertension levels. Among the personal health conditions, obesity ($\beta = 0.041$**) and medical expenses ($\beta = 0.044$**) had a greater impact on residents' hypertension levels. Meanwhile, the effect size and statistical significance of each variable in the model remained unchanged. This indicates that the notable impact of the built environment on the hypertension grade of residents is more substantial when individual health status and unhealthy habits are not taken into account. The nestedness of the data was tested according to Equation 2, and ICC = 0. 034 (<0. 06), so the results of the regression model were still accurate in that the built environment in the city had little effect on individual independence.

Consequently, among the variables pertaining to the built environment, which have been constructed by the community, a negative association was observed between the density of clinics and hypertension class. Conversely, a positive association was identified between the densities of supermarket convenience store and park square, and hypertension class. Among the socioeconomic attribute variables, age was found to be negatively associated with hypertension class. Among the personal health status variables, there was a positive correlation between obesity and hypertension, and a negative correlation between healthcare costs and hypertension. Among the detrimental lifestyle habits, both smoking and alcohol consumption were found to be associated with an increased prevalence of hypertension.

3.2 Constructed pathways of environmental influences on the hypertension grade of the population

The investigation revealed that diverse built environments exerted an impact on hypertension grades through three health behavior pathways, namely, walking time, physical activity time, and frequency of eating fruits and vegetables. In view of the influence of additional control variables on the mediation model, the control variables were removed, and the impact of the independent variable "built environment" on hypertension through the health behaviors was considered in isolation (Figure 4). In particular, walking time was found to be positively associated with population density and road network density, and negatively associated with clinic-hospital density. The time spent engaging in physical activity was found to be positively correlated with road network density and negatively correlated with clinic-hospital density. The frequency of fruit and vegetable consumption was found to be positively correlated with the density of medical facilities.

After analyzing the above model using SPSS, version 29.0 and Mplus 8.2, the study found that (1) the built environment affects the

TABLE 1 Influence of urban built environment on hypertension grade.

Variable	Define	Model 1	Model 2	Model 3	Model 4
Community built environment					
Population density	Population density in the community (unit: 10, 000 people /km^2)	0.022 (0.015)	0.016 (0.015)	0.014 (0.015)	0.014 (0.009)
Road network density	Road network density (unit: km/km^2)	0.031 (0.048)	0.024 (0.048)	0.021 (0.048)	0.02 (0.046)
Clinics and hospital	Density of clinics and hospitals (unit: one /km^2)	−0.028* (0.013)	−0.03* (0.013)	−0.029* (0.013)	−0.028 (0.015)
Supermarket convenience store	Density of convenience stores in supermarkets (unit: one /km^2)	0.028** (0.011)	0.033** (0.011)	0.033** (0.011)	0.033** (0.008)
Park square	Density of Park Square (unit: one /km^2)	0.282** (0.083)	0.277** (0.083)	0.243** (0.083)	0.244* (0.086)
Economic and social attributes					
Gender	Men = 1; Women =0	0.075 (0.045)	0.078 (0.045)	0.074 (0.045)	0.073 (0.044)
Age	Age of respondents (Unit: Years)	0.014** (0.002)	0.012** (0.002)	0.013** (0.002)	0.013** (0.001)
Marital status	Married = 1; Other =0	0.153* (0.062)	0.126* (0.062)	0.117 (0.062)	0.117* (0.05)
Academic degree	Junior high school and above education = 1; Other =0	−0.142* (0.058)	−0.104 (0.058)	−0.113 (0.058)	−0.112 (0.066)
Monthly income[1]	Respondents' personal monthly salary income[1]	0.043* (0.021)	0.039 (0.021)	0.018 (0.022)	0.018 (0.02)
Individual health status					
Fat	Respondents' body mass index (unit: kg/m^2)		0. 041** (0.006)	0. 041** (0.006)	0. 041** (0.009)
Medical expenses[2]	Respondents' current medical expenditure[2]		0. 04** (0.015)	0. 044** (0.015)	0. 044** (0.014)
Bad habit					
Smoke	Respondents smoking = 1; Other =0			0.144* (0.056)	0.144 (0.077)
Drink	Respondents drinking = 1; Other =0			0. 109* (0.053)	0. 109 (0.066)
Constant term		0.021 (0.414)	−0.894* (0.43)	−0.966* (0.43)	−0. 973* (0.455)
R^2		0.077	0.108	0.118	0.118
F value		F (11, 1837) = 13.929 p = 0.000	F (13, 1770) = 16. 561 p = 0.000	F (15, 1751) = 15.489 p = 0.000	F (15, 20) = 143.99 p = 0.000

[1]This variable is an ordered categorical variable, below 1,000 RMB = 1, 1,000–2000 RMB = 2, 2000–3,000 RMB = 3, 3,000–4,000 RMB = 4, and above 4,000 RMB = 5.
[2]This variable is an ordered categorical variable, below 600 RMB = 1, 600–1,000 RMB = 2, 1,000–1,500 RMB = 3, 1,500–2000 RMB = 4, above 2000 RMB = 5; **p < 0. 05, *p < 0. 1.

hypertension class by influencing the walking time of the residents. Table 2 shows that higher road network density and lower clinic-hospital density increase the risk of hypertension among the residents by increasing the residents' walking time. Higher road network density may increase the risk of hypertension by having residents disturbed by street noise, resulting in stressful and depressing emotions. A lower density of clinics and hospitals may increase the time for residents to go to hospitals for regular medical checkups, thus reducing the likelihood that residents take the initiative to have medical checkups to reduce the chance of contracting the disease. (2) The built environment affects hypertension class by influencing the amount of time residents spend in physical activity. Table 3 demonstrates that higher road network density (c' = 0. 054) and lower clinic-hospital density (*c*' = −0. 034*) increase the risk of hypertension among residents by increasing the time they spent on physical activity. Higher road network density may increase residents' activity time and activity intensity, increasing the cardiovascular burden and making residents' blood pressure rise significantly in a short period of time. Lower clinic-hospital density may lead to the untimely popularization of antihypertensive knowledge, which does not play a good role in guiding residents to live a healthy life and thus

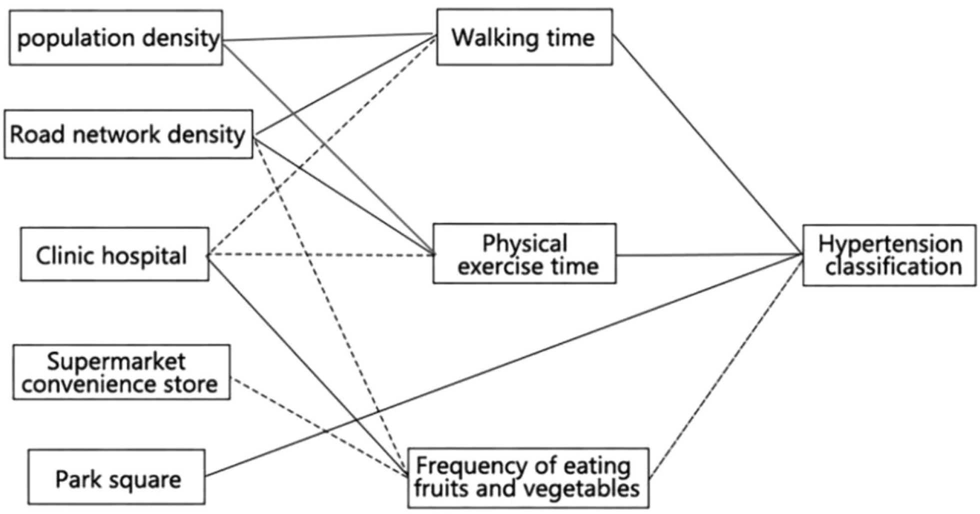

FIGURE 4
Influence of built environment on hypertension and its route summary. The solid line indicates that the sign of the coefficient is positive, and the dotted line indicates that the sign of the coefficient is negative.

TABLE 2 Influence of built environment on hypertension grade through walking time.

Item	c	a	b	a*b	a*b	c'
	Total effect			Mediating effect value	(95% BootCI)	Direct effect
Population density	0.031*	−0.047	0.002**	0	−0.004 ~ 0.003	0.031*
Road network density	0.064	8.695**	0.002**	0.013	0.004 ~ 0.028	0.05
Clinic hospital	−0.037**	−1.943**	0.002**	−0.003	−0.023 ~ −0.003	−0.034*
Supermarket convenience store	0.037**	0.045	0.002**	0	−0.005 ~ 0.005	0.037**
Park square	0.340**	3.255	0.002**	0.005	−0.001 ~ 0. 005	0.335**

*$p < 0.05$, **$p < 0.01$. Bold indicates that the mediation effect is significant.

TABLE 3 Influence of built environment on hypertension level through physical exercise time.

Item	c	a	b	a*b	a*b	c'
	Total effect			Mediating effect value	(95% BootCI)	Direct effect
Population density	0.031*	−0.112	0.001**	0	−0.004 ~ 0.003	0.031*
Road network density	0.064	8.587**	0.001**	0.01	0.002 ~ 0.023	0.054
Clinic hospital	−0.037**	−2.783**	0.001**	−0.003	−0.025 ~ −0.002	−0.034*
Supermarket convenience store	0.037**	0.861	0.001**	0.001	−0.001 ~ 0.010	0.036**
Park square	0.340**	7.346	0.001**	0.009	−0.000 ~ 0.007	0.332**

*$p < 0.05$, **$p < 0.01$.
Bold indicates that the mediation effect is significant.

increases the potential risk of hypertension. (3) The built environment affects hypertension levels by influencing the frequency of consumption of fruits and vegetables. Table 4 indicates that lower road network density ($c' = 0.05$), lower supermarket convenience store density ($c' = 0.034$**), and higher clinic-hospital density ($c' = -0.032$*) reduce the risk of hypertension among residents by increasing the frequency of the consumption of fruits and vegetables by the residents. Lower road network density reduces residents' exposure to harmful gasses such as car exhaust. A lower density of supermarkets and convenience stores reduces the potential risk of hypertension by decreasing calorie intake and increasing fruit and vegetable intake. A higher density of clinics and hospitals helps residents to receive more timely treatment to control the incidence of hypertension before its onset.

TABLE 4 Influence of the frequency of eating fruits and vegetables on hypertension level in built environment.

Item	c Total effect	a	b	a*b Mediating effect value	a*b (95% BootCI)	c′ Direct effect
Population density	0.021	−3.222	−0.001**	0.002	−0.002 ~ 0.010	0.019
Road network density	0.084	−62.770**	−0.001**	0.034	0.016 ~ 0.065	0.05
Clinic hospital	−0.043**	19.800**	−0.001**	−0.011	−0.070 ~ −0.018	−0.032*
Supermarket convenience store	0.039**	−7.975**	−0.001**	0.004	0.007 ~ 0.030	0.034**
Park square	0.359**	−12.355	−0.001**	0.007	−0.002 ~ 0. 007	0.352**

*$p < 0.05$, **$p < 0.01$.
Bold indicates that the mediation effect is significant.

4 Discussion

Previous literature has explored the impact of the built environment on residents' health from environmental perspectives such as compact use of urban space, functional mixing, and pedestrian friendliness. However, in the context of an aging population in old urban areas, there are fewer studies focusing on the impact of the built environment on the incidence of hypertension through the behavior of residents (24). Nowadays, in the face of population aging, it is of practical significance to study the impact of the built environment on hypertension, a common disease among the older adult (25).

In studying the effects of built environment on residents' health, among the community's built environment variables, clinic density was negatively associated with hypertension class. This is consistent with previous research findings (9), where the presence of more number of clinics provided residents with more opportunities for blood pressure measurement and health education, making it possible for residents to reduce the risk of hypertension in advance. The density of supermarkets and convenience stores was found to be positively associated with the grade of hypertension, which is also consistent with previous findings (10). In other words, the greater the density of supermarkets and convenience stores, the greater the likelihood that residents will consume foods high in oil and salt, and thus be more likely to develop hypertensive disorders. The positive correlation between park square density and hypertension classification differs from the findings of a regional study conducted in cities with a greater abundance of parks and greenery (11). In these cities, an increase in park square density may result in greater exposure to natural environments, which could contribute to a reduction in the incidence of hypertensive disorders. However, some scholars have also found that park squares may also have a risk of damaging health (26), and this study further validates their findings. Furthermore, the study area's location in an older urban setting resulted in a relatively low number of parks per neighborhood (M=0.239), accompanied by a high degree of clustering. This may result in a discrepancy between the findings of the study and the conclusion that an increased density of park squares is associated with an increased risk of hypertension (27, 28).

In addition, among the socioeconomic attribute variables, age was negatively associated with hypertension grade. This finding is consistent with previous studies (29), where the human cardiovascular system undergoes degenerative changes with age and increased blood pressure may lead to an increase in hypertension grade. Among the individual health status variables, obesity can lead to increased hypertension, while obese individuals have thicker subcutaneous fat and increased blood volume, leading to higher blood pressure (30). Higher medical expenses of residents will indirectly lead to the increase in hypertension risk, and higher medical expenses often mean that residents have low immunity or chronic diseases, which will lead to an increase of hypertension risk (31). Among the bad habit variables, both smoking and drinking increase the risk of hypertension, probably because harmful components in tobacco (32) and alcohol (33) cause damage to blood vessel walls, as well as other hazards, which increase the risk of hypertension. Therefore, in daily life, to strengthen health education for the residents, community workers should regularly publicize the dangers of hypertension and the knowledge on how to prevent it, such as reducing smoking and drinking (34, 35). At the same time, strengthening health education for teenagers in schools and developing good living habits from childhood will indirectly affect the future level of hypertension (36).

Higher road network density and lower clinic-hospital density can increase the risk of hypertension among residents by increasing the walking time. A higher density of road network increases the daily walking time of residents, which is in accordance with the previous research results (37). The dense road network shows that the streets are closely connected and plays an important role in facilitating residents' walking habits (38). However, the study area is located in the old city, and longer outdoor walking time on both sides of the road will increase the possibility of being exposed to pollution (39, 40), which will increase the risk of hypertension (41). A reduction in the density of both clinics and hospitals has been found to result in an increase in the amount of time residents spend walking on a daily basis. This finding is consistent with the results of a previous study (42). In other words, a reduction in the number of healthcare service destinations results in a decrease in accessibility to treatment (43). This indicates that the daily journey to healthcare facilities becomes more onerous, thereby increasing the time residents spend walking per day.

Higher road network density and lower clinic hospital density increase the risk of hypertension for residents by increasing their physical exercise time. The increase in road network density increases the time of residents' sports activities, which is consistent with the previous research results (44). Specifically, the increase of road network density improves the accessibility of sports venues, thus increasing the frequency of sports activities (45). A novel finding is that a reduction in clinic-hospital density in the study sample is associated with an increase in the frequency of physical activity among the residents. This may be attributed to the observation that the residents of communities with a reduced number of clinics and hospitals have diminished access to healthcare services (46), which may result in a greater propensity to engage in rigorous physical activity. In particular, residents with cardiovascular disease will engage in more unguided exercise. However, research shows that high-frequency exercise increases patients' blood pressure and intensifies the risk of hypertension (47), especially when hypertensive patients exercise in a blind way (48).

Lower road network density and supermarket convenience store density but higher clinic hospital density would reduce the risk of hypertension among residents by increasing the frequency of eating fruits and vegetables. The frequency of eating fruits and vegetables had a significant negative association with hypertension grade under the influence of the built environment in older urban areas, which is consistent with previous studies (49). Vegetables and fruits are a rich source of essential nutrients, including dietary fiber and vitamins, which can play a role in the prevention of hypertension. Nevertheless, a reduction in the consumption of other food items with a high salt and fat content has been demonstrated to enhance immunity and safeguard the cardiovascular system, thereby reducing the likelihood of hypertension. A reduction in road network density has been observed to result in an increase in the frequency of fruit and vegetable consumption among the residents. This may be attributed to the observation that neighborhoods with lower densities of surrounding road networks typically exhibit superior environmental quality. A more favorable natural environment is conducive to the adoption of a healthier diet among the residents. Residents far from the city center will also grow some vegetables and fruits in their own yards, which will increase their consumption of fruits and vegetables and reduce their risk of chronic diseases (50). An increase in the density of clinics and hospitals is associated with a higher frequency of fruit and vegetable consumption among the residents. This may be attributed to the prevalence of health awareness slogans and health education talks in hospital clinics. This will facilitate an improvement in residents' attitudes toward healthy eating, which will in turn result in an increase in the frequency of consumption of fruits and vegetables. An increase in the density of supermarket convenience stores decreases the frequency of eating fruits and vegetables among residents, which is in line with previous studies (14). Supermarket convenience stores will sell more high-calorie food, fast food, and other types of unhealthy food, which will make residents choose fewer fresh fruits and vegetables.

Therefore, the study area needs to optimize the corresponding community built environment and reduce the risk of hypertension by improving the density of road network, clinics, hospitals, supermarkets, convenience stores, and park squares. This article provides the following recommendations. (1) The road network needs to be improved. In the renewal of the old city, road network should be reorganized to reduce the relative walking time of residents on both sides of the road and increase other activities (51). (2) A high density of clinics and hospitals will reduce the risk of hypertension through residents' behavior. It is desirable that land for clinics and hospitals be reserved at the beginning of planning, and it is advisable to gradually increase medical land and investment in urban renewal, and increase the current density through pilot planning of "smart health stations." (3) In terms of supermarket convenience stores, more supermarket convenience stores will increase the risk of hypertension among residents' who may consume less fruits and vegetables. Consequently, in future planning, some supermarket convenience stores should be transformed into vegetable and fruit markets and stores.

Since related research in the context of heavy aging in old urban areas is still in its infancy, and in view of the existing research on healthy cities, future empirical analyses on this issue can focus on the following aspects: (1) based on the residents' traveling surveys, the spatial analysis scope that meets the actual activities of individuals can be delineated and the accuracy of the activity space and the amount of their activities can be improved and increased; (2) on the hypertension level of residents, the Internet open-source data and field survey data can be combined to test the similarities and differences between objective built environment indicators and subjective environmental perceptions; (3) the differences in the mechanism of action among different populations can be explored, with particular emphasis on the impact of the urban built environment on the health status of disadvantaged social classes.

5 Conclusion

Each of the built environment factors had a significant effect on the level of hypertension in the population, but were not interfered with by their individual health status or bad habits. A high density of supermarkets and convenience stores, parks and squares, and a low density of clinics and hospitals increase the risk of hypertension and are detrimental to residents' health. The built environment will influence residents' health-related behavior and affect their own hypertension levels. To be more specific, higher road network density and lower density of clinics and hospitals increase walking and physical exercise time and reduce the frequency of eating fruits and vegetables, thus increasing the risk of hypertension. Higher supermarket and convenience store densities increase the risk of hypertension by decreasing the frequency of fruit and vegetable consumption.

This article is based on cross-sectional survey data only, and future studies utilizing longitudinal survey data are needed to further explore the effects due to environmental changes, which will more accurately explain the relationship between the built environment and residents' hypertension.

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

The studies involving humans were approved by Ethics Committee of Bengbu Medical College. The studies were conducted in accordance with the local legislation and institutional requirements. The participants provided their written informed consent to participate in this study.

Author contributions

KG: Funding acquisition, Resources, Supervision, Writing – original draft, Writing – review & editing. YJ: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Software, Visualization, Writing – original draft, Writing – review & editing. JT: Conceptualization, Investigation, Software, Writing – original draft, Writing – review & editing. XJ: Writing – original draft, Writing – review & editing. XZ: Writing – original draft, Writing – review & editing. BW: Writing – original draft, Writing – review & 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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References

1. Kwan SC, Ismail R, Ismail NH, Mohamed N. An ecological study of the relationship between urban built environment and cardiovascular hospital admissions (2004–2016) in an Asian developing country. *Soc Sci Med*. (2021) 276:113868. doi: 10.1016/j.socscimed.2021.113868

2. Zhao J, Seubsman SA, Sleigh AThai Cohort Study Team. Timing of urbanisation and cardiovascular risks in Thailand: evidence from 51 936 members of the Thai Cohort Study, 2005–2009. *J Epidemiol*. (2014) 24:484–93. doi: 10.2188/jea.JE20140063

3. Wang L, Chen R, Sun W, Yang X, Li X. Impact of high-density urban built environment on chronic obstructive pulmonary disease: a case Study of Jing'an district, Shanghai. *Int J Environ Res Public Health*. (2020) 17:252. doi: 10.3390/ijerph17010252

4. Dzhambov AM, Lercher P, Markevych I, MHEM B, Rüdisser J. Natural and built environments and blood pressure of alpine schoolchildren. *Environ Res*. (2021) 204(Pt A):111925. doi: 10.1016/j.envres.2021.111925

5. Hergault H, Beauchet A, Hauguel-Moreau M, Mustaphic H, Lannou S, Mallet S, et al. Impact of neighborhood socioeconomic status on cardiovascular risk factors in a French urban population. *Arch Cardiovas Dis Supp*. (2021) 13:124–5. doi: 10.1016/j.acvdsp.2020.10.260

6. Ballester F, Tenías J, Pérez-Hoyos S. Air pollution and emergency hospital admissions for cardiovascular diseases in Valencia, Spain. *Br J Soc Med*. (2001) 55:57–65. doi: 10.1136/jech.55.1.57

7. Oh M, Shin K, Kim K, Shin J. Influence of noise exposure on cardiocerebrovascular disease in Korea(J). *Sci Total Environ*. (2018) 651:1867–76. doi: 10.1016/j.scitotenv.2018.10.081

8. Yca B, Rra B, Kra B. Long-term exposure to traffic noise and mortality: a systematic review and meta-analysis of epidemiological evidence between 2000 and 2020. *Environ Pollut*. 15:116222. doi: 10.1016/j.envpol.2020.116222

9. Das B, Neupane D, Singh Gill S, Bir Singh G. Factors affecting non-adherence to medical appointments among patients with hypertension at public health facilities in Punjab. *India J Clin Hypertens*. (2021) 23:713–9. doi: 10.1111/jch.14142

10. Fan C, Law SH, Ibrahim S, Naseem NAM. The new economic era analysis of the structure system of Chinese household consumption expenditure based on the ELES model. *Comput Intell Neurosci*. (2022) 2022:1–8. doi: 10.1155/2022/3278194

11. Villanueva K, Badland H, Hooper P, Koohsari MJ, Mavoa S, Davern M, et al. Developing indicators of public open space to promote health and wellbeing in communities. *Appl Geogr*. (2015) 57:113–114. doi: 10.1016/j.apgeog.2014.12.003

12. Handy SL, Cao X, Mokhtarian PL. The causal influence of neighborhood design on physical activity within the neighborhood: evidence from northern California. *Am J Health Promot*. (2008) 22:350–8. doi: 10.4278/ajhp.22.5.350

13. Frank LD, Iroz-Elardo N, Macleod KE, Hong A. Pathways from built environment to health: a conceptual framework linking behavior and exposure-based impacts. *J Transp Health*. (2019) 12:319–35. doi: 10.1016/j.jth.2018.11.008

14. Drewnowski A. Obesity and the food environment: dietary energy density and diet costs. *Am J Prev Med*. (2004) 27:154–62. doi: 10.1016/j.amepre.2004.06.011

15. Bhaskaran K, Hajat S, Haines A, Herrett E, Wilkinson P, Smeeth L. Short term effects of temperature on risk of myocardial infarction in England and Wales: daily time series regression analysis of the myocardial Ischaemia National Audit Project (MINAP) registry. *BMJ*. (2010) 341:338–8. doi: 10.1136/bmj.c3823

16. Hobbs M, Griffiths C, Green MA, Jordan H, Saunders J, McKenna J. Neighbourhood typologies and associations with body mass index and obesity: a cross-sectional study. *Prev Med*. (2017) 111:351–7. doi: 10.1016/j.ypmed.2017.11.024

17. Xie B, Jiao J, An Z, Zheng Y, Li Z. Deciphering the stroke-built environment nexus in transitional cities: conceptual framework, empirical evidence, and implications for proactive planning intervention. *Cities*. (2019) 94:116–28. doi: 10.1016/j.cities.2019.05.035

18. Chan F, Adamo S, Coxson P, Goldman L, Gu D, Zhao D, et al. Projected impact of urbanization on cardiovascular disease in China. *Int J Public Health*. (2012) 57:849–54. doi: 10.1007/s00038-012-0400-y

19. Glazier RH, Creatore MI, Weyman JT, Fazli G, Matheson FI, Gozdyra P, et al. Density, destinations or both? A comparison of measures of walkability in relation to transportation behaviors, obesity and diabetes in Toronto, Canada. *PLoS One*. (2014) 9:9. doi: 10.1371/journal.pone.0085295

20. Sallis J, Glanz K. The physical activity environment and food environments: Toward solutions to the obesity epidemic. *Milbank Q*. (2009) 87:123–54. doi: 10.1111/j.1468-0009.2009.00550.x

21. Liu Y, Wang R, Xiao Y, Huang B, Chen H, Li Z, et al. Exploring the linkage between greenness exposure and depression among Chinese people: mediating roles of physical activity, stress and social cohesion and moderating role of urbanicity. *Health Place*. (2019) 58:102168–8. doi: 10.1016/j.healthplace.2019.102168

22. Greena LW, Brancatib FL, Albrightc APrimary Prevention of Diabetes Working Group. Primary prevention of type 2 diabetes: integrative public health and primary care opportunities, challenges and strategies. *Fam Pract*. (2012) 29:i13–23. doi: 10.1093/fampra/cmr126

23. Kumar N, Mastrangelo C, Montgomery D. Hierarchical modeling using generalized linear models. *Qual Reliab Engng Int*. (2011) 27:835–42. doi: 10.1002/qre.1176

24. Yifan Y. Impacts of the built environment on the health of older people: a cognitive foundation and methodological exploration. *Inter Urban Plan*. (2020) 35:1–7. doi: 10.19830/j.upi.2019.669

25. Cailing J, Zhongyu H. Path analysis of the impact of community built environment on the physical and mental health of the elderly - a comparative study based on three cities in Jiangsu, Zhejiang and Anhui[J]. *Shanghai Urban Plan*. (2023) 2:125–32. doi: 10.3969/j.issn.1004-9479.2023.05.2021485

26. Sypion-Dutkowska N, Leitner M. Land use influencing the spatial distribution of urban crime: a case Study of Szczecin, Poland. *ISPRS Int J Geo Inf*. (2017) 6:74. doi: 10.3390/ijgi6030074

27. Pozanco A, Fernández S, Borrajo D. On-line modelling and planning for urban traffic control. *Expert Syst*. (2021) 38:e12693. doi: 10.1111/exsy.12693

28. Handy SL, Boarnet MG, Ewing R, Killingsworth RE. How the built environment affects physical activity: views from urban planning. *Am J Prev Med*. (2002) 23:64–73. doi: 10.1016/S0749-3797(02)00475-0

29. Gupta R, CVS R. Hypertension epidemiology in India: emerging aspects. *Curr Opin Cardiol*. (2019) 34:331–41. doi: 10.1097/HCO.0000000000000632

30. Tsai CH, Liou JC, Chang MC. Interview to study the determinants of hypertension in older adults in Taiwan: a population based cross-sectional survey. *Asia Pac J Clin Nutr*. (2007) 16:338–45.

31. Floch MHMDMACG, AGAF. Intestinal microecology in health and wellness. *J Clin Gastroenterol*. (2011) 45:S108–10. doi: 10.1097/MCG.0b013e3182309276

32. Narkiewicz K, Van D, Hausberg M, Cooley RL, Winniford MD, Davison DE, et al. Cigarette smoking increases sympathetic outflow in humans. *Circulation*. (1998) 98:528–34. doi: 10.1161/01.CIR.98.6.528

33. Moreira LB, Fuchs FD, Moraes RS, Wiehe M, Pereira GM, Gus M, et al. Alcohol consumption and the incidence of hypertension: absence of association in a population-based cohort study: P 176. *J Hypertens*. (2004) 22:S52. doi: 10.1097/00004872-200402001-00213

34. Tziraki C, Grimes C, Ventura F, O'Caoimh R, Santana S, Zavagli V, et al. Rethinking palliative care in a public health context: addressing the needs of persons with non-communicable chronic diseases – CORRIGENDUM. *Prim Health Care Res Dev*. (2020) 21:21. doi: 10.1017/S1463423620000602

35. Dallman MF. Stress-induced obesity and the emotional nervous system. *Trends Endocrinol Metabol*. (2010) 21:159–65. doi: 10.1016/j.tem.2009.10.004

36. Caprara G. Mediterranean-Type Dietary Pattern and Physical Activity: The Winning Combination to Counteract the Rising Burden of Non-Communicable Diseases (NCDs). *Nutrients*. (2021) 13:429. doi: 10.3390/nu13020429

37. Marshall SJ, Merchant G. Advancing the science of sedentary behavior measurement. *Am J Prev Med*. (2013) 44:190–1. doi: 10.1016/j.amepre.2012.11.001

38. Owen N, Cerin E, Leslie E, duToit L, Coffee N, Frank LD, et al. Neighborhood walkability and the walking behavior of Australian adults(J). *Am J Prev Med*. (2007) 33:387–95. doi: 10.1016/j.amepre.2007.07.025

39. Nazelle AD, Rodríguez D, Crawford-Brown D. The built environment and health: impacts of pedestrian-friendly designs on air pollution exposure. *Sci Total Environ*. (2009) 407:2525–35. doi: 10.1016/j.scitotenv.2009.01.006

40. Hoek G, Beelen R, Hoogh KD, Vienneau D, Gulliver J, Fischer P, et al. A review of land-use regression models to assess spatial variation of outdoor air pollution. *Atmos Environ*. (2008) 42:7561–78. doi: 10.1016/j.atmosenv.2008.05.057

41. Coogan PF, White LF, Jerrett M, Brook RD, Su JG, Seto E, et al. Air pollution and incidence of hypertension and diabetes mellitus in black women living in Los Angeles. *Circulation*. (2012) 125:767–72. doi: 10.1161/CIRCULATIONAHA.111.052753

42. Morris JM, Dumble PL, Wigan MR. Accessibility indicators for transport planning. *Trans Res Part A Gen*. (1979) 13:91–109. doi: 10.1001/jama.289.19.2560

43. Van de Poel E, O'Donnell O, Van Doorslaer E. Is there a health penalty of China's rapid urbanization? *Health Econ*. (2012) 21:367–85. doi: 10.1002/hec.1717

44. Liu Y, Wang H, Sun C, Wu H. Equity measurement of public sports space in central urban areas based on residential scale data. *Int J Environ Res Public Health*. (2022) 19:3104. doi: 10.3390/ijerph19053104

45. Edginton CR. Leisure and life satisfaction: foundational perspectives. leisure & life satisfaction foundational perspectives. New York, NY: McGraw-Hill (1995).

46. Shen Q. International public physical education and keep fit exercise for the Chinese Journal of Shanghai Teachers University (1999).

47. Schwaab B. Telemedizin in der Rehabilitation nach Herzinfarkt. *Herz*. (2012) 37:63–7. doi: 10.1007/s00059-011-3550-4

48. Aram VC, George LB, Henry RB, William CC, Lee AG, Joseph LI, et al. Seventh report of the joint national committee on prevention, detection. *Sci Technol*. (2016) xviii:165–9. doi: 10.3969/j.issn.1004-9479.2023.05.202148

49. Karatzi K, Georgiopoulos G, Yannakoulia M, Efthimiou E, Voidonikola P, Mitrakou A, et al. Eating frequency predicts new onset hypertension and the rate of progression of blood pressure, arterial stiffness, and wave reflections. *J Hypertens*. (2016) 34:429–37. doi: 10.1097/HJH.0000000000000822

50. Ochodo C, Ndetei DM, Moturi WN, Otieno JO. External built residential environment characteristics that affect mental health of adults. *J Urban Health*. (2014) 91:908–27. doi: 10.1007/s11524-013-9852-5

51. Seanna E, McMartin A, Felice N, Jacka BC, Ian Colman A. The association between fruit and vegetable consumption and mental health disorders: evidence from five waves of a national survey of Canadians. *Prev Med*. (2013) 56:225–30. doi: 10.1016/j.ypmed.2012.12.016

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How to improve public environmental health by facilitating metro usage on weekend: exploring the non-linear and threshold impacts of the built environment

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Introduction: The accelerated motorization has brought a series of environmental concerns and damaged public environmental health by causing severe air and noise pollution. The advocate of urban rail transit system such as metro is effective to reduce the private car dependence and alleviate associated environmental outcomes. Meanwhile, the increased metro usage can also benefit public and individual health by facilitating physical activities such as walking or cycling to the metro station. Therefore, promoting metro usage by discovering the nonlinear associations between the built environment and metro ridership is critical for the government to benefit public health, while most studies ignored the non-linear and threshold effects of built environment on weekend metro usage.

Method: Using multi-source datasets in Shanghai, this study applies Gradient Boosting Decision Trees (GBDT), a nonlinear machine learning approach to estimate the non-linear and threshold effects of the built environment on weekend metro ridership.

Results: Results show that land use mixture, distance to CBD, number of bus line, employment density and rooftop density are top five most important variables by both relative importance analysis and Shapley additive explanations (SHAP) values. Employment density and distance to city center are top five important variables by feature importance. According to the Partial Dependence Plots (PDPs), every built environment variable shows non-linear impacts on weekend metro ridership, while most of them have certain effective ranges to facilitate the metro usage. Maximum weekend ridership occurs when land use mixture entropy index is less than 0.7, number of bus lines reaches 35, rooftop density reaches 0.25, and number of bus stops reaches 10.

Implication: Research findings can not only help government the non-linear and threshold effects of the built environment in planning practice, but also benefit public health by providing practical guidance for policymakers to increase weekend metro usage with station-level built environment optimization.

KEYWORDS

built environment, metro ridership, machine learning, nonlinearity, public environmental health

1 Introduction

The accelerated urbanization and motorization have brought severe environmental challenges, including air pollution, traffic congestion and climate change (1). The air and noise pollution brought by car dependence are the critical threats to public health, which can damage the physical and mental health of people (2). Under this circumstance, transit-oriented development (TOD) has been advocated among many countries to promote urban rail transit system (3). The large-scale construction of metro system has shifted from developed countries to developing contexts (4). In China, the metro system has been constructed in 59 cities and the total length has reached 11232.65 km by the end of 2023 (5). Since the urban traffic carbon emission is a critical reason of climate change, it is imperative for urban planners to improve public environmental health by facilitating metro usage.

Due to the large capacity, low cost and travel time reliability, metro system has become an effective transport alternative for not only the commuting trips on weekdays but also the leisure trips on weekends (1). The trip purpose and travel behavior of metro users can be significantly different between weekdays and weekends (6). For example, there are more commuting trips on weekdays with obvious rush hours, while more entertaining trips with no obvious peak hours on weekends (7). Since the travel modes for commuting people are relatively fixed, promoting metro usage on weekend can not only mitigate traffic congestion and reduce carbon emissions, but also benefit public health from multiple perspectives.

Compared to other factors which may influence the metro ridership (e.g., weather, fare, etc.), the built environment is more suitable to optimize at different metro stations (8). With the development of geographic information systems (GIS) and availability of big data, direct ridership models (DRMs) become more popular in recent metro ridership literature (9). Many of DRMs derived from ordinary least squares (OLS) regression (10), multilevel regression (11), or geographically weighted regression (12), by assuming a linear or loglinear relationship. However, the nonlinearity between the built environment and metro usage has been recently investigated by different DRMs based on several machine learning algorithms, such as Gradient Boosting Decision Tree (GBDT), Random Forest (RF), eXtreme Gradient Boosting (XGBoost) and Light Gradient Boosting Machine (LightGBM) (4, 13, 14). Moreover, the non-linear influences of built environment have been discovered on different travel behavior, including shared bikes (15), shared e-scooters (16), ride-splitting (17), driving distance (18) and ride-sourcing (19). Among these emerging non-linear studies on metro ridership, most of them focused on non-linear effects of the built environment on weekday metro ridership (4, 13, 14), ignoring the temporal heterogeneity on weekend metro usage. The non-linear associations between built environment and metro ridership can be quite diverse between weekdays and weekends, while previous studies failed to address this issue.

To fill the gap, this study aims to promote the metro usage and improve the public environmental health by discovering the non-linear impacts of built environment on weekend metro usage. By utilizing various datasets and GBDT approach, this study attempts to address two research questions: (1) What is the relative importance of each built environment variable in affecting weekend metro ridership? (2) Does the built environment show non-linear impacts on weekend metro usage? What are the threshold and effective ranges?

The remaining part of this paper is structured as follows. Next section reviews the studies on associations between the built environment and metro ridership. Section three introduces the data, variables and methodology. Section four concludes the results. Section five discusses the research findings. The last section summarizes the paper and points out the limitation.

2 Literature review

Due to the popularity of urban rail transit system and transit-oriented development, studies on impacts of built environment on metro usage have brought increasing attentions in the past few decades (4, 13, 14, 20). In the past few years, DRMs have become popular than traditional ridership prediction model because of the convenience of data collection (13).

Although scholars have evaluated the built environment from different aspects, most measured the built environment by "5Ds," including density, diversity, design, destination accessibility and distance to transit (21). Higher activity density can increase the possibility of using metro system. For example, population density or employment density have significant and positive impacts on metro usage (22), both in developed countries (23) and developing countries (24–26). However, recent studies employed GBDT model and proposed that non-linear impacts of density on metro usage may appear negligible if it beyond certain threshold (4, 13, 14, 20).

Diversity, such as mixed land use, can improve metro usage by making the metro station surroundings more appealing. For example, land use mixture has been explored to have positive impacts on metro ridership in Spain, South Korea and China (12, 27, 28), but studies in other countries show insignificant effects of land use mix (23, 29–31). Recently, the non-linear impacts of diversity on metro ridership has been found to be non-trivial only when they are within certain ranges (13, 14).

Design measures road network within the station area. Design features, including street or intersection density can show positive impacts (14, 23, 24, 32–34) or negative effects on metro ridership (26, 28, 35). Recently, studies on DRMs have pointed out that design features have positive impacts on metro usage only if they are in certain ranges (13, 14).

Destination accessibility measures the accessibility to certain areas (city center) or facilities (shopping center). For example, some studies examined the non-linear associations between distance to city center and metro ridership (4, 13). However, the impacts of distance to city center are found to be insignificant in other studies (24, 34). Distance to transit, including bus stop and bus route, have also been explored by studies in different contexts (14, 20, 36, 37).

To sum up, some studies have used DRMs to analyze the impacts of built environment on metro usage, but almost neglect the metro usage on weekends. For these gaps, this study tries to improve the public environmental health by discovering the non-linear impacts of built environment on weekend metro usage.

FIGURE 1
Weekend metro ridership of 328 metro stations in Shanghai.

3 Materials and methods

3.1 Study area

In this study, we utilized 1 month smartcard data on May 2023, including 17 lines and 328 stations in Shanghai (Figure 1). The smartcard data was provided by the Shanghai Government Data Portal[1] with hourly passengers. The raw smartcard data included number of hourly inbound and outbound passengers for each metro station. Daily ridership on weekends of each station was then aggregated by adding up hourly inbound and outbound passengers. The average station ridership on weekends is 27,259 riders per day. People's Square Station, the interchange station of three lines which located at the city center, has the highest ridership of 243,938 passengers. Thirty-two stations have more than 50,000 riders per day, while 55 stations have fewer than 10,000 daily ridership.

3.2 Variables

Twelve built environment variables were included to measure 5Ds built environment in this study. Multiple sources and platforms are used to collected the data of the built environment characteristics, including OpenStreetMap and AMAP API.

3.2.1 Density

Population density around metro station is calculated within 500 m buffer, based on the WorldPop population data with 100 m resolution. Using POI data from AMAP API, employment density is determined by the percentage of employment-related point of interests within 500 m buffer. Rooftop density, the measure of land development, was also calculated within 500 m buffer based on the rooftop area datasets (38).

3.2.2 Diversity

Land use mix, the entropy index for different land use, was utilized to measure station level land use diversity. Since the land use data was not open access to the public, 23 categories of point of interests are used as the alternative to calculate the land use mix entropy within 500 m buffer, including catering, shopping, education, employment, entertainment, tourism, public service, sports, green space, etc.

3.2.3 Design

Intersection and road density were used to measure street design, based on the data from OpenStreetMap. Road density was measured by removing highways and sidewalks from the OpenStreetMap street

1 https://data.sh.gov.cn/

network, while number of intersections is measured by counting 3-way or more intersections.

3.2.4 Destination accessibility

Network distance to CBD and straight distance to the nearest Sub-CBD were involved to measure the effects of accessibility. The CBD and several city Sub-CBDs were chosen according to the official document by Shanghai government (39). Network distance to the nearest highway entrance is was also used to assess the destination accessibility.

3.2.5 Distance to transit

Bus stop and bus line are counted within the station service area, while straight distance to the nearest bus stop is selected to measure the distance to transit.

All the built environment characteristics are measured within 500 m buffer by QGIS (Figure 2). Table 1 summarizes the statistics of all built environment variables.

3.3 Methodology

We employ Gradient Boosting Decision Tree (GBDT) approach to analyze the non-linear effects of the built environment on weekend metro usage. GBDT has several merits for this study. GBDT do not pre-assume linear association between different variables (40). It can also visualize the non-linear relationship by depicting partial dependent plot, which shows the marginal effect on the predictions (41). Meanwhile, GBDT helps to evaluate the contribution of each feature by automatically calculating feature importance (14). Moreover, GBDT is not sensitive to multicollinearity problems, which makes it possible to examine non-linear impacts of different features on weekend metro usage, even they are highly correlated. The effectiveness of GBDT has been recently proved by several studies to evaluate the non-linear effects of built environment on different kinds of travel behavior.

Mathematically, GBDT sets the approximation function $F_T(x)$ by combined several decision trees, and aims to minimize the loss function $L[y, F(x)] = [y - F(x)]^2$. The approximation function $F_T(x)$ is given by Equation 1:

$$F_T(x) = \sum_{t=1}^{T} f_t(x) = \sum_{t=1}^{T} \theta_t h(x;\eta_t) \tag{1}$$

where T is number of trees, η_t is the parameter of the t^{th} tree $h(x;\eta_t)$, θ_t is the weight of $h(x;\eta_t)$ which can be calculated by minimizing the loss function. The optimization process includes several iterative steps. First, the initialization function is determined as Equation 2:

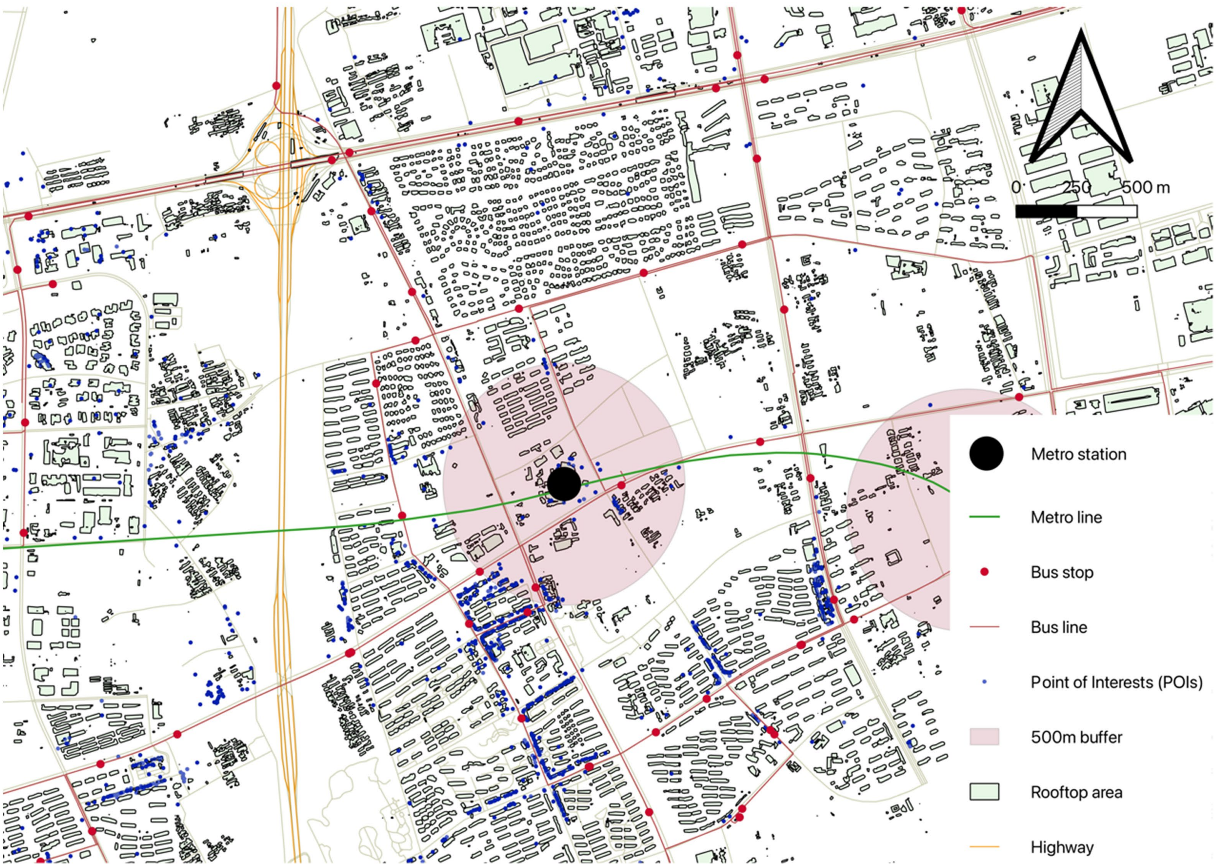

FIGURE 2
An example of built environment variables within station area.

$$f_0(x) = \text{argmin}_\theta \sum_{i=1}^{N} L(y_i, \theta) \tag{2}$$

Second, the residual error $r_{t,i}$ is derived for each sample i in t^{th} iteration as Equation 3:

$$r_{t,i} = -\left[\frac{\partial L(y_i, f(x_i))}{\partial f(x_i)}\right]_{f(x)=f_{t-1}(x)} \tag{3}$$

Third, $(x_i, r_{t,i})$ are utilized to fit the $t^{th}(t = 1,2,\ldots,T)$ tree $h(x;\eta_t)$ by getting the $R_{t,j}, (j = 1,2,\ldots,J_t)$, while J_t is the tree size. After that, we can use tree traversal to determine the optimal gradient as Equation 4:

$$\theta_t = \text{argmin}_\theta \sum_{i=1}^{N} L(y_i, F_{t-1}(x_i) + \theta h(x;\eta_t)) \tag{4}$$

Thus, we can rewrite the iterative equation as Equation 5:

$$f_t(x) = f_{t-1}(x) + \theta_t h(x;\eta_t) \tag{5}$$

To moderate overfitting, learning rate is proposed as the shrinkage parameter $\varepsilon\ (0 < \varepsilon \le 1)$ (41). Therefore, the final function could be written as Equation 6:

$$F(x) = f_t(x) = f_{t-1}(x) + \varepsilon\, \theta_t h(x;\eta_t) \tag{6}$$

For each feature, the feature importance can be calculated by the final model. The importance of feature x_i can be determined as Equation 7 (42):

$$I_{x_i} = \sqrt{\frac{1}{T}\sum_{t=1}^{T}\sum_{j=1}^{J_t} d_j} \tag{7}$$

where j denotes tree nodes, and d_j refers the differences of loss function when make j^{th} tree splitting.

Mathematically, the partial dependence of an independent variable x_s can be calculated as Equation 8 (43):

$$F_s(x_s) = E_{x_c}\left[F(x_s, x_c)\right] \tag{8}$$

where x_c represents other variables. Then, the partial function $F_s(x_s)$ can be determined by averaging over all samples as Equation 9:

$$\overline{F_s}(x_s) = \frac{1}{N}\sum_{i=1}^{N} F(x_s, x_c) \tag{9}$$

Shapley additive explanations (SHAP) can also interpret the model outputs by machine learning models (44). Shapley value (45) are used in SHAP to evaluate the effects of each variable as Equation 10 (44):

$$\varphi_v = \sum_{z' \subseteq x'} \frac{|z'|!(V - |z'| - 1)!}{V!}\left[f_x(z') - f_x(z'/V)\right] \tag{10}$$

where V denotes number of variables, φ_v represents the contribution of variable v, $f(x)$ refers model outputs, $|z'|$ counts non-zero entries in z'.

However, GBDT does have certain restrictions. For example, it cannot perform significance tests and produce coefficient of variables, while feature importance can be used as the substitution. It is also easy to overfit, while using cross-validation and suitable shrinkage parameter can solve this problem (41). In this study, we conduct 5-fold cross-validation and selected the learning rate as 0.001. We get the optimal GBDT model with the lowest RMSE after 2,893 iterations, and the pseudo-R^2 is 0.83.

4 Results

4.1 Feature importance of the built environment

Table 2 presents the relative feature importance and ranking in determining metro usage on weekends. Land use mixture has the largest predictive power, with the relative importance of 16.26%. As the measurement of diversity, it has been observed as a critical factor on metro ridership prediction by many previous studies in different contexts (4, 13, 28, 33). Distance to CBD, a measure of regional accessibility, has the second large relative importance, with a contribution of 13.61%. Other destination accessibility variables, including distance to highway (7.21%) and distance to Sub-CBD (5.21%), also have non-trivial impacts on weekend metro usage. The importance of bus line is also substantial, accounting for 12.17% and ranking 3rd over all independent variables. This corresponds to the existing findings that distance to transit can notably affect the metro usage (4, 13). Among five categories of built environment, density features have the largest relative importance of 29.29% on ridership prediction, collectively contributed by three density variables. By contrast, design variables (e.g., intersection and street density) only shown trivial impacts on weekend metro usage, with relative importance of only 2.78 and 2.61%, respectively.

4.2 SHAP beeswarm plot of the built environment

To discover the contribution of each variable and analyze how variables of stations influence the metro usage, SHAP beeswarm plots (also called the SHAP summary plots) are employed in this study.

The SHAP beeswarm plot sorts variables by mean absolute value of SHAP values, while uses SHAP value to show the effect distribution of variables (Figure 3). Each station is displayed by one point for each variable, while the horizontal axis presents SHAP values. Value of each feature is shown in different colors.

As shown in Figure 3, land use mixture ranks first by SHAP values, which is similar to the feature importance results. Meanwhile, Number of bus line, distance to CBD, employment and rooftop area are other top five significant variables, which is same

TABLE 1 Statistics of all variables.

Variables	Description	Mean	S.D.	Min	Max	Data source
Dependent variable						
Weekend ridership	Daily metro ridership on weekends (count)	27,259	27,839	1,011	243,938	Metro smartcard data of Shanghai on May 2023
Built environment variables						
Density						
Population density	Population density within 500 m buffer (1,000 people/km^2)	16.83	10.52	0.04	41.58	WorldPop population data 2023
Employment density	Ratio of employment POI within 500 m buffer	0.14	0.15	0.03	0.95	Point-of-interest (POI) data 2023
Rooftop density	Rooftop area ratio within 500 m buffer	0.18	0.06	0.02	0.45	Vectorized rooftop area data 2020
Diversity						
Land use mixture	The entropy index $\frac{-\sum_{i=1}^{m}(p_i)\ln(p_i)}{\ln(m)}$ where m denotes different POI and p_i represents the ratio.	0.72	0.13	0.14	0.87	Point-of-interest (POI) data 2023
Design						
Road density	Road centerline length per km^2 (km/km^2)	5.83	1.94	1.22	13.84	OpenStreetMap data 2023
Intersection	Number of intersections within 500 m buffer (count)	9.24	6.12	0.00	42.00	OpenStreetMap data 2023
Destination accessibility						
CBD	Network distance to CBD (km)	14.14	10.29	0.16	65.90	OpenStreetMap data 2023
Sub-CBD	Straight distance to the nearest Sub-CBD (km)	6.75	5.22	0.00	37.85	OpenStreetMap data 2023
Highway	Network distance to the nearest highway (km)	1.25	1.46	0.04	6.62	OpenStreetMap data 2023
Distance to transit						
Bus stop	Number of bus stops within 500 m buffer (count)	6.42	3.50	1.00	26.00	Point-of-interest (POI) data 2023
Bus line	Number of bus routes within 500 m buffer (count)	17.15	10.27	0.00	62.00	Point-of-interest (POI) data 2023
Nearest bus stop	Straight distance to the nearest bus stop (km)	0.12	0.07	0.01	0.42	Point-of-interest (POI) data 2023

TABLE 2 Relative importance and ranking of variables.

Category	Features	Ranking	Relative importance
Density (29.29%)	Population density	6	9.18%
	Employment density	4	10.06%
	Rooftop density	5	10.05%
Diversity (16.26%)	Land use mixture	1	16.26%
Design (5.39%)	Road density	12	2.61%
	Intersection	11	2.78%
Destination accessibility (26.03%)	CBD	2	13.61%
	Sub-CBD	9	5.21%
	Highway	7	7.21%
Distance to transit (23.03%)	Bus stop	8	7.06%
	Bus line	3	12.16%
	Nearest bus stop	10	3.81%

with the feature importance results but with little difference with ranking. Moreover, number of bus stops, which ranked only 8th by relative importance, are the 6th most significant variable by SHAP values.

Bus line, rooftop density, bus stop and population density are positively related with SHAP value, while land use mixture, CBD and employment density show negative associations. It means that large number of bus lines and bus stops, high rooftop density and population density (in red color) can increase more metro ridership on weekends, while high land use diversity, long distance to CBD and high employment density (in red color) lower the weekend metro ridership.

4.3 Non-linear impacts of built environment on weekend metro usage

To explore the relationship between the built environment and weekend metro ridership, partial dependence plots (PDPs) are employed in this study. Overall, all independent variables shown non-linear associations with weekend metro usage. Figure 4 presents the non-linear impacts of built environment variables on weekend metro usage.

As shown in Figure 4, the weekend metro ridership remains (at about 40,000) when land use mixture entropy is smaller than 0.65. However, the weekend metro ridership drops substantially to less than 25,000 when the entropy moves from 0.65 to 0.75, and no further decrease occurs.

Bus line is positively associated with weekend metro usage. The metro usage keeps stable at less than 25,000 when bus route is

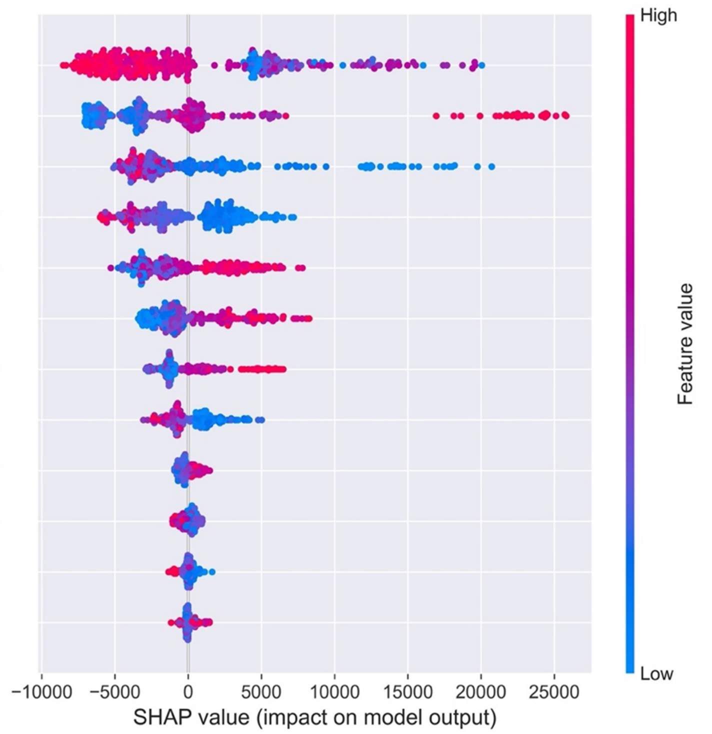

FIGURE 3
SHAP beeswarm plot of built environment.

TABLE 3 Effective ranges of variables.

Variables	Effective range/ Threshold	Association
Land use mixture	0.65–0.75 (scale)	Negative
Bus line	15–20, 30–35 (count)	Positive
CBD	2–10 (km)	Negative
Employment density	0–0.2 (scale)	Negative
Rooftop density	0.2–0.25 (scale)	Positive
Bus stop	3–10 (count)	Positive
Road density	5–7 (km/km^2)	Positive
Highway	0.5–2 (km)	Negative

less than 15. After that, the ridership suddenly increases to 30,000 as bus route moves from 15 to 20, and no increase in metro ridership has been found when bus line is between 20 and 30. However, the weekend metro ridership sharply increases from 30,000 to 50,000 when number of bus line reaches 35, and then remain constant.

The association between distance to CBD and weekend metro ridership is negative. The weekend ridership drops dramatically from 45,000 to 25,000 when the distance to CBD grows from 0 to 10 km. However, no further decrease of metro ridership has been found when the distance to CBD exceeds 10 km. Similar pattern has been found for distance to Sub-CBD.

Rooftop density has positive effects on weekend metro ridership. When the rooftop density is less than 0.2, metro ridership keeps 25,000. After that, the weekend ridership rises substantially from 25,000 to 31,000 when rooftop density between 0.2 and 0.25. As shown in the PDPs, as bus stop increases from 0 to 10, weekend metro ridership rises by 6,000. However, this effect looks negligible when there are more than 10 bus stops.

Meanwhile, the distance between metro station and nearest transit station has negative impacts to weekend metro usage, with an effective interval of 100–200 m. However, this effect is limited and the difference in metro ridership is only about 1,500, echoing the small relative importance of this variable in metro ridership prediction.

Overall, PDPs show the average effect of the built environment variables without specific instances. To visualize the partial dependence of one variable on weekend metro ridership for each station, we also combined Individual Conditional Expectation (ICE) curves with PDPs as shown in Figure 5. In Figure 5, the ICE curves are presented in light blue lines, while the PDP is shown in dark blue line as the average.

As shown in Figure 5, for each independent variable, all the ICE curves seem to follow the similar pattern with the partial dependence plot. It means that there is no obvious heterogeneous relationship created by interactions. Under this circumstance, employing PDPs in this study can provide good summary of the impacts of built environment on predicted metro usage on weekends.

5 Discussion

Promoting metro usage on weekends by optimizing station-level built environment is a critical way to address a series of

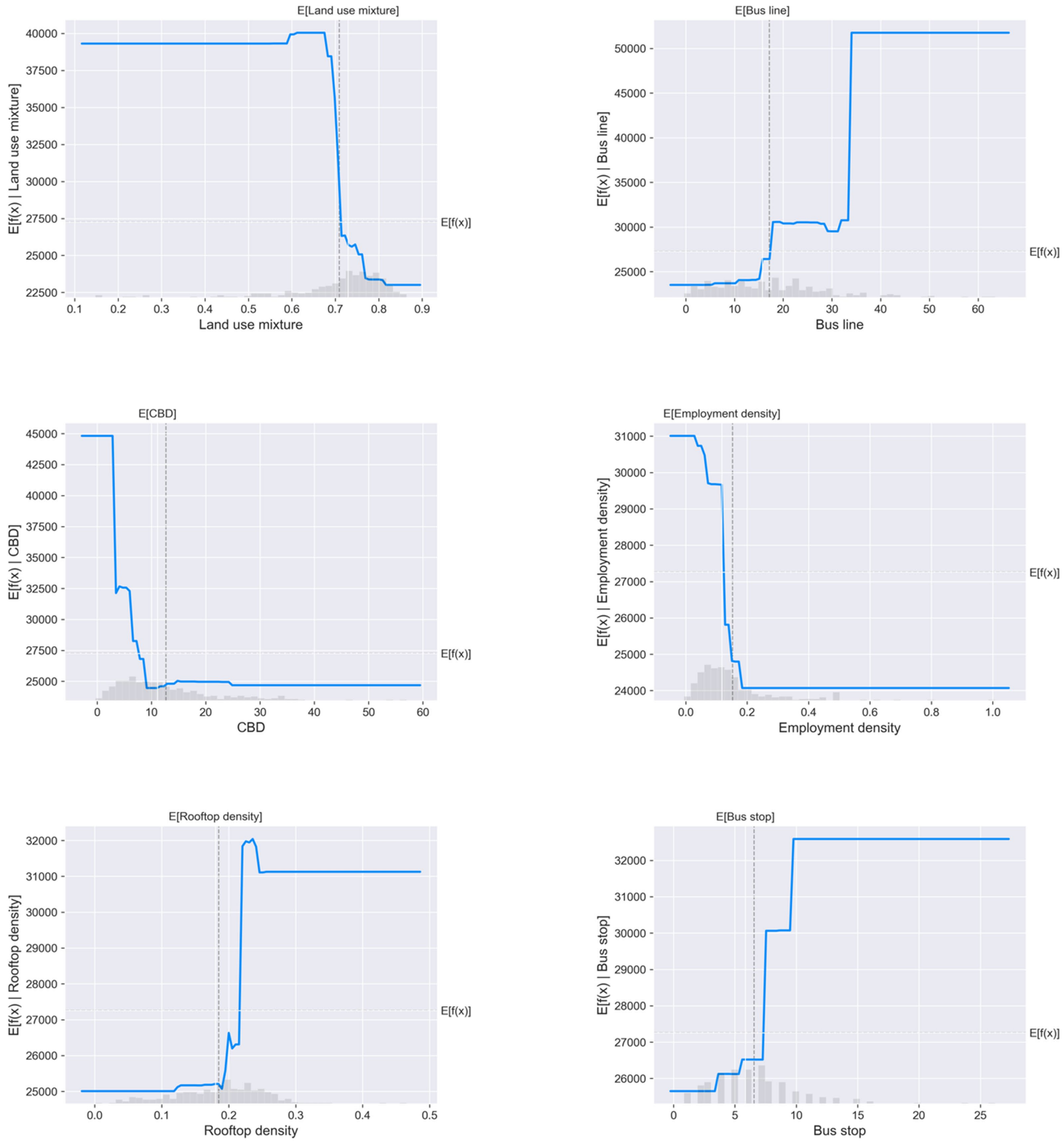

FIGURE 4 (Continued)

environmental challenges from accelerated urbanization and mobilization. This study employed GBDT approach to evaluate the non-linear associations between the built environment and weekend metro ridership in Shanghai. Several model interpretation methods are utilized to unravel the non-linear impacts of factors on weekend metro usage.

Based on the results of relative importance and SHAP values, we recognized that land use mixture, the distance to CBD and number of bus lines are three most important factors on affecting weekend metro usage.

Among these three factors, land use mixture and distance to CBD are found to be negative associated with weekend metro ridership, while number of bus lines is found to be positive related with weekend metro usage. Higher land use mixture usually represents more average land use types within the station catchment area. However, many metro users take metro on weekend for a specific purpose (e.g., shopping, food, or tourism), and stations with relatively lower land use mixture may thus have more metro riders. It is intuitive that distance to CBD is negative related with weekend metro usage. Due to the traffic jam and shortage of parking spaces within CBD area in megacities like Shanghai, driving to the CBD on weekends may not as convenient as taking the metro. Therefore, metro stations which are close to the CBD can attract more metro users during the weekend. More bus lines near the metro station can provide sufficient first/last-mile services for

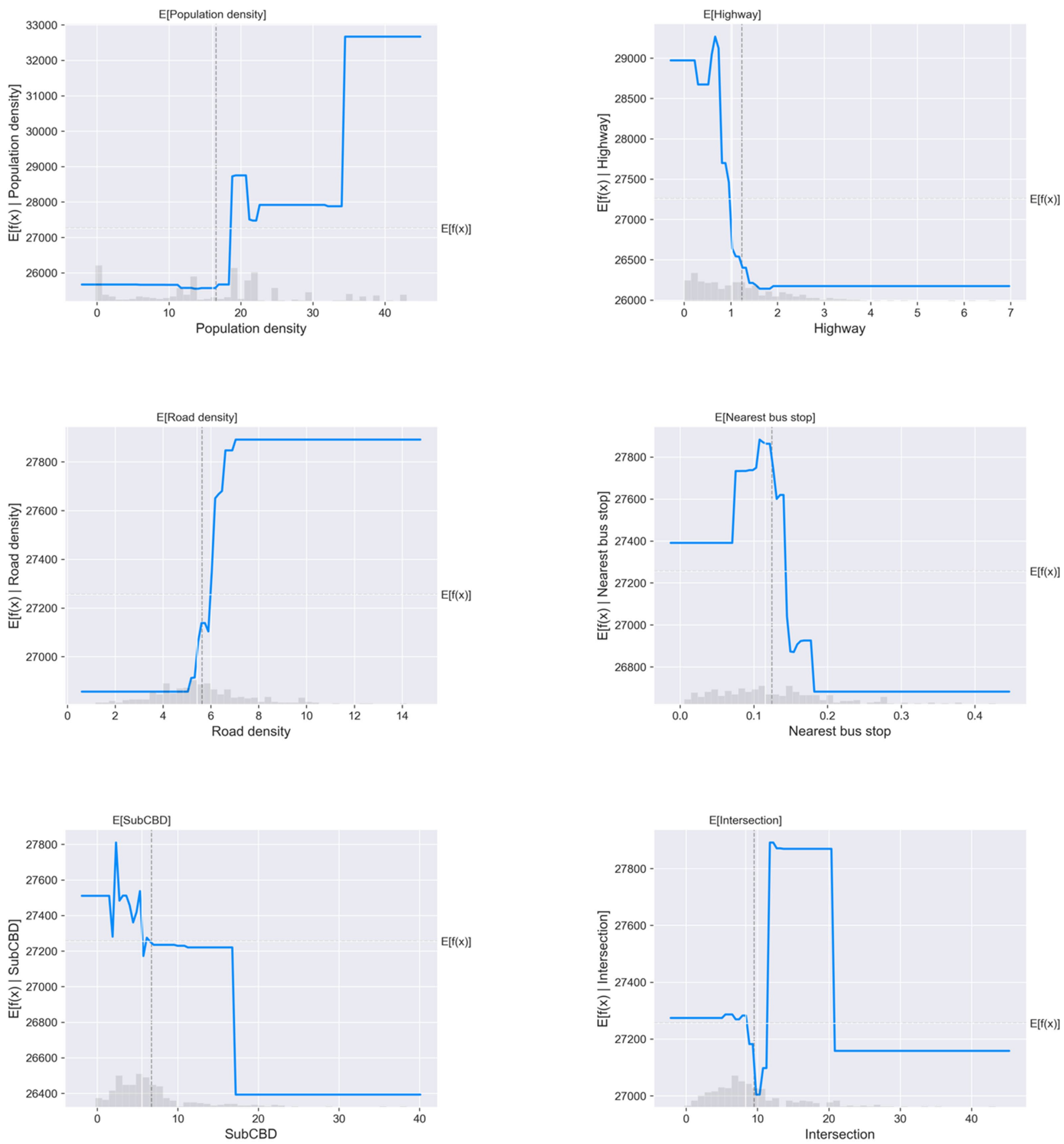

FIGURE 4
Partial dependence plots on weekend metro usage.

metro users to access the metro station on weekend, which enlarge the station catchment area and facilitate weekend metro usage.

Based on the results of partial dependence plots, all the built environment variables show non-linear impacts on weekend metro usage with certain threshold and effective ranges (Table 3). Weekend metro ridership shows a significant decrease when land use mixture moves from 0.65 to 0.75. The complex relationship between land-use diversity and weekday or weekend metro usage is also found by many literature in different contexts (4, 14, 20).

The distance to CBD is negatively related with weekend metro usage between 2 to 10 km, which seems to be reasonable that metro stations near city center may have densified population and thus more metro passengers. The distance to CBD has no significant impact on weekend metro usage when it is beyond this range. The sharp rise of weekend metro usage has been found when number of bus lines increases from 15 to 20 and 30 to 35, while the ridership remains nearly constant when number of bus lines is within other ranges. Existing literature has also suggested the positive impacts of bus lines on metro usage, while the impacts can be mediated if bus route is more than 40 (4). Rooftop area has a positive association with weekend metro ridership, with a dramatic rise between 0.20 and 0.25. This indicates that high level of land use development can facilitate the weekend metro usage, but excessive development may have trivial effects on further increase. Number of bus stops has positive effects on weekend metro ridership, with an effective

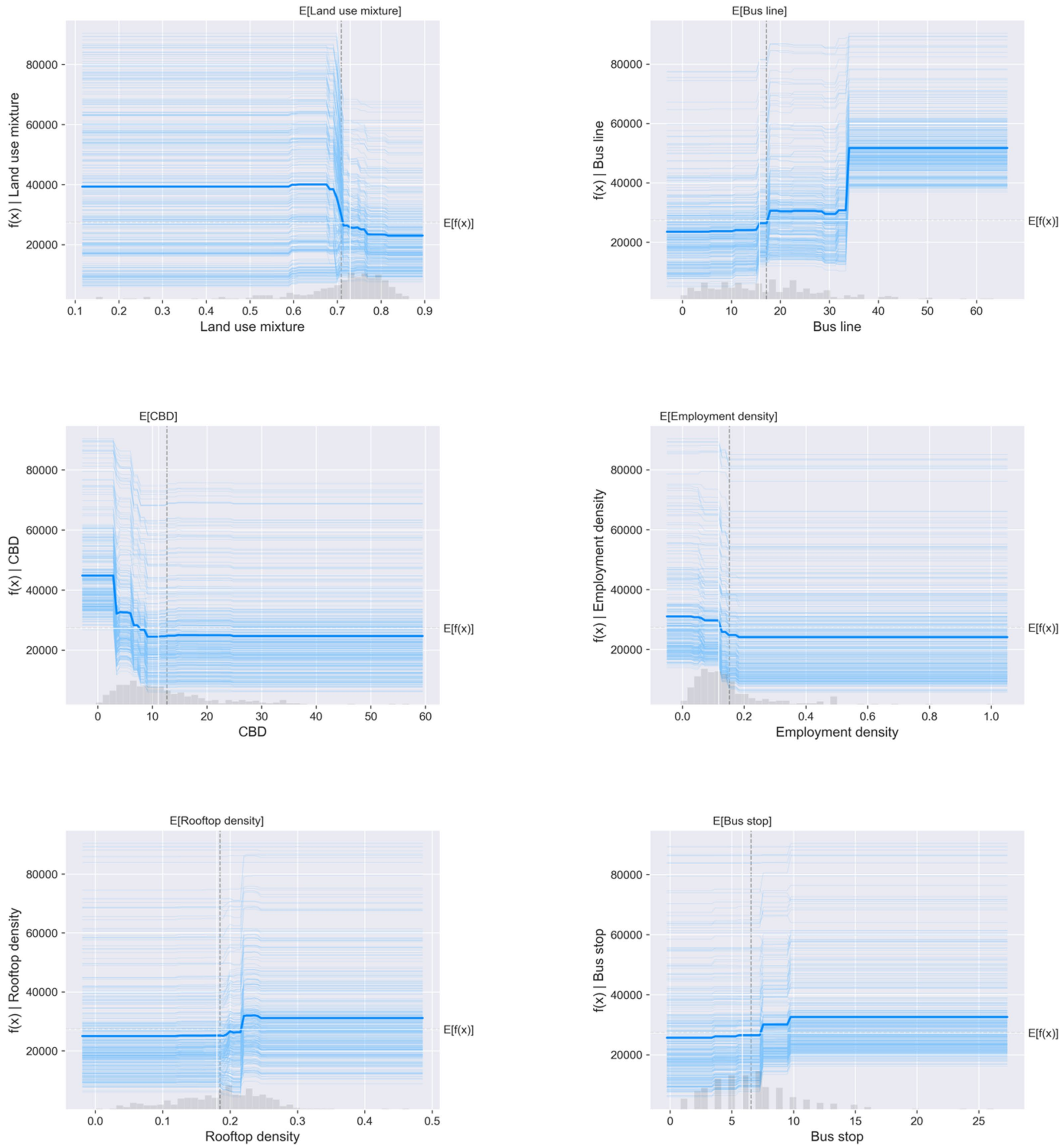

FIGURE 5 (Continued)

range between 3 and 10. Similar threshold impacts of bus stops are found in different cities but with different thresholds (13, 14).

6 Conclusion

To improve the public environmental health by facilitating metro usage on weekend, this study employed GBDT approach to evaluate the non-linear and threshold impacts of the built environment on weekend metro ridership. Compared to conventional models with linear presumption, investigating the non-linear effects help policymakers and urban planners recognize the thresholds and effective ranges of the built environment characteristics, which can benefit public health by making customized strategies and policy interventions. The empirical finding may contribute threefold to the existing studies.

First, this study estimates the feature importance of built environment characteristics in predicting weekend metro ridership. According to the results, the top-five variables with highest importance are land use mixture (16.26%), distance to CBD (13.61%), bus line (12.17%), employment density (10.06%) and rooftop density (10.05%). Results can help urban planners identify the role of different built environment characteristic and issue differentiation strategies.

Second, it depicts SHAP beeswarm plot to show the impact of each variable on the prediction. The top-5 important variables by

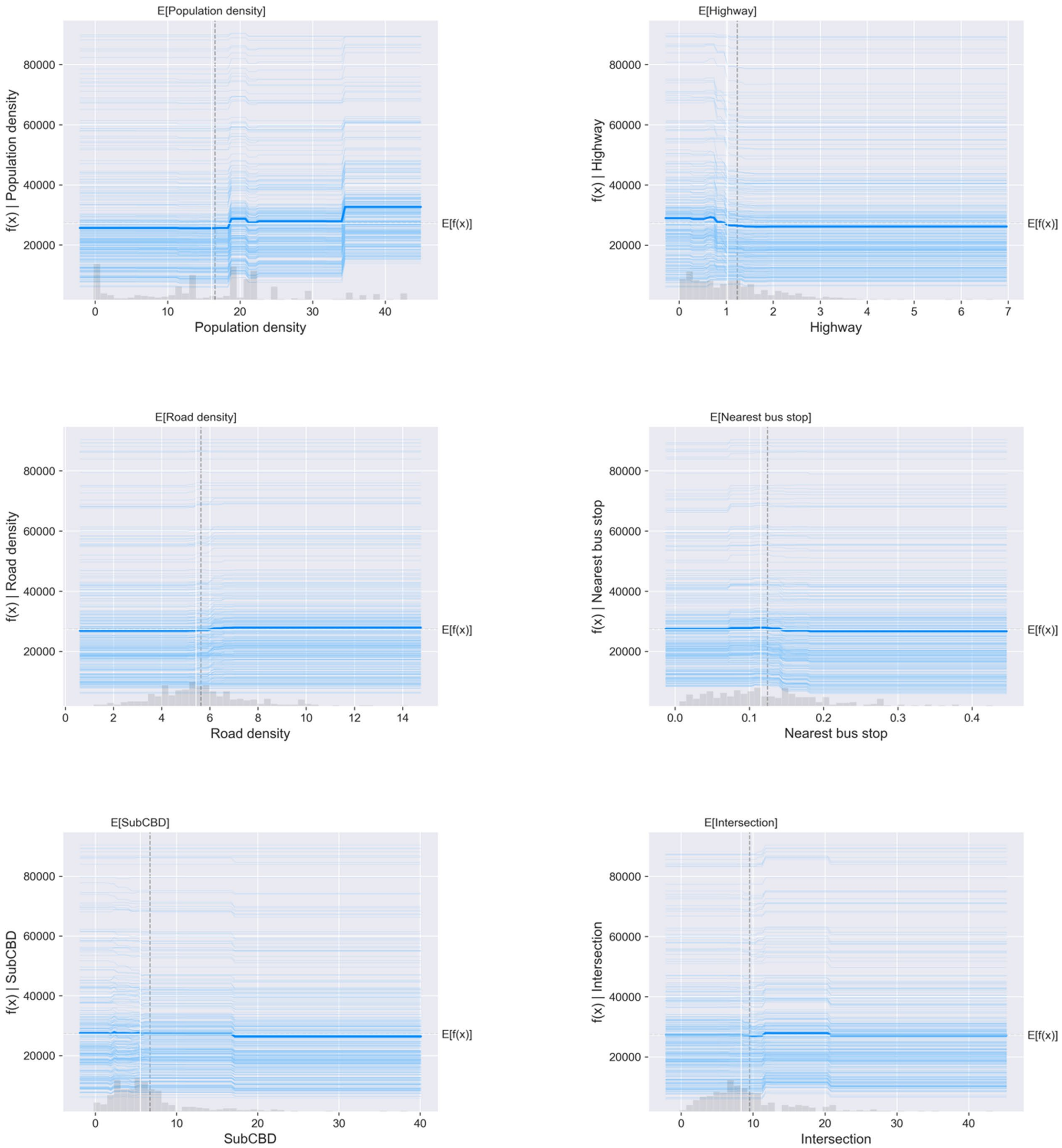

FIGURE 5
Combination of PDPs and ICEs of built environment on metro usage.

SHAP beeswarm plot are same to relative importance. Bus line, rooftop density, bus stop and population density are positively related with SHAP value, while land use mixture, distance to CBD and employment density are negativity associated with SHAP value. Therefore, urban designers should pay different attention to the built environment characteristics to promote metro usage.

Third, we depict the non-linear impacts of the built environment by combining PDPs with ICEs. Most variables have obvious thresholds on determining weekend metro ridership. Results show that maximum weekend ridership occurs when land use mixture entropy is smaller than 0.7, number of bus lines reaches 35, rooftop density reaches 0.25, and number of bus stops reaches 10. The non-linear relationship and their effective ranges help policymakers increase metro ridership on weekends by optimizing station-level land use.

Several limitations merit further study. First, the influences of built environment features on weekend metro usage may vary in different contexts. Therefore, relevant studies are encouraged to explore or validate the non-linear associations between the built environment and weekend metro ridership. Second, this study uses the 500 m buffer for most independent variables, while 400 m buffer (13) and 800 m (20) are used by different station-level built environment studies. Because the real service area of metro stations may vary in different cities and stations, future studies are welcome to testify the results with different buffer zones. Third, we only explore the effects of a limited number of built environment characteristics. With the development of big data and GIS, more comprehensive built environment attributes (e.g., number of parking spaces, demographics, sidewalk density) with finer data are welcomed for further exploration in different contexts. Fourth, PDPs may be misguided when independent variables are correlated with each other (e.g., bus stop and bus line), while accumulated local effects (ALE) plots can be used as an unbiased alternative to address the multicollinearity issue in further studies. Fifth, most data used in this study are before the pandemic, while the comparison between pre-pandemic and post-pandemic need further exploration in the future.

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

BP: Conceptualization, Data curation, Methodology, Software, Visualization, Writing – original draft, Writing – review & editing. TW: Data curation, Resources, Supervision, Writing – review & editing. YZ: Conceptualization, Methodology, Supervision, Writing – original draft, Writing – review & editing. CL: Conceptualization, Funding acquisition, Project administration, Supervision, Validation, Writing – review & 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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References

1. Liu B, Xu Y, Guo S, Yu M, Lin Z, Yang H. Examining the nonlinear impacts of origin-destination built environment on metro ridership at Station-To-Station level. *ISPRS Int J Geo Inf*. (2023) 12:59. doi: 10.3390/ijgi12020059

2. Wu J, Li C, Zhu L, Liu X, Peng B, Wang T, et al. Nonlinear and threshold effects of built environment on older adults' walking duration: do age and retirement status matter? *Front Public Health*. (2024) 12:1418733. doi: 10.3389/fpubh.2024.1418733

3. Calthorpe P. The next American metropolis: Ecology, community, and the American dream. NYC, USA: Princeton Architectural Press (1993).

4. Gan Z, Yang M, Feng T, Timmermans HJP. Examining the relationship between built environment and metro ridership at station-to-station level. *Transp Res Part D: Transp Environ*. (2020) 82:102332. doi: 10.1016/j.trd.2020.102332

5. CAMET. Overview of urban rail transit lines in Mainland China in 2022. Beijing, China: China Association of Metros (2023).

6. Kuby M, Barranda A, Upchurch C. Factors influencing light-rail station boardings in the United States. *Transp Res A Policy Pract*. (2004) 38:223–47. doi: 10.1016/j.tra.2003.10.006

7. Ma X, Liu C, Wen H, Wang Y, Wu YJ. Understanding commuting patterns using transit smart card data. *J Transp Geogr*. (2017) 58:135–45. doi: 10.1016/j.jtrangeo.2016.12.001

8. He Y, Zhao Y, Tsui K-L. Modeling and analyzing impact factors of metro station ridership: An approach based on a general estimating equation. *IEEE Intell Transp Syst Mag*. (2020) 12:195–207. doi: 10.1109/MITS.2020.3014438

9. Cao J, Tao T. Using machine-learning models to understand nonlinear relationships between land use and travel. *Transp Res Part D: Transp Environ*. (2023) 123:103930. doi: 10.1016/j.trd.2023.103930

10. Zhao J, Deng W, Song Y, Zhu Y. What influences metro station ridership in China? Insights from Nanjing. *Cities*. (2013) 35:114–24. doi: 10.1016/j.cities.2013.07.002

11. Iseki H, Liu C, Knaap G. The determinants of travel demand between rail stations: a direct transit demand model using multilevel analysis for the Washington D.C. Metrorail system. *Transp Res A Policy Pract*. (2018) 116:635–49. doi: 10.1016/j.tra.2018.06.011

12. Li S, Lyu D, Huang G, Zhang X, Gao F, Chen Y, et al. Spatially varying impacts of built environment factors on rail transit ridership at station level: a case study in Guangzhou, China. *J Transp Geogr*. (2020) 82:102631. doi: 10.1016/j.jtrangeo.2019.102631

13. Ding C, Cao X, Liu C. How does the station-area built environment influence Metrorail ridership? Using gradient boosting decision trees to identify non-linear thresholds. *J Transp Geogr*. (2019) 77:70–8. doi: 10.1016/j.jtrangeo.2019.04.011

14. Shao Q, Zhang W, Cao X, Yang J, Yin J. Threshold and moderating effects of land use on metro ridership in Shenzhen: implications for TOD planning. *J Transp Geogr*. (2020) 89:102878. doi: 10.1016/j.jtrangeo.2020.102878

15. Caigang Z, Shaoying L, Zhangzhi T, Feng G, Zhifeng W. Nonlinear and threshold effects of traffic condition and built environment on dockless bike sharing at street level. *J Transp Geogr*. (2022) 102:103375. doi: 10.1016/j.jtrangeo.2022.103375

16. Yang H, Zheng R, Li X, Huo J, Yang L, Zhu T. Nonlinear and threshold effects of the built environment on e-scooter sharing ridership. *J Transp Geogr*. (2022) 104:103453. doi: 10.1016/j.jtrangeo.2022.103453

17. Yang H, Luo P, Li C, Zhai G, Yeh AGO. Nonlinear effects of fare discounts and built environment on ridesplitting adoption rates. *Transp Res A Policy Pract*. (2023) 169:103577. doi: 10.1016/j.tra.2022.103577

18. Tao T, Næss P. Exploring nonlinear built environment effects on driving with a mixed-methods approach. *Transp Res Part D: Transp Environ*. (2022) 111:103443. doi: 10.1016/j.trd.2022.103443

19. Jin T, Cheng L, Zhang X, Cao J, Qian X, Witlox F. Nonlinear effects of the built environment on metro-integrated ridesourcing usage. *Transp Res Part D: Transp Environ*. (2022) 110:103426. doi: 10.1016/j.trd.2022.103426

20. Yang L, Yu B, Liang Y, Lu Y, Li W. Time-varying and non-linear associations between metro ridership and the built environment. *Tunn Undergr Space Technol*. (2023) 132:104931. doi: 10.1016/j.tust.2022.104931

21. Ewing R, Cervero R. Travel and the built environment: a meta-analysis. *J Am Plan Assoc*. (2010) 76:265–94. doi: 10.1080/01944361003766766

22. Cervero R. Alternative approaches to modeling the travel-demand impacts of smart growth. *J Am Plan Assoc*. (2006) 72:285–95. doi: 10.1080/01944360608976751

23. Durning M, Townsend C. Direct ridership model of rail rapid transit systems in Canada. *Transp Res Rec*. (2015) 2537:96–102. doi: 10.3141/2537-11

24. Zhao J, Deng W, Song Y, Zhu Y. Analysis of metro ridership at station level and station-to-station level in Nanjing: an approach based on direct demand models. *Transportation*. (2014) 41:133–55. doi: 10.1007/s11116-013-9492-3

25. Loo BPY, Chen C, Chan ETH. Rail-based transit-oriented development: lessons from New York City and Hong Kong. *Landsc Urban Plan*. (2010) 97:202–12. doi: 10.1016/j.landurbplan.2010.06.002

26. Huang J, Chen S, Xu Q, Chen Y, Hu J. Relationship between built environment characteristics of TOD and subway ridership: a causal inference and regression analysis of the Beijing subway. *J Rail Transport Plan Manag*. (2022) 24:100341. doi: 10.1016/j.jrtpm.2022.100341

27. Gutiérrez J, Cardozo OD, García-Palomares JC. Transit ridership forecasting at station level: an approach based on distance-decay weighted regression. *J Transp Geogr*. (2011) 19:1081–92. doi: 10.1016/j.jtrangeo.2011.05.004

28. Jun M-J, Choi K, Jeong JE, Kwon KH, Kim HJ. Land use characteristics of subway catchment areas and their influence on subway ridership in Seoul. *J Transp Geogr*. (2015) 48:30–40. doi: 10.1016/j.jtrangeo.2015.08.002

29. Ryan S, Frank LF. Pedestrian environments and transit ridership. *J Public Transp*. (2009) 12:39–57. doi: 10.5038/2375-0901.12.1.3

30. Cardozo OD, García-Palomares JC, Gutiérrez J. Application of geographically weighted regression to the direct forecasting of transit ridership at station-level. *Appl Geogr*. (2012) 34:548–58. doi: 10.1016/j.apgeog.2012.01.005

31. Liu C, Erdogan S, Ma T, Ducca FW. How to increase rail ridership in Maryland: direct ridership models for policy guidance. *J Urban Plan Develop*. (2016) 142:04016017. doi: 10.1061/(ASCE)UP.1943-5444.0000340

32. Ewing R, Hamidi S, Gallivan F, Nelson AC, Grace JB. Combined effects of compact development, transportation investments, and road user pricing on vehicle miles traveled in urbanized areas. *Transp Res Rec*. (2013) 2397:117–24. doi: 10.3141/2397-14

33. Tu W, Cao R, Yue Y, Zhou B, Li Q, Li Q. Spatial variations in urban public ridership derived from GPS trajectories and smart card data. *J Transp Geogr*. (2018) 69:45–57. doi: 10.1016/j.jtrangeo.2018.04.013

34. Gan Z, Feng T, Yang M, Timmermans H, Luo J. Analysis of metro station ridership considering spatial heterogeneity. *Chin Geogr Sci*. (2019) 29:1065–77. doi: 10.1007/s11769-019-1065-8

35. An D, Tong X, Liu K, Chan EHW. Understanding the impact of built environment on metro ridership using open source in Shanghai. *Cities*. (2019) 93:177–87. doi: 10.1016/j.cities.2019.05.013

36. Li S, Lyu D, Liu X, Tan Z, Gao F, Huang G, et al. The varying patterns of rail transit ridership and their relationships with fine-scale built environment factors: big data analytics from Guangzhou. *Cities*. (2020) 99:102580. doi: 10.1016/j.cities.2019.102580

37. Gao F, Yang L, Han C, Tang J, Li Z. A network-distance-based geographically weighted regression model to examine spatiotemporal effects of station-level built environments on metro ridership. *J Transp Geogr*. (2022) 105:103472. doi: 10.1016/j.jtrangeo.2022.103472

38. Zhang Z, Qian Z, Zhong T, Chen M, Zhang K, Yang Y, et al. Vectorized rooftop area data for 90 cities in China. *Scientific Data*. (2022) 9:66. doi: 10.1038/s41597-022-01168-x

39. SUPLRAB, Shanghai Master Plan (2017–2035) (2018) Shanghai, China: Shanghai Urban Planning and Land Resource Administration Bureau.

40. Ding C, Cao X, Wang Y. Synergistic effects of the built environment and commuting programs on commute mode choice. *Transp Res A Policy Pract*. (2018) 118:104–18. doi: 10.1016/j.tra.2018.08.041

41. Friedman JH. Greedy function approximation: a gradient boosting machine. *Ann Stat*. (2001) 29:1189–232. doi: 10.1214/aos/1013203451

42. Ding C, Wang D, Ma X, Li H. Predicting short-term Subway ridership and prioritizing its influential factors using gradient boosting decision trees. *Sustainability*. (2016) 8. doi: 10.3390/su8111100

43. Hastie T, et al. The elements of statistical learning: data mining, inference, and prediction, vol. *2* NYC, USA: Springer (2009).

44. Lundberg SM, Lee S-I. A unified approach to interpreting model predictions. *Adv Neural Inf Proces Syst*. (2017) 30

45. Shapley L.S., A value for n-person games (1953). doi: 10.7249/P0295

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Neighborhood social environment and mental health of older adults in China: the mediating role of subjective well-being and the moderating role of green space

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Introduction: With the continuous development of the global aging trend, the mental health of older adults has been a concern by the world. The living space of older adults is limited due to the decline of their activity function. Neighborhood environment, especially the neighborhood social environment, has become an important factor affecting the mental health of older adults. Therefore, this study explores the mechanism that influences the social environment of the neighborhood and the mental health of older adults, the mediating effect of subjective well-being (SWB), and the moderating effect of green space.

Methods: Based on the 2018 China Labor Dynamics Survey, this study used the structural equation model to explore the mediating effect of neighborhood social environment (neighborhood ties, social trust, community security) on the mental health of older adults through SWB and the moderating effect of green space.

Results: Social trust and community security are both directly and positively associated with older adults' mental health. At the same time, neighborhood ties, social trust, and community security can promote the mental health of older adults by positively affecting SWB, while green space has an enhanced moderating effect between neighborhood ties and mental health.

Discussion: This study enriches the empirical research on neighborhood social environment and mental health. First of all, older adults living in communities with good safety conditions and high social trust are less affected by negative emotions and tend to have good mental health. Second, deeper neighborhood ties, higher social trust, and safer community environments help older adults to be less disturbed by negative situations, have a positive effect on their SWB, and indirectly promote mental health. At the same time, green space can provide a place for older adults to socialize, enhance the positive impact of neighborhood ties on SWB, and further promote the mental health of older adults. Finally, this study suggests that the government and community managers pay attention to the construction of neighborhood social environment and green space, and provide support for "healthy community" and "healthy aging" planning.

KEYWORDS

mental health, social environment, subjective well-being, green space, older adults

1 Introduction

The aging population presents a global challenge to social and economic growth. Compared to younger adults, emotional expression and communication channels constitute the primary spiritual needs of older adults owing to functional decline and physical disease; therefore, mental health problems caused by aging have gradually attracted increasing attention (1, 2). The World Health Organization (WHO) has pointed out that the mental health issues of older adults increase as their mental health declines over time. Suicide rates are higher among older adults than among teenagers and middle-aged persons; the rate of suicide in this population reached 27.2% in 2019 (3). In addition, spaces for daily activities and social interaction for older adults shrink as they age (4). This also stems from older adults' lack of knowledge about potential mental health risks. Emerging economies may face more complicated risks of population aging owing to the imbalance between population growth and economic development. China is predicted to have a deeply aging population by 2036–2050. Moreover, the neighborhood environment, as the main location for activities and a source of social interaction, can influence the health of older adults (4–6). In this context, we must consider the importance of neighborhood social environment, including neighborhood ties (7, 8), social trust (9, 10), community security (11, 12), neighborhood greenness (13, 14), and other factors. Neighborhoods with high population density and land diversity enable residents to have more routes or destination choices for leisurely activities and build close community ties; this encourages people to participate in group exercises, which can help reduce the risk of depression (15, 16). People who enjoy communicating with family and neighbors and who actively participate in community group activities and social interactions tend to have a positive mental state (17). Wang et al. hold that with improvements in community security, residents are more likely to trust their neighbors and communicate with them frequently (18).

Previous studies have focused on how the neighborhood environment in general affects the mental health of older adults. However, there are few studies on the potential mechanism of neighborhood environment affecting the mental health of older adults, especially the mediating effect of neighborhood social environment on the mental health of older adults and the moderating effect of various factors (19, 20). Thus, this study aimed to systematically examine the relationship between the neighborhood social environment and the mental health of older adults and further explored the important moderating and mediating pathways between them. Our conclusions aim to optimize urban construction and implement construction strategies for a healthy environment to create healthy aging communities and age-friendly cities.

2 Literature review

2.1 Research on neighborhood environment and mental health of older adults

According to the WHO, mental health is generally defined as a state of well-being in which an individual realizes his/her abilities, copes with the normal stresses of life, works productively, and can contribute to his/her community (21). It encompasses emotional, psychological, and social well-being, influencing how individuals think, feel, and behave across different stages of life (22). In older adults, mental health is particularly important, as it significantly affects quality of life, functional independence, and overall well-being. This highlights the need for targeted interventions that promote positive mental health and prevent related issues in this age group (23). As an abstract concept, mental health is often assessed using multiple indicators, which are identified through both subjective and objective approaches. Internationally recognized scales that are frequently used include the Symptom Checklist-90 (SCL-90), the Positive and Negative Affect Schedule (PANAS), the Center for Epidemiological Studies Depression (CES-D) Scale, and the Self-Rating Depression Scale (SDS). At the same time, advances in technology have enabled digital health tools, including smartphone applications and wearable devices, to play an increasing role in real-time mental health monitoring (24).Among them, the CES-D-20 is a reliable, valid, easy-to-administer tool that is sensitive to changes in depressive symptoms, making it ideal for both large-scale studies and clinical settings (25–28). Thus, we derived our information from questionnaire data of the 2018 China Labor Dynamics Survey (CLDS), in which the assessment of mental health was based on the CES-D Scale as a reference. Currently, research on the mental health of older adults revolves around four main pathways: individual factors (e.g., medical history, age, gender, habits) (29, 30), family factors (31, 32), community factors (33), and aging care services (34, 35). Different family structures have varying effects on the mental health of older adults. Important social relationships with family can have both positive and negative health effects, depending on the quality, frequency, and strength of that connection (36). Moreover, residents' subjective perceptions of the neighborhood environment have a strong impact on their well-being and health status. People who live in a cohesive community can obtain information and support from their neighbors, thereby benefiting their mental health (37, 38). In addition, with the decline in physical function and mobility as well as the shrinking of social networks, older adults' dependence on the community increases with age. Hence, neighborhood ties in the community help to alleviate loneliness and anxiety in older adults and provide emotional value through neighborhood interactions (39). Further, with the community being the basic unit of China's current social governance, the older adult care model is rooted in home-based care, supported by community-based care, and supplemented by institutional care. Community-based care for older adults is more effective at mitigating physical and mental health problems caused by aging (40, 41).

To date, numerous studies have examined the effects of neighborhood environments on mental health. From the standpoint of person-environment fit theory, the neighborhood environment mostly affects older adults' mental health through interactions involving functional ability (42, 43). Some studies suggest that although the functioning of older adults may have declined, the neighborhood environment meets their social needs and enhances their sense of belonging. This helps reduce loneliness and social anxiety in older adults, which positively affects their mental health (44). Neighborhood environments primarily include social and built environments. The social environment reflects interactions between neighbors, which encourages older adults to participate in social interactions and disseminate and share information. Neighbors with abundant facilities offer them the opportunity to communicate, which improves active social interaction and formulates excellent neighborhood ties (45, 46). Liu et al. emphasized the important role of the social environment in neighborhood attachment and alleviating feelings of exclusion and isolation (40); they asserted that a cohesive, supportive community provides neighborhood support to residents and reduces stress in their lives. Stressors inside socioeconomically deprived neighborhoods (such as anti-social behavior or environmental disorders) stimulate negative emotions, thus influencing mental health. Baranyi et al. proposed that living in a high-crime neighborhood may directly or indirectly impact mental health (47). Social trust can promote engagement with social networks, thereby improving mental health (48). Moreover, individuals who interact with trustworthy neighbors or are willing to help their neighbors may develop a positive psychological state by acquiring a sense of security and acceptance within the community and by recognizing their self-worth (49, 50).

The built environment is defined as an objective material setting constructed by humans for living and production activities in cities (51). Thus far, several studies have been grounded in the "5Ds" theory, which holds that density (e.g., building density, population density, etc.), diversity (e.g., diverse leisurely activities), design (e.g., sidewalk coverage, street trees, average street widths, etc.), destination accessibility (e.g., points of interest, accessibility to the nearest parks and squares, etc.), and distance to transit (e.g., the distance between transit stops) are significantly associated with the mental health of older adults (52–54). Under the current development trend of urban spatial agglomeration, scholars are paying more attention to and finding evidence of a positive relationship between green space and mental health. Urban greenness provides a safe, attractive, and accessible walking place for surrounding residents, potentially alleviating depressive symptoms (55). Green spaces, such as parks and gardens, have been widely studied for their positive effects on mental health. Research suggests that exposure to green spaces can reduce stress, enhance mood, and improve overall mental well-being (56, 57). These spaces offer restorative environments, encouraging relaxation and physical activity, which are beneficial for both cognitive function and emotional regulation (58). In older populations, the mental health benefits of green spaces are particularly significant. Older adults often face increased risks of depression and cognitive decline due to reduced social interaction and physical activity. Green spaces can mitigate these risks by providing opportunities for social engagement, exercise, and sensory stimulation (59). Walking in parks or spending time in green areas has been linked to lower levels of anxiety and depression among older individuals, improving their overall quality of life (60). Moreover, studies have shown that accessibility and proximity to green spaces are crucial for older populations, as these factors determine the likelihood of frequent visits and engagement (61). Urban planning initiatives that increase access to green areas have the potential to promote healthier aging by supporting both mental and physical health in older adults. Additionally, green spaces contribute to a sense of community, helping alleviate feelings of isolation, which is a common challenge among older adults (62). Furthermore, satisfaction with neighborhood green space encourages people to use green areas more frequently, resulting in greater esthetics, pleasure, and relaxation (63). At the same time, some scholars believe that there are potential variables in the moderating and mediating roles between them.

2.2 SWB and mental health

The mental health of older adults has become a significant issue investigated in the fields of health psychology, genealogy, and other areas (64). In light of the recent strides in positive psychology, SWB has turned into one of its crucial contents (65). Studies have shown that is an important index to measure the mental health and life quality of older adults. Factors affecting SWB are subjectivity, stability, and wholeness (66). Research indicates that long-term physical health problems often lead to mental health problems like depression and anxiety, reducing SWB and quality of life under the conditions of China's rapid aging (67). With regard to mental health, it not only prevents depression but also contributes to SWB. For instance, people with better mental health can have optimistic attitudes that enable them to cope effectively with life's adversities and challenges, resulting in higher SWB. As for SWB, generally speaking, people with higher levels of SWB are found to lead a healthier life or live longer (68). The possibility is that positive SWB is a protective factor for health. Furthermore, prospective-epidemiological research suggests that positive life evaluations and hedonic states such as well-being predict lower future mortality and morbidity (69). In addition, SWB and mental health are closely linked to age while their relation is probably bidirectional which means SWB and mental health interrelate. Additionally, according to Baird's point, the SWB follows a U-shaped trajectory, rising with age before declining, notably after 70 years (70).

Neighborhood environments have been identified as being relevant to promoting human health and enhancing well-being (71). Studies have shown that SWB as a crucial indicator is used for evaluating residents' well-being, and Huppert et al. considered happiness to measure the characteristics of residents and communities (72). On this basis, the built environment and the social environment are two domains of neighborhood context that are related to mental health. In terms of the built environment, green space is a vital factor, and there is growing evidence that green space is beneficial for mental health. Especially among vulnerable groups (e.g., older adults), green space in cities can be associated with improved overall well-being and self-perceived health status, suppressed morbidity and increased life expectancy, and increased satisfaction with life prospects, among other ways to promote healthy aging in older adults (73). Green space not only provides a place for social activities and physical activities for older adults, but also its rich natural landscape can reduce loneliness and improve emotional health, thus promoting SWB (74). As for the social environments, neighborhood social environment such as community security, social trust, and other factors have a great influence on people's interaction in the community, which plays a vital role in mental health and well-being. According to Ballas and Tranmer, the neighborhood with a high-security situation can often improve the SWB of individuals (75). Meanwhile, neighborhood ties lead to the creation of a friendly neighborhood atmosphere with high levels of trust and reciprocity, protecting residents from pathological mental states such as depression and anxiety which contributes to SWB (76). Although no study has clearly demonstrated the mediating role of SWB, most research approves of the viewpoint that neighborhood factors are significantly related to daily life, mental health, and SWB (53, 77). SWB has the potential to be an intermediate variable among these variables (13). Based on this, this study aims to explore pathways linking neighborhood social environment (neighborhood ties, social trust, and community security) to older adults' mental health in the Chinese context. In the meanwhile, it particularly investigates the extent to which SWB mediates the linkage between neighborhood social environment and older adults' mental health (Figure 1). What is more, it further explores the moderating role of green space and puts forward the following hypotheses:

> *Hypothesis* 1: Neighborhood ties, social trust, and community security directly affect the mental health of older adults.
>
> *Hypothesis* 2: Neighborhood ties, social trust, and community security affect the mental health of older adults by mediating SWB.
>
> *Hypothesis* 3: Green spaces moderate the association between neighborhood ties, social trust, community security, and the mental health of older adults.
>
> *Hypothesis* 4: Green spaces moderate the mediation of neighborhood ties, social trust, and community security on the mental health of older adults through the mediator of SWB.

3 Research design

3.1 Study area and dataset

Data for this study came from the 2018 CLDS, a large-scale, nationally representative tracking survey of labor force dynamics designed and implemented by the Center for Social Science Research at Sun Yat-sen University. The 2018 CLDS involved data gathered from 28 provinces in China, excluding Hong Kong, Macao, Taiwan, Tibet, Hainan, and Xinjiang. The database contains comprehensive data on 368 communities, 13,501 households, and 16,537 individuals in the labor force. The 2018 CLDS adopted multistage, multilevel probability sampling proportional to the size of the labor force, which minimizes sampling errors and ensures the randomness and scientific nature of sample selection. This study included men and women aged 60 and 55 years, respectively. The final sample comprised 3,315 individuals from 255 communities across 26 provinces (Figure 2).

Table 1 presents the descriptive statistics for all variables. The mean mental health score was 71.91 (SD ± 9.19), which is much higher than the cutoff (2/3 of the total score of 80), indicating that the participants had good mental health. The mean SWB score was 10.95 (SD ± 2.33), which is above the threshold, suggesting that the participants had a high level of SWB. The average levels of neighborhood ties, social trust, and community security were 7.66 (SD ± 1.58), 30.65 (SD ± 4.18), and 21.74 (SD ± 3.53), respectively. In terms of covariates, 59.4% of the respondents were female, 91.2% were not single, and 15.1% had suffered an illness or injury in the past 2 weeks. Their average age was 67.69 years old, and their average annual income in 2017 was 17,333.85 yuan.

3.2 Variables and measurement

3.2.1 Independent variables: neighborhood social environment

Neighborhood ties. Based on Hays et al., Liu et al., Dang et al., the measurement of neighborhood ties includes indicators such as neighborhood interactions, mutual assistance, neighborhood trust, neighborhood friendship, and community connections (78–80). This study considered older adults as the research object, focusing on their familiarity with the community and the frequency of mutual assistance. Neighborhood familiarity is measured via the question, "How familiar are you with your neighbors and other residents in your community?" A 5-point scale is used to provide an answer (1 = *very unfamiliar*, 2 = *not very familiar*, 3 = *generally familiar*, 4 = *relatively familiar*, and 5 = *very familiar*). Neighborhood mutual assistance is measured via the question, "Do you help your neighbors and other residents in your community (village)?" A 5-point scale is used to provide an answer (1 = *very little*, 2 = *relatively little*, 3) *in general*, (4) *relatively more*, and (5) *a lot.* The above items were summed to obtain the total score to generate the indicator of neighborhood ties. The overall scale score ranges from 2 to 10, and the higher the scale score, the better the neighborhood ties experienced by the respondent.

Social trust. This study assessed social trust via the question, "How much do you trust people in the following nine categories?" The categories include family members, relatives, friends, neighbors, classmates, strangers, people who work or do things together, businessmen who buy things, and people with religious beliefs. This study determined social trust scores using a 5-point Likert scale (1 = *not trustworthy* at all; 5 = *totally trustworthy*). The total score ranged from 9 to 45, with higher scores suggesting deeper levels of social trust. The Cronbach's α of the social trust subscale was 0.74, implying that the questionnaire had reliability.

Community security. This study evaluated community security using the following question: "Within this community, do you have any of the following concerns?" The categories include the safety risk of hanging out, the safety risk of going out alone at night, the risk of burglary if one does not lock one's doors and windows, the risk of being targeted after exposing one's money, and the risk of one's children being trafficked when they are out alone. This question is answered using a 5-point reverse scale (1 = *never*; 5 = *often*). The total score ranges from 5 to 25, with higher scores implying a greater sense of community security. The Cronbach's α of the community security subscale was 0.816, indicating that the questionnaire had reliability.

3.2.2 Dependent variable: mental health

This study employed the CES-D Scale to assess mental health; it contains 20 items used to evaluate depressive symptoms (81) and is scored on a 4-point reverse scale (1 = *almost always or 5–7 days per week*; 2 = *often or 3–4 days per week*; 3 = *rarely or 1–2 days per week*; and 4 = *never or < 1 day per week*). The total score ranges from 20 to 80, with higher scores suggesting improvement in the mental health of older adults compared to the previous week. The Cronbach's α for the mental health subscale was 0.946, meaning the questionnaire was reliable.

3.2.3 Mediator: SWB

At present, one of the common ways to measure subjective well-being (SWB) is the life satisfaction orientation, which includes both general and specific assessments of happiness and life satisfaction (82). Life Happiness, Life Satisfaction are recognized as key indicators for measuring SWB (83). Life Happiness has demonstrated significant advantages in assessing emotional experiences, capturing short-term feelings of joy or contentment (84). Life Satisfaction is commonly

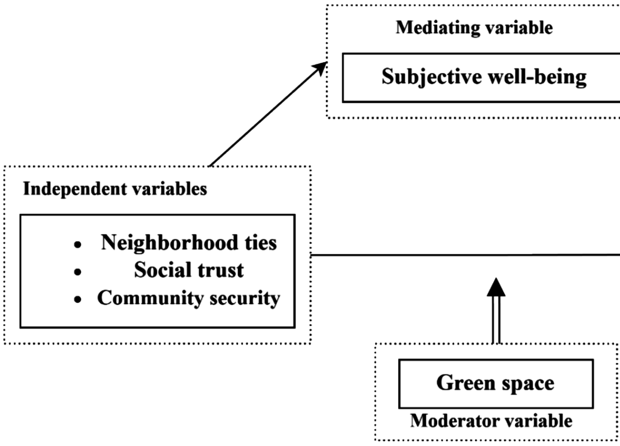

FIGURE 1
Theoretical framework for the SEM construction.

used for the subjective evaluation of overall life quality and long-term well-being (85). Furthermore, Economic Satisfaction has proven to be a significant predictor of SWB, effectively capturing the impact of economic circumstances on individual well-being (86). Ouyang et al. also used similar indicators of life happiness, life satisfaction and economic satisfaction to measure SWB (87). Therefore, this study uses the "Happiness Scale" in the questionnaire of CLDS database to measure SWB of individuals, which mainly includes three measurement items: "life happiness, life satisfaction and economic satisfaction." This study measured happiness in life via the question, "Do you think you are living a happy life?" This study measured life satisfaction using the question, "Are you satisfied with your life?" based on the Measurement of Life Satisfaction Scale. This study measured financial satisfaction via the question, "Are you satisfied with your family's financial situation?" The answers are rated on a 5-point Likert scale. This study summed up the scores of the three items to form an SWB index. The total score for the three items ranges from 3 to 15 points. The higher the score, the greater the SWB of older adults. The Cronbach's α of the SWB scale was 0.824, suggesting that the questionnaire had reliability.

3.2.4 Moderator: green space

Referring to existing studies that use the proportion of green space to measure green space (88), this study employed the coverage rate of green space in built-up regions as an index to quantify UGS and study the moderating effect. The greenspace coverage rate of built-up regions refers to the share of urban built-up areas covered by greenery to the total built-up area obtained from the 2018 China Urban Statistical Yearbook (89). Owing to the random treatment of communities in the questionnaire, this study could not locate each respondent's community but rather only the city information related to each respondent. As such, this study assigned values according to the city information related to each respondent and each city's greenspace coverage rate.

3.2.5 Covariates

This study adjusted the study for covariates of older adults' sociodemographic and individual health characteristics (90). For individual-level covariates, this study included gender (binary variable: male vs. female), marital status (binary variable: not single vs. single), and annual individual income (continuous variable). For covariates of individual health characteristics, this study used disease and injury status indicators (binary variables: no disease or injury in the past 2 weeks vs. illness and injury within the past 2 weeks). As the mental health of older adults may be affected by chronic disease, as there were no chronic disease-related problems in the CLDS in 2018, the illness and injury conditions of older adults could replace this problem to a certain extent (91).

3.3 Methods

This study used SEM to examine the mediating and moderating effects of neighborhood ties, social trust, community security, and the mental health of older adults in a neighborhood social environment. Notably, SEM can measure the total, direct, and indirect effects of one variable (such as neighborhood ties) on another (such as mental health) to explore the mechanisms underlying the ties between the neighborhood social environment and mental health in the community (92). This study tested the chain-mediation model using SEM. In the baseline model, mental health, SWB, neighborhood ties, social trust, and community security are continuous variables. In this study, green space, socio-demographic characteristics, and personal health characteristics were taken as exogenous variables, while neighborhood ties, social trust, community security, SWB, and mental health were taken as endogenous variables. At the same time, considering the possible collinearity between mental health and SWB variables, we used SPSS to conduct a collinearity test. The test results show that the VIF value between variables is less than 2 and the tolerance greater than 0.1, which alleviates the collinearity problem between variables. Additionally, we considered existing research to determine the fit parameters for SEM (93), which allowed us to test the proposed models. We used the following parameter criteria for model fit: the root mean square error of approximation (RMSEA) ≤ 0.05; the goodness-of-fit index (GFI) ≥ 0.90; the normed fit index (NFI) ≥ 0.80; the incremental fit index (IFI) ≥ 0.80; the Tucker-Lewis index (TLI) ≥ 0.80; and the comparative fit index (CFI) ≥ 0.80. We employed SPSS Amos 26 for SEM and STATA version 13.1 for basic pre-analysis data cleaning.

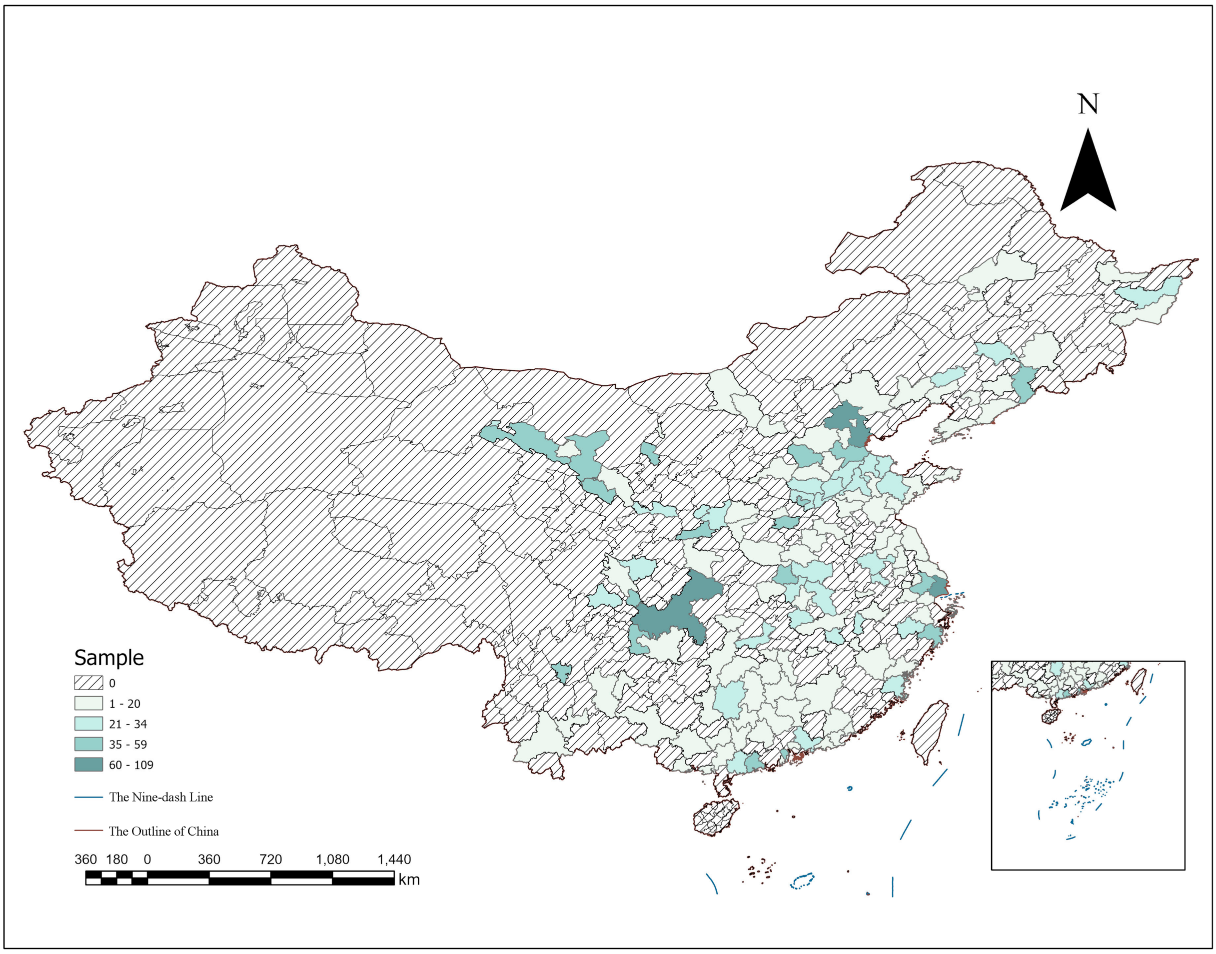

FIGURE 2
Distribution map of sample urban across the country. Based on the Department of Natural Resources Standard Map Service website GS(2019)18224. Standard maps are produced with no modifications to the base map boundaries, same as below.

4 Results

4.1 Relation between neighborhood social environment and mental health of older adults

This study uses SEM models to investigate the association between neighborhood ties, social trust, community security, and mental health of older adults in the neighborhood social environment, exploring the mediating role played by SWB in this association, while adjusting for control variables at the sociodemographic and personal health levels of older adults. The fitting parameter criteria for the mediation effect model with moderation are shown in Section 3.3. The model path coefficients are shown in Table 2. Regarding sociodemographic characteristics control variables, older adults with younger age, higher annual income, and male gender were more likely to report better mental health status. At the level of personal health, older adults who have not been injured in the past 2 weeks are more likely to have good mental health. The direct path coefficient from social trust to the mental health of older adults is significant and positively correlated ($\beta = 0.155$, $p < 0.05$), which indicates that the improvement of social trust of older adults is helpful in promoting their mental health level. At the same time, the sense of community security of older adults also has a positive and direct impact on their psychological health ($\beta = 0.098$, $p < 0.01$). Therefore, Hypothesis 1 is partially supported. Additionally, there is a positive correlation between neighborhood ties, social trust, community security, and SWB. Closer neighborhood ties contributed to the improvement of SWB in older adults ($\beta = 0.141$, $p < 0.01$). Moreover, the improvement of older adults 's social trust also helps to maintain better SWB ($\beta = 0.272$, $p < 0.01$). A good sense of community security had a positive effect on the SWB of older adults ($\beta = 0.039$, $p < 0.01$). Furthermore, Older adults with better SWB also have a direct and positive impact on their mental health status ($\beta = 0.445$, $p < 0.01$).

4.2 The mediating effect of SWB

Table 3 and Figure 2 present the results of the mediating effects. Among the mediating effects of neighborhood social environment-related indicators on mental health, neighborhood ties, social trust, and community security were all significant and positively correlated with the mental health path coefficients of SWB through the mediating variables (neighborhood ties: $\beta = 0.061$, $p < 0.01$; social trust:

TABLE 1 Statistics of variables.

Variables	Assignments	Total (N = 3,315)
Dependent variables		
Mental health [mean (SD)]	Continuous variables (20–80)	71.91(9.19)
Independent variable		
Neighborhood ties [mean (SD)]	Continuous variables (2–10)	7.66(1.58)
Social trust [mean (SD)]	Continuous variables (9–45)	30.65(4.18)
Community security [mean (SD)]	Continuous variables (5–25)	21.74 (3.53)
Mediators		
Subjective well-being [mean (SD)]	Continuous variables (3–15)	10.95 (2.33)
Moderator variable green space [mean (SD)]	Continuous variables	41.16 (3.66)
Covariates		
Annual personal income (mean)	Continuous variables	17,333.85
Marital status [N (%)]	1 = Non-single	3,023(91.2%)
	0 = Single	292(8.8%)
Age (mean)	Continuous variables	67.69
Gender [N (%)]	1 = Male	1,347(40.6%)
	0 = Female	1968(59.4%)
Sickness and injury status [N (%)]	1 = No sickness or injury within the last 2 weeks	2,816(84.9%)
	0 = Sickness and injury within	499(15.1%)

TABLE 2 Model path coefficient diagram.

Path	Estimate	S.E.	C.R.	p
Neighborhood ties → mental health	0.007	0.039	0.184	0.854
Social trust → mental health	0.155	0.061	2.541	**
Community security → mental health	0.098	0.017	5.778	***
Neighborhood ties → SWB	0.141	0.029	4.943	***
Social trust →SWB	0.272	0.047	5.781	***
Community security → SWB	0.039	0.012	3.171	***
Age → mental health	−0.008	0.003	−2.297	**
Marital status → mental health	0.059	0.057	1.024	0.306
Gender → mental health	0.162	0.036	4.505	***
Annual income → mental health	0.056	0.009	6.209	***
Injury status → mental health	0.411	0.045	9.065	***

SWB, subjective well-being; *All the coefficients are standardized regression coefficients. *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.

$\beta = 0.127$, $p < 0.01$; community security: $\beta = 0.017$, $p < 0.01$). Thus, Hypothesis 2 is supported. The neighborhood ties index showed a complete mediating effect. The higher the neighborhood ties index, the more frequent the contact and interaction between the individual and a neighbor, and the stronger the social bond. Such a connection is conducive to improving the SWB of older adults and thus has a positive impact on their mental health. Moreover, social trust and community security had partially mediating effects. Improving social trust in older adults can contribute to good mental health by promoting SWB. A high level of community security indicates that older adults are in a relatively safe community and are not troubled by the presence of community security, which also helps to improve their SWB and mental health (Figure 3).

4.3 The moderating effect of green space

We examined the moderating effect of green space on the mediating effect of the neighborhood social environment and the mental health of older adults. Table 4 shows the results of this model, which indicate that green space had no moderating effect on the direct relationship between neighborhood ties, social trust, community security, and the mental health of older adults. As for the mediating effect, we found that green space had a moderating effect on the mediating effect of neighborhood ties and mental health ($\beta = 0.012$, $p < 0.01$). Hence, Hypothesis 4 is partially supported. The improvement in the greenspace index helped enhance the positive, indirect correlation between neighborhood ties and mental health

TABLE 3 Mediation effect test results.

Path		Estimate	Bootstrapping				S.E.	*p*
			Bias-corrected		Percentile			
			Lower	Upper	Lower	Upper		
Direct effect	Neighborhood ties → mental health	0.007	−0.068	0.087	−0.070	0.085	0.040	0.813
	Social trust → mental health	0.155	0.030	0. 295	0.029	0.293	0.066	**
	Community security → mental health	0.098	0.060	0. 133	0.061	0.133	0.018	***
Indirect effect	Neighborhood ties → SWB → Mental health	0.063	0.035	0.096	0.034	0.094	0.015	***
	Social trust → SWB → Mental health	0.121	0.075	0.179	0.073	0.176	0.027	***
	Community security → SWB → Mental health	0.017	0.006	0.030	0.006	0.030	0.006	***
Total effect	Neighborhood ties → mental health	0.070	−0.014	0.156	−0.014	0.156	0.043	0.107
	Social trust → mental health	0.276	0.150	0.428	0.149	0.427	0.071	***
	Community security → mental health	0.115	0.078	0.151	0.078	0.152	0.019	***

SWB, subjective well-being; *All the coefficients are standardized regression coefficients. **p* < 0.1, ***p* < 0.05, ****p* < 0.01.

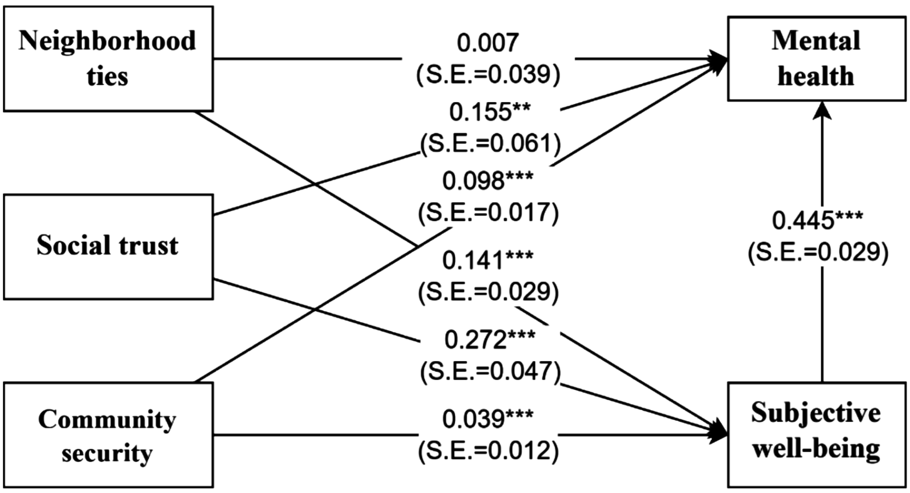

FIGURE 3
Structural equation modeling of the mediating role of subjective well-being among neighborhood relationships, social trust, community security, and mental health status. **p* < 0.1, ***p* < 0.05, ****p* < 0.01.

through SWB. Green Spaces not only play a role as places where ties are initially established but also where they are re-established. As leisure spaces, green spaces provide opportunities for social interaction, thereby contributing to developing new social connections and strengthening existing ones, thereby promoting neighborhood ties (94). Favorable and intimate neighborhood ties can enhance SWB. The improvement of green space coverage may provide a more possible social interaction space for the close neighborhood ties of older adults, enhance their SWB, and further promote the improvement of the mental health level of older adults. However, this study did not find that green spaces have a moderating effect on the indirect relationships between social trust, community security, and mental health. A possible explanation is that trust is promoted by the social function of green space (95). The measure of green space used in this study is green space coverage, which is insufficient in evaluating the social function of green space. Relevant studies also prove that the relationship between green space and trust is more likely to be related to the weekly use frequency and single-use duration (96). Secondly, the moderating effect of green space on community security and the mental health of older adults is not significant, which may be related to the complex relationship between green space and community security. To date, the evidence on the relationship between green Spaces and feelings of safety and crime is mixed. Some studies show that green space vegetation may provide convenience for crime (97), but other studies believe that green space vegetation can help reduce residents' fear of crime and enhance their sense of security (98). In a more detailed study of the relationship between green space vegetation types and crime, a higher proportion of grassland was associated with a lower rate of crime only for areas with relatively low crime rates, while a higher proportion of woodland was associated with a lower rate of crime only for areas with relatively high crime rates (99). Therefore, many other factors may influence the relationship between green space and security, which could explain why the moderating effect of green space was not significant.

TABLE 4 Moderation effect test results.

Path	Estimate	Bootstrapping				S.E.	*p*
		Bias-corrected		Percentile			
		Lower	Upper	Lower	Upper		
GNT → mental health	0.000	−0.038	0.038	−0.037	0.040	0.020	0.151
GST → mental health	−0.012	−0.054	0.032	−0.058	0.028	0.022	0.632
GCS → mental health	0.000	−0.058	0.009	−0.058	0.009	0.017	0.978
GNT → SWB → Mental health	0.011	0.000	0.023	0.000	0.024	0.006	*
GST → SWB → Mental health	−0.005	−0.017	0.008	−0.017	0.007	0.006	0.474
GCS → SWB → Mental health	0.000	−0.010	0.011	−0.010	0.011	0.005	0.964

GNT, Interaction Terms of Green Space and Neighborhood ties; GST, Interaction Terms of Green Space and Social Trust; GCS, Interaction Terms between Green Space and Community Security; SWB, subjective well-being; *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.

5 Discussion

In the past 30 years, China's rapid migration and urbanization processes have led to significant changes in the composition and characteristics of urban communities. Various empirical studies conducted in Western countries have reported significant impacts of neighborhood social environmental characteristics such as green space, neighborhood social trust, and neighborhood ties on residents' mental health (100, 101). By facilitating neighborhood ties, neighborhood green space can contribute to the development of neighborhood social trust, which has proven to benefit people's health (102). Nevertheless, the moderating role of the built environment (e.g., green space) in the influence of the social environment (e.g., neighborhood ties, social trust, and community security) on mental health has not been sufficiently considered. Besides, numerous scholars have conducted research on the relationship between SWB and mental health and concluded that the close connection between health and SWB grows with age (103). Whereas, considering SWB as the mediator in the relationship between neighborhood social environment and mental health has not been adequately explored in existing research. For the purpose of enhancing our understanding of the bond between them, we identify SWB as the mediator through which neighborhood social environment may affect older adults' mental health. Additionally, we examined whether green space served as a moderator in the nexus between neighborhood social environment and mental health on the basis of using the SEM. Our results can serve as a valuable resource for urban planners and decision-makers, helping to improve the mental health of older adults and promoting healthy aging.

Previous studies conducted in Western countries that have explored the neighborhood environment and mental health indicate that the neighborhood environment primarily affects mental health by influencing the frequency of fitness activities and social interactions, while the neighborhood social environment affects the health-related behaviors of others (104). For instance, people who live in neighborhoods with less community security are prone to stress, and social chaos and unsafe neighborhoods affect their mental health (105). Neighborhood social attributes—including interaction, trust, civic engagement, and perceptions of community security—are determinants of residents' mental health (106). A stable neighborhood enhances face-to-face interactions, strengthens participation among residents, provides a sense of consistency and belonging, and promotes emotional support and access to material resources when individuals are exposed to stressors (107). Our findings support these views, social trust, and community security were positively associated with mental health, whereas neighborhood ties did not directly affect the mental health of older adults. Evidence suggests that older adults are more likely to be confined to residential areas because of retirement and mobility problems. Attractive and safe neighborhoods diminish mental problems and negative emotions, evoke positive emotions, and lead to better conscious evaluation of life circumstances; conversely, people's mental health is negatively impacted when they are exposed to environmental stressors, which lead to psychological stress, mental problems, and a greater likelihood of depression (106). As for social trust, Wang et al. deduced that social trust may benefit the mental health of older adults by providing a source of mutual connection and respect and by improving older adults' sense of purpose in life (108). When it comes to neighborhood ties, our findings extend previous research by suggesting that it has no direct impact on the mental health of older adults. According to a study of different life stages, the increase of social ties can help relieve depression and anxiety, and the strongest influence of adolescents and adults, but without statistical significance for older adults. This may be because adolescents and adults are more inclined to develop their social ties, but older adults are more likely to prune their social networks based on their emotional experiences (109). Thus, the findings of this study may stem from their mutually conflicting features and negative effects on health. This finding concurs with the claim that the link between neighborhood social ties and mental health is highly variable and complex (37, 110).

Regarding SWB, previous studies suggest that the strong association between health and SWB increases with age in both developed and developing countries, while older adults with higher SWB live longer and healthier than those with lower SWB (103). This study further verified the role of SWB as the mediator in the relationship between the neighborhood social environment and mental health. The perceived neighborhood environment cannot only promote healthy physical activity and reduce the risk of chronic disease (such as obesity and cardiovascular disease) but also provide psychological recovery and spiritual release for older adults and improve their happiness, thus promoting their mental health (111). Our research puts forwards conclusion that in line with previous works, we provided unequivocal evidence of an association between social trust, community security, neighborhood ties and mental health among SWB. Firstly, the finding of our study is the indirect effect of social trust on the mental health of older adults through the mediation of SWB, which aligns with the results of an earlier research which demonstrated that older adults with higher SWB have a strong ability to cope with mental health risks and lessen the impact of social interactions on their mental health (112). In addition, the results of the mediation analysis showed that SWB plays a mediating role between community security and the mental health of older adults. Our results confirmed the insights of Cramm and Nieboer, who have understood that community-dwelling older people who perceive their neighborhood as very safe benefit more from solidarity among neighbors, resulting in higher SWB (39). Moreover, concerning neighborhood ties, current studies assume that ties with older people of the same age (which make it easier to obtain social support from others) induce faster recovery from fatigue and discomfort, which can indirectly affect SWB and further improve mental health (113). As expected, neighborhood ties affected the mental health of older adults through SWB. Social interactions weaken social anxiety and loneliness in older adults, leading to more positive emotions in this demographic, thereby benefiting their mental health.

Furthermore, the result of this study found that green space played a moderating role in the mediating effect of SWB on the neighborhood social environment and mental health. As part of the neighborhood environment, green spaces are closely tied to the daily lives of older adults and provide numerous social and ecological services, thus representing an important part of an age-friendly environment (114). Green spaces have been associated with promoting human health and enhancing well-being (115). For instance, watching plants for 5 min improved psychological relaxation in older adults; participating in gardening activities related to green spaces can also increase psychological relaxation in older adults (116). Our empirical results provide further insight into the remarkable role of green space in that it played a moderating role in the relationship between neighborhood ties and mental health, whereas social trust and community security did not achieve the desired outcomes. The improvement of green space promotes the positive influence of neighborhood ties on SWB, and then improves the mental health state of older adults. Initially, green space provides spaces for people to experience nature and encourages older adults to enter such areas for social and physical activity (117). Green spaces offer opportunities for neighborhood interactions among older adults, thereby increasing the possibility of communication within the community. Moreover, older adults who regularly socialize have higher SWB and better mental health (118). Subsequently, based on the Biophilia Hypothesis, people's psychological health is associated with their relationship to nature (119). Owing to the scarcity of urban green space resources and the decline of older adults' individual functions, it may be difficult for older adults living in urban areas to access green space. In contrast to older adults, the younger with stronger physiological functions and weaker demand for surrounding green space prefer a longer distance for physical exercise (120). Therefore, this may make access to natural green spaces more valuable and important for older adults. Contact with nature promotes the prosperity of private personal lives and public social lives. Those who are highly nature-connected may derive a sense of meaningful presence from their closeness with nature, which may promote well-being (121). Increased contact with nature through green spaces in older adults has a positive impact on emotions (122), contributing to more meaningful neighborhood connections and prosperous social lives, thus deepening neighborhood ties has a positive indirect impact on mental health by promoting SWB. Additionally, the Stress Recovery Theory suggests that natural environments, as restorative environments, can provide residents with opportunities to appreciate natural landscapes, thereby enhancing their ability to cope with stress and promoting individuals to recover faster from stress (123). Frequent interaction with neighbors has a positive effect on SWB (124). Having positive, non-difficult relationships helps reduce stress and promote well-being (125). Green spaces may provide an environment for individuals to relieve stress and socialize, which encourages individuals to have a more relaxed attitude toward neighborhood interactions and promotes an improvement in overall well-being. Simultaneously, green spaces may act as stress-relief amplifiers, enhancing the benefits of neighborhood relationships to improve the SWB of older adults better, thereby achieving higher levels of mental health. Regarding the role of green space in the relationship between neighborhood ties and mental health, our conclusion is consistent with most studies. In addition, green space contributes to an area's livability, particularly in deprived urban neighborhoods; green space is viewed as "safe, secure, attractive, socially cohesive and inclusive, and environmentally sustainable" (126, 127). This is inconsistent with our findings, which may be because our data for measuring the green space index is the green space coverage rate of built-up areas, which makes the research findings different.

Our results are of great significance for promoting the construction of healthy and livable cities in China and the successful aging of older adults. First, the government, community organizations, and housing managers should pay more attention to the social and neighborhood connections of older adults, recognize their diverse social needs, and create more opportunities for them to connect with other residents in the community, such as by providing more conducive places for older adults to socialize and holding more abundant neighborhood activities to encourage interactions. Second, as important natural and social spaces in the community, the government and community organizations should pay attention to the construction of green spaces. This study recommends that relevant departments regularly maintain and improve green spaces and promote their positive factors to benefit older adults. In addition, regarding the direct and indirect beneficial effects of social trust on the mental health of older adults, this study suggests that the government and community organizations build a harmonious, friendly community environment, organize community activities and lectures, and deepen the understanding of older adults' social context to enhance their social trust and promote the improvement of their mental health. Finally, regarding the importance of community security, the government should issue scientific and accurate community management regulations. Community management institutions should strictly implement community management and improve community security; these institutions regularly listen to community residents to receive their feedback on community services and safety measures according to their needs. Adjustments are later made to create a safe community environment.

This study has some limitations. To begin with, the data selected in this study is cross-sectional, and there may be missing variables or unobservable differences between individuals in the statistical collection of cross-sectional data. Moreover, owing to data limitations, this study did not consider other attributes of neighborhood green space (e.g., quality, usage frequency, duration, visibility, accessibility), which may have influenced the mental health of older adults. Furthermore, relying solely on the coverage rate of green space inadequately captures the accessibility and quality green spaces, which introduces bias into the findings. Future research should employ more precise indicators for a more accurate assessment of green space characteristics. Ultimately, although our research is based on older adults, this study did not consider the impact of different family structures and different age groups of older adults.

6 Conclusion

To sum up, this study used the SEM model and statistical data from the nationally representative 2018 CLDS database to study the relationship between neighborhood society, the built environment, and the mental health of older adults in the Chinese community. This study focused on exploring the indirect impact of neighborhood ties, social trust, and community security on the mental health of older adults through SWB while paying attention to the moderating effect of green space on the mental health of older adults. The results show that (1) in the neighborhood social environment, social trust and community security had a direct, positive impact on the mental health of older adults. (2) Neighborhood ties, social trust, and community security indirectly improved the mental health of older adults through their positive effects on SWB. (3) Green spaces reinforced the positive and indirect effects of neighborhood ties on the mental health of older adults through SWB. The results of this study further confirm the importance of neighborhood social and built environments for the mental health of older adults. As such, relevant government departments and community managers should pay attention to the living experiences of older adults in the community and promote the construction of aging-friendly communities to cope with the trend of population aging and promote the development of healthy aging.

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

TL: Conceptualization, Methodology, Writing – original draft. QW: Conceptualization, Methodology, Software, Writing – original draft. ZT: Formal analysis, Validation, Writing – original draft. WZ: Investigation, Resources, Software, Writing – original draft. RW: Supervision, Writing – original draft.

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Conflict of interest

TL was employed by the company Guangzhou Urban Planning and Design Company Limited.

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.

Generative AI statement

The author(s) declare that no Generative AI was used in the creation of this manuscript.

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References

1. Parkar SR. Elderly mental health: needs. *Mens Sana Monogr*. (2015) 13:91–9. doi: 10.4103/0973-1229.153311

2. Domènech-Abella J, Mundó J, Haro JM, Rubio-Valera M. Anxiety, depression, loneliness and social network in the elderly: longitudinal associations from the Irish longitudinal study on ageing (TILDA). *J Affect Disord*. (2019) 246:82–8. doi: 10.1016/j.jad.2018.12.043

3. World Health Organization. Suicide Worldwide in 2019. *Global Health Estimates*. (2021)

4. Zhao Y, Chung P-K. Neighborhood environment walkability and health-related quality of life among older adults in Hong Kong. *Arch Gerontol Geriatr*. (2017) 73:182–6. doi: 10.1016/j.archger.2017.08.2003

5. Scharlach AE. Aging in context: individual and environmental pathways to aging-friendly communities-the 2015 Matthew a. Pollack award lecture. *Gerontological Society Newsletter*. (2017) 57:606–18. doi: 10.1093/geront/gnx017

6. Smith RJ, Lehning AJ, Dunkle RE. Conceptualizing age-friendly community characteristics in a sample of urban elders: an exploratory factor analysis. *J Gerontol Soc Work*. (2013) 56:90–111. doi: 10.1080/01634372.2012.739267

7. Miao J, Wu X, Sun X. Neighborhood, social cohesion, and the Elderly's depression in Shanghai. *Soc Sci Med*. (2019) 229:134–43. doi: 10.1016/j.socscimed.2018.08.022

8. Chen Y-Y, Wong GHY, Lum TY, Lou VWQ, Ho AHY, Luo H, et al. Neighborhood support network, perceived proximity to community facilities and depressive symptoms among low socioeconomic status Chinese elders. *Aging Ment Health*. (2016) 20:423–31. doi: 10.1080/13607863.2015.1018867

9. Ross CE, Jang SJ. Neighborhood disorder, fear, and mistrust: the buffering role of social ties with neighbors. *Am J Community Psychol*. (2000) 28:401–20. doi: 10.1023/A:1005137713332

10. Garcia RM, Taylor RB, Lawton BA. Impacts of violent crime and neighborhood structure on trusting your neighbors. *Justice Q*. (2007) 24:679–704. doi: 10.1080/07418820701717169

11. Won J, Lee C, Forjuoh SN, Ory MG. Neighborhood safety factors associated with older adults' health-related outcomes:. A systematic literature review. *Soc Sci Med*. (2016) 165:177–86. doi: 10.1016/j.socscimed.2016.07.024

12. Levasseur M, Genereux M, Bruneau J-F, Vanasse A, Chabot E, Beaulac C, et al. Importance of proximity to resources, social support, transportation and neighborhood security for mobility and social participation in older adults: results from a scoping study. *BMC Public Health*. (2015) 15:1–19. doi: 10.1186/s12889-015-1824-0

13. Liu Y, Wang R, Grekousis G, Liu Y, Yuan Y, Li Z. Neighbourhood greenness and mental wellbeing in Guangzhou, China: what are the pathways? *Landsc Urban Plan*. (2019) 190:103602. doi: 10.1016/j.landurbplan.2019.103602

14. Ruijsbroek A, Mohnen SM, Droomers M, Kruize H, Gidlow C, Gražulevičiene R, et al. Neighbourhood green space, social environment and mental health: an examination in four European cities. *Int J Public Health*. (2017) 62:657–67. doi: 10.1007/s00038-017-0963-8

15. van den Berg P, Sharmeen F, Weijs-Perree M. On the subjective quality of social interactions: influence of neighborhood walkability, social cohesion and mobility choices. *Transp Res Pt A-Policy Pract*. (2017) 106:309–19. doi: 10.1016/j.tra.2017.09.021

16. Duncan DT, Piras G, Dunn EC, Johnson RM, Melly SJ, Molnar BE. The built environment and depressive symptoms among urban youth: a spatial regression study. *Spat Spatiotemporal Epidemiol*. (2013) 5:11–25. doi: 10.1016/j.sste.2013.03.001

17. Zhang L, Zhou S, Kwan M-P. A comparative analysis of the impacts of objective versus subjective neighborhood environment on physical, mental, and social health. *Health Place*. (2019) 59:102170. doi: 10.1016/j.healthplace.2019.102170

18. Wang R, Yuan Y, Liu Y, Zhang J, Liu P, Lu Y, et al. Using street view data and machine learning to assess how perception of neighborhood safety influences urban residents' mental health. *Health Place*. (2019) 59:102186. doi: 10.1016/j.healthplace.2019.102186

19. Chen Y, Yuan Y. The neighborhood effect of exposure to blue space on elderly individuals' mental health: a case study in Guangzhou, China. *Health Place*. (2020) 63:102348. doi: 10.1016/j.healthplace.2020.102348

20. Chen C, Luo W, Kang N, Li H, Yang X, Xia Y. Study on the impact of residential outdoor environments on mood in the elderly in Guangzhou, China. *Sustain For*. (2020) 12:3933. doi: 10.3390/su12093933

21. Herrman H, Saxena S, Moodie R. Promoting mental health: Concepts, Emerging Evidence, Practice. US: A Report of the World Health Organization, Department of Mental Health and Substance Abuse in Collaboration with the Victorian Health Promotion Foundation and the University of Melbourne (2005).

22. Keyes CL. The mental health continuum: from languishing to flourishing in life. *J Health Soc Behav*. (2002) 43:207–22. doi: 10.2307/3090197

23. Prince MJ, Wu F, Guo Y, Robledo LMG, O'Donnell M, Sullivan R, et al. The burden of disease in older people and implications for health policy and practice. *Lancet*. (2015) 385:549–62. doi: 10.1016/S0140-6736(14)61347-7

24. Mohr DC, Zhang M, Schueller SM. Personal sensing: understanding mental health using ubiquitous sensors and machine learning. *Annu Rev Clin Psychol*. (2017) 13:23–47. doi: 10.1146/annurev-clinpsy-032816-044949

25. Knight RG, Williams S, McGee R, Olaman S. Psychometric properties of the Centre for Epidemiologic Studies Depression Scale (CES-D) in a sample of women in middle life. *Behav Res Ther*. (1997) 35:373–80. doi: 10.1016/S0005-7967(96)00107-6

26. Schulz AJ, Gravlee CC, Williams DR, Israel BA, Mentz G, Rowe Z. Discrimination, symptoms of depression, and self-rated health among African American women in Detroit: results from a longitudinal analysis. *Am J Public Health*. (2006) 96:1265–70. doi: 10.2105/AJPH.2005.064543

27. Vilagut G, Forero CG, Barbaglia G, Alonso J. Screening for depression in the general population with the Center for Epidemiologic Studies Depression (CES-D): a systematic review with Meta-analysis. *PLoS One*. (2016) 11:e0155431. doi: 10.1371/journal.pone.0155431

28. Grossman M, Wood W. Sex differences in intensity of emotional experience: a social role interpretation. *J Pers Soc Psychol*. (1993) 65:1010–22. doi: 10.1037/0022-3514.65.5.1010

29. Kiely KM, Brady B, Byles J. Gender, mental health and ageing. *European menopause J*. (2019) 129:76–84. doi: 10.1016/j.maturitas.2019.09.004

30. Weissman JD, Russell D. Relationships between living arrangements and health status among older adults in the United States, 2009-2014: findings from the National Health Interview Survey. *J Appl Gerontol*. (2018) 37:7–25. doi: 10.1177/0733464816655439

31. White M, Casey L. Helping older adults to help themselves: the role of mental health literacy in family members. *Aging Ment Health*. (2017) 21:1129–37. doi: 10.1080/13607863.2016.1206513

32. Dang M, Chen Y, Ji JS, Zhang Y, Chen C, Zhang Z. The association between household and family composition and mental health of the elderly: mediating role of lifestyle. *BMC Public Health*. (2024) 24:2055. doi: 10.1186/s12889-024-19516-4

33. Mair C, Roux AD, Galea S. Are Neighbourhood characteristics associated with depressive symptoms? A review of evidence. *J Epidemiol Community Health*. (2008) 62:940–6. doi: 10.1136/jech.2007.066605

34. Yang L, Wang L, Dai X. Rural-urban and gender differences in the association between community care services and elderly individuals' mental health: a case from Shaanxi Province, China. *BMC Health Serv Res*. (2021) 21:1–12. doi: 10.1186/s12913-021-06113-z

35. Barnay T, Juin S. Does home Care for Dependent Elderly People Improve Their Mental Health? *J Health Econ*. (2016) 45:149–60. doi: 10.1016/j.jhealeco.2015.10.008

36. Michaelson V, Pilato KA, Davison CM. Family as a health promotion setting: a scoping review of conceptual models of the health-promoting family. *PLoS One*. (2021) 16:e0249707. doi: 10.1371/journal.pone.0249707

37. Ziersch AM, Baum FE, Macdougall C, Putland C. Neighbourhood life and social capital: the implications for health. *Soc Sci Med*. (2005) 60:71–86. doi: 10.1016/j.socscimed.2004.04.027

38. Hill TD, Ross CE, Angel RJ. Neighborhood disorder, psychophysiological distress, and health. *J Health Soc Behav*. (2005) 46:170–86. doi: 10.1177/002214650504600204

39. Cramm JM, Nieboer AP. Relationships between frailty, neighborhood security, social cohesion and sense of belonging among community-dwelling older people. *Geriatr Gerontol Int*. (2013) 13:759–63. doi: 10.1111/j.1447-0594.2012.00967.x

40. He Y, Wei B, Li Y. The impact of using community home-based elderly care services on older adults' self-reported health: fresh evidence from China. *Front Public Health*. (2023) 11:1257463. doi: 10.3389/fpubh.2023.1257463

41. Zhang Z, Mao Y, Shui Y, Deng R, Hu Y. Do Community home-based elderly care services improve life satisfaction of Chinese older adults? An empirical analysis based on the 2018 CLHLS dataset. *Int J Environ Res Public Health*. (2022) 19:15462. doi: 10.3390/ijerph192315462

42. Rantakokko M, Tormakangas T, Rantanen T, Haak M, Iwarsson S. Environmental barriers, person-environment fit and mortality among community-dwelling very old people. *BMC Public Health*. (2013) 13:783. doi: 10.1186/1471-2458-13-783

43. Kahana E, Lovegreen L, Kahana B, Kahana M. Person, environment, and person-environment fit as influences on residential satisfaction of elders. *Environ Behav*. (2003) 35:434–53. doi: 10.1177/0013916503035003007

44. Xia D, Gong R, Hu Y, Hu Z, Xiang H. Neighborhood effects on the health of elderly persons: evidence from China. *BMC Geriatr*. (2023) 23:879. doi: 10.1186/s12877-023-04609-3

45. Ibem EO, Aduwo EB. Assessment of residential satisfaction in public housing in Ogun state, Nigeria. *Habitat Int*. (2013) 40:163–75. doi: 10.1016/j.habitatint.2013.04.001

46. Kleinhans R, Priemus H, Engbersen G. Understanding social Capital in Recently Restructured Urban Neighbourhoods: two case studies in Rotterdam. *Urban Stud*. (2007) 44:1069–91. doi: 10.1080/00420980701256047

47. Baranyi G, Di Marco MH, Russ TC, Dibben C, Pearce J. The impact of Neighbourhood crime on mental health: a systematic review and Meta-analysis. *Soc Sci Med*. (2021) 282:114106. doi: 10.1016/j.socscimed.2021.114106

48. Jen MH, Sund ER, Johnston R, Jones K. Trustful societies, trustful individuals, and health: an analysis of self-rated health and social trust using the world value survey. *Health Place*. (2010) 16:1022–9. doi: 10.1016/j.healthplace.2010.06.008

49. Kim S-S, Chung Y, Perry MJ, Kawachi I, Subramanian SV. Association between interpersonal trust, reciprocity, and depression in South Korea: a prospective analysis. *PLoS One*. (2012) 7:e30602. doi: 10.1371/journal.pone.0030602

50. Fujiwara T, Kawachi I. A prospective study of individual-level social capital and major depression in the United States. *J Epidemiol Community Health*. (2008) 62:627–33. doi: 10.1136/jech.2007.064261

51. Saelens BE, Handy SL. Built environment correlates of walking: a review. *Med Sci Sports Exerc*. (2008) 40:S550–66. doi: 10.1249/MSS.0b013e31817c67a4

52. Lee H-Y, Yu C-P, Wu C-D, Pan W-C. The effect of leisure activity diversity and exercise time on the prevention of depression in the middle-aged and elderly residents of Taiwan. *Int J Environ Res Public Health*. (2018) 15:654. doi: 10.3390/ijerph15040654

53. Wang R, Liu Y, Lu Y, Zhang J, Liu P, Yao Y, et al. Perceptions of built environment and health outcomes for older Chinese in Beijing: a big data approach with street view images and deep learning technique. *Comput Environ Urban Syst*. (2019) 78:101386. doi: 10.1016/j.compenvurbsys.2019.101386

54. Ewing R, Cervero R. Travel and the built environment. *J Am Plan Assoc*. (2010) 76:265–94. doi: 10.1080/01944361003766766

55. Julien D, Gauvin L, Richard L, Kestens Y, Payette H. Associations, between walking and depressive symptoms among older adults: do purposes and amounts of walking matter? Results from the VoisiNuAge study. *Ment Health Phys Act*. (2015) 8:37–43. doi: 10.1016/j.mhpa.2015.02.001

56. Ulrich RS. View through a window may influence recovery from surgery. *Science*. (1984) 224:420–1. doi: 10.1126/science.6143402

57. Kaplan R, Kaplan S. The experience of nature: A psychological perspective. US: Cambridge university press (1989).

58. Hartig T, Mang M, Evans GW. Restorative effects of natural environment experiences. *Environ Behav*. (1991) 23:3–26. doi: 10.1177/0013916591231001

59. Sugiyama T, Leslie E, Giles-Corti B, Owen N. Associations of Neighbourhood greenness with physical and mental health: do walking, social coherence and local social interaction explain the relationships? *J Epidemiol Community Health*. (2008) 62:e9–9. doi: 10.1136/jech.2007.064287

60. Gong Y, Gallacher J, Palmer S, Fone D. Neighbourhood green space, physical function and participation in physical activities among elderly men: the Caerphilly prospective study. *Int J Behav Nutr Phys Act*. (2014) 11:1–11. doi: 10.1186/1479-5868-11-40

61. Sugiyama T, Thompson CW. Older People's health, outdoor activity and supportiveness of Neighbourhood environments. *Landsc Urban Plan*. (2007) 83:168–75. doi: 10.1016/j.landurbplan.2007.04.002

62. Maas J, Van Dillen SM, Verheij RA, Groenewegen PP. Social contacts as a possible mechanism behind the relation between green space and health. *Health Place*. (2009) 15:586–95. doi: 10.1016/j.healthplace.2008.09.006

63. Cleary A, Fielding KS, Bell SL, Murray Z, Roiko A. Exploring potential mechanisms involved in the relationship between Eudaimonic wellbeing and nature connection. *Landsc Urban Plan*. (2017) 158:119–28. doi: 10.1016/j.landurbplan.2016.10.003

64. Liu L, Gou Z, Zuo J. Social support mediates loneliness and depression in elderly people. *J Health Psychol*. (2016) 21:750–8. doi: 10.1177/1359105314536941

65. Jiaxi P, Xihua J, Jiaxi Z, Runxuan X, Yunyun S, Xi F, et al. The impact of psychological capital on job burnout of Chinese nurses: the mediator role of organizational commitment. *PLoS One*. (2013) 8:e84193. doi: 10.1371/journal.pone.0084193

66. Chaurasia H, Brajesh S, Sarode S. Exploring potential linkages between social support, retirement and subjective wellbeing among older Indians: does it a challenge to policy makers? *Ageing Int*. (2018) 43:207–36. doi: 10.1007/s12126-017-9317-3

67. Malone C, Wachholtz A. The relationship of anxiety and depression to subjective well-being in a mainland Chinese sample. *J Relig Health*. (2018) 57:266–78. doi: 10.1007/s10943-017-0447-4

68. Pressman S.D., Cohen S. Does positive affect influence health? *Psychological bulletin*. (2005). 131:925

69. Chida Y, Steptoe A. Positive psychological well-being and mortality: a quantitative review of prospective observational studies. *Psychosom Med*. (2008) 70:741–56. doi: 10.1097/PSY.0b013e31818105ba

70. Brendan M, Baird Richard E, LucasM B. Donnellan life satisfaction across the lifespan: findings from two nationally representative panel studies. *Soc Indic Res*. (2010) 106:591. doi: 10.1007/s11205-010-9584-9

71. Yingzhi Q, et al. Zhigang exploring the linkage between the neighborhood environment and mental health in Guangzhou, China. *Int. J. Environ. Res. Public Health* (2019) 16:3206. doi: 10.3390/ijerph16173206

72. Huppert FA, So TTC. Exploring the linkage between the neighborhood environment and mental health in Guangzhou, China. *Soc Indic Res*. (2013) 110:837–61. doi: 10.1007/s11205-011-9966-7

73. Mitchell R, Popham F. Greenspace, urbanity and health: relationships in England. *J Epidemiol Community Health*. (2007) 61:681–3. doi: 10.1136/jech.2006.053553

74. Reid CE, Rieves ES, Carlson K. Perceptions of green space usage, abundance, and quality of green space were associated with better mental health during the COVID-19 pandemic among residents of Denver. *PLoS One*. (2022) 17. doi: 10.1371/journal.pone.0263779

75. Ballas D, Tranmer M. Happy people or happy places? A multilevel modelling approach to Theanalysis of happiness and well-being. *Int Reg Sci Rev*. (2012) 35:70–102. doi: 10.1177/0160017611403737

76. Tao Y, Yang J, Chai Y. The anatomy of health-supportive neighborhoods: a multilevel analysis of built environment, perceived disorder, social interaction and mental health in Beijing. *IJERPH*. (2019) 17:13. doi: 10.3390/ijerph17010013

77. Zhang J, Zhang J, Zhou M, Yu NX. Neighborhood characteristics and older adults' well-being: the roles of sense of community and personal resilience. *Soc Indic Res*. (2018) 137:949–63. doi: 10.1007/s11205-017-1626-0

78. Liu Y, Zhang F, Liu Y, Li Z, Wu F. The effect of Neighbourhood social ties on migrants' subjective wellbeing in Chinese cities. *Habitat Int*. (2017) 66:86–94. doi: 10.1016/j.habitatint.2017.05.011

79. Hays RA, Kogl AM. Neighborhood attachment, social capital building, and political participation: a case study of low-and moderate-income residents of Waterloo. *Iowa J Urban Affairs*. (2007) 29:181–205. doi: 10.1111/j.1467-9906.2007.00333.x

80. Dang L, Seemann A-K, Lindenmeier J, Saliterer I. Explaining civic engagement: the role of neighborhood ties, place attachment, and civic responsibility. *J Community Psychol*. (2022) 50:1736–55. doi: 10.1002/jcop.22751

81. Radloff LS. The CES-D scale: a self-report depression scale for research in the general population. *Appl Psychol Meas*. (1977) 1:385–401. doi: 10.1177/014662167700100306

82. Neugarten BL, Havighurst RJ, Tobin SS. The measurement of life satisfaction. *J Gerontol*. (1961) 16:134–43. doi: 10.1093/geronj/16.2.134

83. Diener E. Subjective well-being. *Psychol Bull*. (1984) 95:542–75. doi: 10.1037/0033-2909.95.3.542

84. Lyubomirsky S, Lepper HS. A measure of subjective happiness: preliminary reliability and construct validation. *Soc Indic Res*. (1999) 46:137–55.

85. Pavot W, Diener E. The satisfaction with life scale and the emerging construct of life satisfaction. *J Posit Psychol*. (2008) 3:137–52. doi: 10.1080/17439760701756946

86. Headey B, Wooden M. The effects of wealth and income on subjective well-being and ill-being. *Econ Rec*. (2004) 80:S24–33. doi: 10.1111/j.1475-4932.2004.00181.x

87. Ouyang X, Pan Z. Social quality and residents' subjective well-being in China—an empirical analysis based on CSS2021 data. *Sustain For*. (2023) 15:13219. doi: 10.3390/su151713219

88. Helbich M, Klein N, Roberts H, Hagedoorn P, Groenewegen PP. More green space is related to less antidepressant prescription rates in the Netherlands: a Bayesian Geoadditive quantile regression approach. *Environ Res*. (2018) 166:290–7. doi: 10.1016/j.envres.2018.06.010

89. National Bureau of Statistics of China (NBS). Urban socio-economic survey division, National Bureau of statistics 2018. *China Urban Statistical Yearbook*. (2019).

90. Guo Y, Liu Y, Lu S, Chan OF, Chui CHK, Lum TYS. Objective and perceived built environment, sense of community, and mental wellbeing in older adults in Hong Kong: a multilevel structural equation study. *Landsc Urban Plan*. (2021) 209:104058. doi: 10.1016/j.landurbplan.2021.104058

91. Zheng Y, Cheng B, Dong L, Zheng T, Wu R. The moderating effect of social participation on the relationship between urban green space and the mental health of older adults: a case study in China. *Landscape*. (2024) 13:317. doi: 10.3390/land13030317

92. Ullman JB, Bentler PM. Structural equation modeling In: JR Graham, JA Naglieri. (Eds.), Handbook of Psychology. Second edn (2012). 2. doi: 10.1002/9781118133880.hop202023

93. Hu L, Bentler PM. Cutoff criteria for fit indexes in covariance structure analysis: conventional criteria versus new alternatives. *Struct Equ Model Multidiscip J*. (1999) 6:1–55. doi: 10.1080/10705519909540118

94. Kazmierczak A. The contribution of local parks to Neighbourhood social ties. *Landsc Urban Plan*. (2013) 109:31–44. doi: 10.1016/j.landurbplan.2012.05.007

95. Ng HKS, Chow SY. On the relationship between green space and civic engagement: the roles of well-being, outgroup trust, and activity level. *Am J Community Psychol*. (2023) 72:170–86. doi: 10.1002/ajcp.12692

96. Su Y, Zhang X, Xuan Y. Linking neighborhood green spaces to loneliness among elderly residents-a path analysis of social capital. *Cities*. (2024) 149:104952. doi: 10.1016/j.cities.2024.104952

97. Nasar JL, Fisher B, Grannis M. Proximate physical cues to fear of crime. *Landsc Urban Plan*. (1993) 26:161–78. doi: 10.1016/0169-2046(93)90014-5

98. Maas J, Spreeuwenberg P, Van Winsum-Westra M, Verheij RA, Vries S, Groenewegen PP. Is green space in the living environment associated with People's feelings of social safety? *Environ Plan A*. (2009) 41:1763–77. doi: 10.1068/a4196

99. Wang R, Cleland CL, Weir R, McManus S, Martire A, Grekousis G, et al. Rethinking the association between green space and crime using spatial quantile regression modelling: do vegetation type, crime type, and crime rates matter? *Urban For Urban Green*. (2024) 101:128523. doi: 10.1016/j.ufug.2024.128523

100. Liu Y, Wang R, Xiao Y, Huang B, Chen H, Li Z. Exploring the linkage between greenness exposure and depression among Chinese people: mediating roles of physical activity, stress and social cohesion and moderating role of Urbanicity. *Health Place*. (2019) 58:102168. doi: 10.1016/j.healthplace.2019.102168

101. Markevych I, Schoierer J, Hartig T, Chudnovsky A, Hystad P, Dzhambov AM, et al. Exploring pathways linking greenspace to health: theoretical and methodological guidance. *Environ Res*. (2017) 158:301–17. doi: 10.1016/j.envres.2017.06.028

102. Nardo FD, Saulle R, Torre GL. Green areas and health outcomes: a systematic review of the scientific literature. *Epidemiol Biostat Public Health*. (2010) 7:402–13. doi: 10.2427/5699

103. Steptoe A, Leigh ES, Kumari M. Positive affect and distressed affect over the day in older people. *Psychol Aging*. (2011) 26:956–65. doi: 10.1037/a0023303

104. Kent J, Thompson S. Health and the built environment: exploring foundations for a new interdisciplinary profession. *J Environ Public Health*. (2012) 2012:958175:1–10. doi: 10.1155/2012/958175

105. Lorenc T, Clayton S, Neary D, Whitehead M, Petticrew M, Thomson H, et al. Crime, fear of crime, environment, and mental health and wellbeing: mapping review of theories and causal pathways. *Health Place*. (2012) 18:757–65. doi: 10.1016/j.healthplace.2012.04.001

106. Toma A, Hamer M, Shankar A. Associations between neighborhood perceptions and mental well-being among older adults. *Health Place*. (2015) 34:46–53. doi: 10.1016/j.healthplace.2015.03.014

107. Berkman LF, Glass T, Brissette I, Seeman TE. From social integration to health: Durkheim in the new millennium. *Soc Sci Med*. (2000) 51:843–57. doi: 10.1016/S0277-9536(00)00065-4

108. Wang X, Zhou P, Liu Z. Neighborhood social capital and self-rated mental health: disparities between migrants and native residents in Beijing. *Front Public Health*. (2022) 10:1055712. doi: 10.3389/fpubh.2022.1055712

109. Levula A, Harré M, Wilson A. The association between social network factors with depression and anxiety at different life stages. *Community Ment Health J*. (2018) 54:842–54. doi: 10.1007/s10597-017-0195-7

110. Gu N. The effects of neighborhood social ties and networks on mental health and well-being: a qualitative case study of women residents in a middle-class Korean urban neighborhood. *Soc Sci Med*. (2020) 265:113336. doi: 10.1016/j.socscimed.2020.113336

111. Liu Y, Zhang F, Wu F, Liu Y, Li Z. The subjective wellbeing of migrants in Guangzhou, China: the impacts of the social and physical environment. *Cities*. (2017) 60:333–42. doi: 10.1016/j.cities.2016.10.008

112. Chen H, Zhu Z. Social trust and emotional health in rural older adults in China: the mediating and moderating role of subjective well-being and subjective social status. *BMC Public Health*. (2021) 21:556. doi: 10.1186/s12889-021-10617-y

113. Leslie E, Cerin E. Are perceptions of the local environment related to Neighbourhood satisfaction and mental health in adults? *Prev Med*. (2008) 47:273–8. doi: 10.1016/j.ypmed.2008.01.014

114. Wang R, Feng Z, Pearce J, Zhou S, Zhang L, Liu Y. Dynamic greenspace exposure and residents' mental health in Guangzhou, China: from over-head to eye-level perspective, from quantity to quality. *Landsc Urban Plan*. (2021) 215:104230. doi: 10.1016/j.landurbplan.2021.104230

115. Reyes-Riveros R, Altamirano A, De la Barrera F, Rozas-Vasquez D, Vieli L, Meli P. Linking public urban green spaces and human well-being: a systematic review. *Urban For Urban Green*. (2021) 61:127105. doi: 10.1016/j.ufug.2021.127105

116. Hassan A, Chen Q, Jiang T. Physiological and psychological effects of gardening activity in older adults. *Geriatr Gerontol Int*. (2018) 18:1147–52. doi: 10.1111/ggi.13327

117. Xu T, Nordin NA, Aini AM. Urban green space and subjective well-being of older people: a systematic literature review. *Int J Environ Res Public Health*. (2022) 19:14227. doi: 10.3390/ijerph192114227

118. Hong A, Sallis JF, King AC, Conway TL, Saelens B, Cain KL, et al. Linking green space to neighborhood social Capital in Older Adults: the role of perceived safety. *Soc Sci Med*. (2018) 207:38–45. doi: 10.1016/j.socscimed.2018.04.051

119. Wilson EO. Biophilia and the conservation ethic In: TP, Kajanus (Ed.), Evolutionary perspectives on environmental problems. UK: Routledge (2017). 250–8.

120. Zhang W, Gao Y, Li S, Liu W, Zeng C, Gao L, et al. Accessibility measurements for urban parks considering age-grouped walkers' sectorial travel behavior and built environment. *Urban For Urban Green*. (2022) 76:127715. doi: 10.1016/j.ufug.2022.127715

121. Howell AJ, Dopko RL, Passmore H-A, Buro K. Nature connectedness: associations with well-being and mindfulness. *Personal Individ Differ*. (2011) 51:166–71. doi: 10.1016/j.paid.2011.03.037

122. Klotz AC, Bolino MC. Bringing the great outdoors into the workplace: the energizing effect of Biophilic work design. *Amrudh*. (2021) 46:231–51. doi: 10.5465/amr.2017.0177

123. Liu Y, Wang R, Lu Y, Li Z, Chen H, Cao M, et al. Natural outdoor environment, Neighbourhood social cohesion and mental health: using multilevel structural equation modelling, streetscape and remote-sensing metrics. *Urban For Urban Green*. (2020) 48:126576. doi: 10.1016/j.ufug.2019.126576

124. Helliwell JF, Putnam RD. The social context of well-being. *Philos Trans R Soc B-Biol Sci*. (2004) 359:1435–46. doi: 10.1098/rstb.2004.1522

125. Offer S. They drive me crazy: difficult social ties and subjective well-being. *J Health Soc Behav*. (2020) 61:418–36. doi: 10.1177/0022146520952767

126. Guo S, Song C, Pei T, Liu Y, Ma T, Du Y, et al. Accessibility to urban parks for elderly residents: perspectives from Mobile phone data. *Landsc Urban Plan*. (2019) 191:103642. doi: 10.1016/j.landurbplan.2019.103642

127. Lak A, Khodakarim S, Myint PK, Baradaran HR. The influencing factors of elder-friendly public open spaces promoting older adults' health in deprived urban neighborhoods: partial Least Square structural equation modeling approach. *Front Public Health*. (2023) 11:1143289. doi: 10.3389/fpubh.2023.1143289

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How do neighborhood environments impact adolescent health: a comprehensive study from subjective and objective perspectives using machine learning method

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Existing studies have established a linear relationship between urban environments and adolescent health, but the combined impacts of subjective and objective environments on multi-dimensional health status (including physical and mental health) have not been fully explored. Furthermore, while some studies have examined the non-linear relationship between urban environments and adult health, research specifically focusing on adolescents is sparse. Using Kunming, China, as a case study, we employ Random Forest model to examine the non-linear relationship between subjective/objective neighborhood environments and adolescent physical/mental health. The results indicate that the objective environment plays a more significant role in influencing physical and mental health in adolescents. There are generally non-linear correlations and threshold effects between neighborhood environment variables and adolescents' health status. Specifically, the effects of distance to subway station, ratio of traffic safety facilities, and greening view index on adolescent physical and mental health differ. Additionally, subjective environments characterized by community management, community image, and community capital tend to positively influence adolescents' health status. This study provides valuable insights for the planning of healthy communities, environmental interventions, and health promotion in specific dimensions among adolescents.

KEYWORDS

neighborhood environment, random forest, adolescent, physical health, mental health, non-linear relationship

1 Introduction

Physical and mental health issues have become significant obstacles for adolescents during their physical and emotional development, as well as their cognitive ability formation stages. Studies indicate that between 2015 and 2019, 11.1% of Chinese children and adolescents aged 6 to 17 were overweight, with 7.9% classified as obese (1). A national survey conducted in 2016 revealed that the rate of students in China meeting the standard for physical health was only 23.8% (2). Additionally, evidence suggests that the prevalence of anxiety and depression among adolescents is approximately 4.7 and 3.0% (3), respectively, with the overall prevalence of depression exceeding the global average (4). As the world's second most populous country after India, China has more than 158 million adolescents (5), highlighting the significance of these health issues.

The effective intervention in neighborhood environments to promote positive health status for adolescents has become a significant topic in fields such as urban planning, geography, and transportation. Existing research typically measures neighborhood environments from two perspectives: the objective environment and subjective environment. On one hand, the widespread use of geographic information systems and urban spatial data has facilitated extensive studies on the relationship between objective physical characteristics and health, such as blue and green spaces, road design, land use mix, and accessibility of services and transportation facilities (6–8). However, the objective environmental measurements are mostly overall depictions of the surrounding community environment and are difficult to reflect the perceptual circumstances under individual differences in needs. Therefore, on the other hand, through interviews and questionnaire surveys, some studies have explored the relationship between individual environmental perception and health, such as assessments and perceptions of environment and facilities, neighborhood order and community support (9–11). Nevertheless, while both objective and subjective environmental factors have shown significant effects on adolescent health, only a few studies have explored the combined impact on health.

Most existing studies on the built environment and residents' health are based on linear assumptions. Nevertheless, the influences of built environment elements may fluctuate depending on their scope. As a result, concentrating on a sole relationship and disregarding potential non-linear effects may bring about disparities in results (12). In recent years, with the application of machine learning in the domains of urban planning, geography, and transportation, numerous studies have explored the complex non-linear relationship between the built environment and health. For instance, some evidence has revealed that environmental elements such as greenness and population density have complex effects on residents' health, including inverted U-shaped and N-shaped relationships (13–16). Nevertheless, the limited research has merely investigated the relationship between the built environment and adult health, while there has been virtually no exploration concerning the relationship between the built environment and the health of adolescents who are in the stage of physical and mental development.

In summary, existing research has predominantly examined the relationship between neighborhood environments and adolescent health from a singular perspective, focusing either on the objective or subjective environment. However, there is a notable lack of studies assessing the relative importance and differing impacts of both environments on various health dimensions. Furthermore, research addressing the nonlinear associations between neighborhood environments and health outcomes is limited, with most studies concentrating on adults and offering little insight into the experiences of adolescents.

Therefore, this study uses data from the "Questionnaire Survey on Primary and Secondary School Students' Commuting and Healthy Growth" in Kunming, China, along with multi-source urban spatial data. By employing Random Forest model, it aims to explore the non-linear associations between subjective/objective environments and adolescent physical/mental health. This study attempted to address two questions: (1) What are the contributions of environmental characteristics to adolescent health, and are there differences between subjective and objective environments? (2) Do subjective and objective environments demonstrate a non-linear relationship and threshold effects with adolescent physical and mental health?

2 Literature review

2.1 Objective/subjective environment and adolescent health

The concept of "Healthy Cities" was formally introduced by the World Health Organization (WHO) in 1984, emerging from research on the impact of public health systems on residents' well-being. One of its definitions is that a healthy city should create and improve physical and social environments, and enhance social support through expanded community resources (17). With the advancement of the "Healthy Cities" movement, theoretical discussions between environment and health have increased. Among these, socioecological theory, which provides a framework for sustaining the "individual-environment" system, emphasizes the interactive relationship between individuals and environment (18). It posits that health is influenced by multiple layers, including personal and environmental factors, where environmental factors include the built, natural, and social environment (18, 19). Based on the theoretical explanation of "environment-health," numerous scholars have explored the mechanisms through which multidimensional environments impact health. Among these, the neighborhood environment, where urban residents (particularly adolescents) live for extended periods, has been widely recognized as having a significant impact on health. Recent studies on neighborhood environments and adolescent health commonly measure neighborhood conditions in two dimensions, objective and subjective environments, due to differences in research content and measurement approaches (such as urban spatial big data or questionnaire survey data).

On one hand, the objective environment reflects the physical spatial structure of the community and the opportunities for accessing service facilities, and it can be categorized into natural and built environment based on specific indicators and research focus. The natural environment includes the density, quality, and exposure levels of blue and green spaces (13, 20–22). The built environment includes the road design (e.g., street connectivity, road and intersection density) (7, 8, 13, 23), density and accessibility of service facilities (e.g., parks, restaurants, and sports and recreational facilities) (6, 23, 24), land use mix (7, 25, 26), density and accessibility of transportation (e.g., bus stop and subway station) (7, 8, 13, 25). Regarding the natural environment, appropriate exposure to nature and well-designed landscapes can positively influence adolescents' physical and mental health. For instance, the coverage and proximity to parks, forests, or green spaces have been shown to improve sleep efficiency, reduce body mass index (BMI) (6, 20, 27), and improve mental well-being (including reductions in depression, stress, anxiety, and behavioral health issues) (28, 29). Regarding the built environment, it influences adolescent health by shaping the overall quality of the community (e.g., residential quality, land use mix, and facility distribution). For instance, mixed land-use patterns (7, 25), appropriate intersection density (25), and the proximity of parks and sports facilities (7) promote physical activity, support social interactions, and reduce sedentary behavior (24), thus positively influencing adolescents' physical health and emotional well-being. Conversely, significant environmental pollution, including air and noise pollution, can adversely affect physical health and lead to negative emotions (9, 20, 30). For instance, excessive concentrations of pollutants like NO_2 and $PM_{2.5}$, negatively affect adolescent sleep health (20), and are associated with adolescent psychiatric experiences (31). Although the objective environment effectively represents the physical spaces that adolescents inhabit, it does not fully capture the comprehensive subjective assessments of environmental factors that influence health status or behaviors (32, 33).

On the other hand, the subjective environment reflects adolescents' perceptions and evaluations of the physical and social contexts, which indicates that individual differences may result in varied interpretations of similar neighborhood environments. This includes assessments and perceptions of the natural environment (10, 34), built environment (e.g., walkability, cognitive aspects of buildings, and service facilities) (10, 35), neighborhood order (e.g., crime and safety) (11, 36, 37), community support and interaction (e.g., cohesion, trust, and social capital) (6, 9, 38, 39). Among them, perceptions of the physical environment can indirectly influence adolescent health by promoting or hindering physical activity levels. For instance, perceived favorable landscape conditions (10) and proximity to recreational facilities (35) provide opportunities for positive interactions with the environment, thereby fostering healthy emotional responses and habits. In contrast, perceptions of the social environment significantly impact adolescents' social behaviors and interactions. For example, perceived community safety is positively associated with reductions in adolescents' body mass index (BMI) and well-being (6, 36). Conversely, negative perceptions of neighborhood trust, social cohesion, and social capital are associated with a higher likelihood of adolescents reporting internalizing and externalizing problem behaviors (40, 41).

Previous studies highlight that both objective and subjective environments are critical factors influencing adolescent health. Recognizing the limitations of assessing environmental influences on adolescent health through a single-dimensional approach, a few studies have started to examine the relationship between the environment and health by considering both subjective and objective environmental factors (6, 9, 42). However, variations in indicator selection and research focus have led these studies to primarily explore the effects of significant environmental variables. Recently, studies on neighborhood environment and residents' health have increasingly focused on the joint analysis of objective and subjective characteristics (10, 33, 43, 44). Due to differences in measurement approaches and representational meanings, the relative influence of objective and subjective environments on health may vary. For instance, certain study indicates that the objective environment may be more significant (45), as it reflects the actual physical space of the community, thereby confirming the real meaning of the perceived environment and helping to guide planning practices (33). Other studies, however, indicate that the subjective environment is more significant (15, 43, 46), as perceptions of the environment reflect individual cognitive processes and have a particularly significant impact on health (47). Although the relative importance may vary by research aim and context, both objective and subjective environments contribute to reflecting the significant influence of the built environment on health through environmental perception and the promotion of health behaviors.

In summary, using indicators from both subjective and objective environments provides a comprehensive understanding of the neighborhood environments that adolescents experience. However, existing research often examines the relationship between neighborhood environments and adolescent health from a singular perspective (subjective or objective) and single dimension (such as two-dimensional spatial environment). Few studies have investigated the interplay between subjective and objective environments.

2.2 Non-linear association between environment and health

Existing research has mainly investigated the impact of neighborhood environment on adolescent health using linear assumptions, often focusing on single effects. However, variations in indicators and methodologies frequently lead to estimation bias (48, 87). For instance, natural environmental contact has been shown to have a positive effect on health in most studies, and air pollution has a negative effect. But these two environmental conditions have not been able to predict mental health outcomes in some studies (42). Likewise, while proximity to transit stations and road density are generally positively associated with adolescent health, some studies have found no significant correlations with physical health outcomes (7). Additionally, the effects of built environment elements may differ by spatial scale, and focusing only on linear relationships could overlook potential nonlinear effects, leading to inconsistencies in findings (12). For instance, land use mix is generally positively correlated with adolescent physical and mental health (7, 25), but another study indicates that its impact on adolescent BMI is not significant, and may exhibit a possible nonlinear relationship (26). In the only two studies we found that explore the non-linear relationship between neighborhood environment and adolescent health, the non-linear relationships and threshold effects of certain environmental variables have been confirmed. For instance, the distance to transit stations shows a locally significant positive effect on adolescent physical health within specific intervals (7, 13), while green spaces (e.g., park coverage and NDVI) are associated with reduced adolescent obesity rates within certain thresholds (13).

Most existing studies on the built environment and residents' health are based on linear assumptions. Recently, there has been growing interest in the non-linear associations between neighborhood environments and various health-related factors, including health status (15, 49, 50), obesity (13, 51, 52), and positive health behaviors (16, 53, 54). Some studies have identified potential threshold effects for specific built environment variables, indicating that significant effects only emerge within certain ranges. For instance, optimal levels of built environment features, such as proximity to sports facilities and bus stops (15), road density (54), and land use mix (53), can effectively enhance residents' physical and mental health while promoting active travel. Moreover, evidence suggests that the relationships between certain built environment factors and health outcomes can vary across different ranges of influence. For example, green exposure has been widely shown to have complex mechanisms affecting health. Adequate levels of green exposure offer more opportunities for interaction with nature and improved landscape conditions, fostering positive health outcomes and related behaviors. However, negative impacts may arise beyond certain thresholds (12, 13, 15). Similar effects have been observed with road connectivity (15, 55), bus stop density (14, 15), and population density (13, 14).

3 Materials and methods

The three-step workflow in this study is shown in Figure 1. Firstly, this study uses data from the "Questionnaire Survey on Primary and Secondary School Students' Commuting and Healthy Growth" in Kunming, China, along with street view image and multi-source urban spatial data. Secondly, by employing Random Forest model, it evaluates the relative importance of subjective environments, objective environments, and socioeconomic attributes on different dimensions of adolescent health. Additionally, it reveals the non-linear associations and threshold effects of key neighborhood environmental variables on adolescent health.

3.1 Study area and data

Kunming, the capital of Yunnan Province, serves as a key gateway to South and Southeast Asia and is one of the core cities in Southwest China. As of 2023, Kunming has a resident population of 8.68 million (56), and covers an area of 21,012.54 km^2 (57). The study area is defined by the spatial scope outlined in the "Urban Master Plan of Kunming (2011–2020)." It includes the area to the east of the Third Ring Road and enclosed by the Ring Expressway. This region encompasses the core built-up areas of Kunming's four main districts (Wuhua, Panlong, Xishan, and Guandu) and serves as a significant hub for the city's public service facilities (Figure 2).

The data for this study were obtained from the "Online Questionnaire Survey on Primary and Secondary School Students' Commuting and Healthy Growth," conducted in Kunming, China in January 2024. The survey covered five major districts in Kunming: Wuhua, Panlong, Xishan, Guandu, and Chenggong. First, we randomly selected 31 sample schools from a total of 402 primary and middle schools in five districts using a stratified sampling strategy (these schools are within the compulsory education stage). Subsequently, we contacted the Kunming Education and Sports Bureau to obtain permission for the online survey distribution and coordinated with the teachers in charge of each school. We randomly selected approximately 5% of students from grades 1–6 in primary schools or grades 1–3 in middle schools in the sample schools, and distributed a total of 1831 questionnaire QR codes. The online questionnaires were completed jointly by students and their parents. Given that younger students may not fully understand the questions, we specifically noted that sections to be filled out by students should be completed with parental assistance. The legal guardians of all participants signed informed consent forms after being briefed on the purpose of the survey, and their information is strictly protected in accordance with relevant regulations. The survey collected information on various aspects, including students' personal and family backgrounds, health status, and subjective environmental perceptions. After excluding questionnaires with incomplete information (such as home and school addresses), anomalies, and those with low reliability, we obtained 1,583 valid questionnaires, yielding an effective rate of

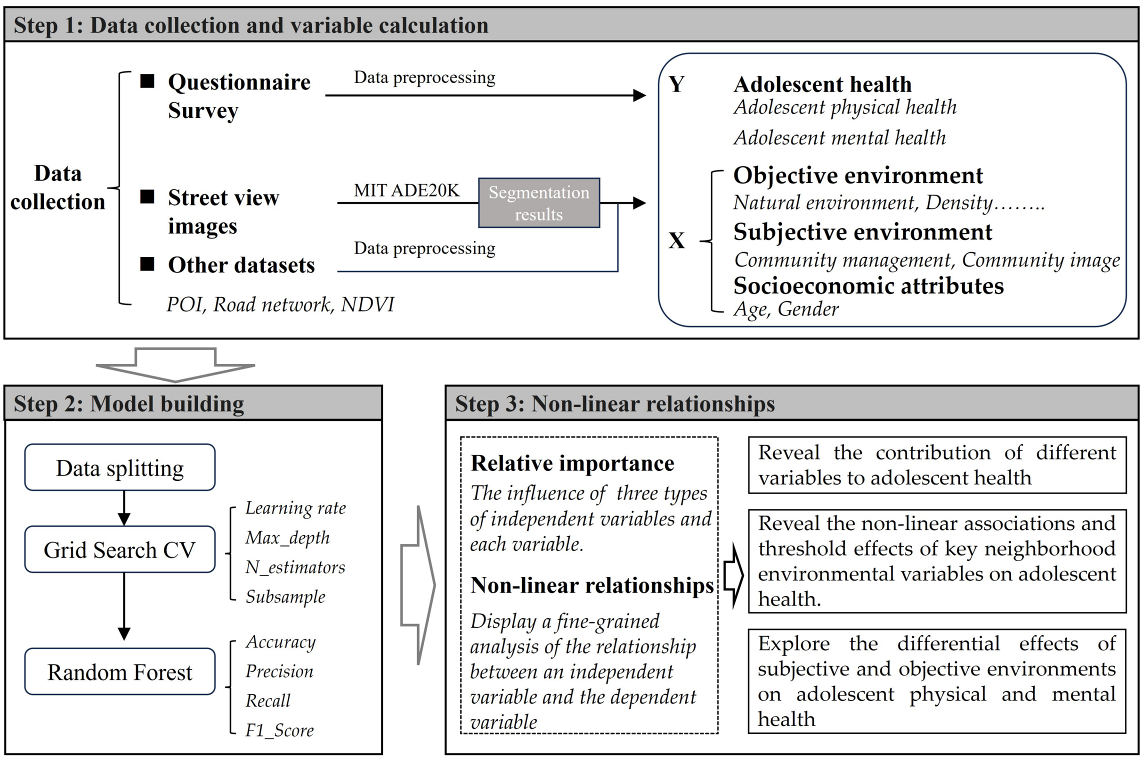

FIGURE 1
Framework.

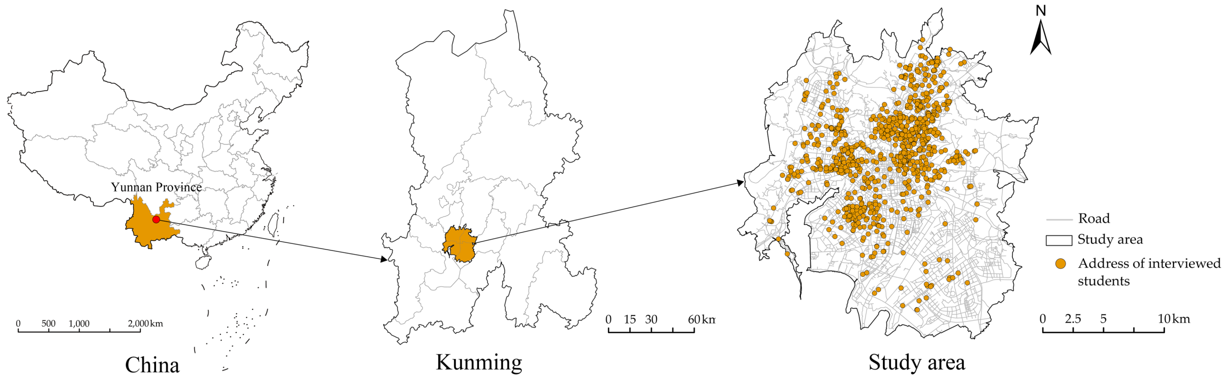

FIGURE 2
Study area.

86.45%. These samples were distributed across 606 residential communities in the five districts. Given the limitations and representativeness of the urban built environment data, we further refined the sample to 1,388 valid responses within the study area. Research indicates that children aged 7 to 12 develop more logical and organized ways of thinking compared to children under the age of 7 (58). Therefore, to more accurately capture adolescents' self-perception of the environment and health conditions, we excluded students under 7 years of age, yielding a final sample of 1,355 for subsequent analysis.

In addition to the survey data, we collected the following multi-source urban spatial data: (1) Road network data was obtained from OpenStreetMap.[1] The raw road network data were processed using ArcMap 10.8.1, including clipping, cleaning, and topological adjustments, with interruptions at intersections. (2) Points of Interest (POI) data was acquired from the Gaode Map.[2] (3) Street view image was collected from the Baidu Map.[3] A Python program was used to sample street view panoramic images at 100-meter intervals from the road network, resulting in 54,431 images. These images were analyzed using a PSP Net model pre-trained on the MIT ADE20K dataset to identify and calculate the area proportions of various visible spatial elements, such as sky, roads, and vegetation. (4) Normalized difference vegetation index (NDVI) was obtained from the National Ecological Science Data Center.[4]

3.2 Variables

3.2.1 Dependent variables

The dependent variables include participants' self-reported status for physical and mental health. In terms of the physical health, students were asked, "How would you rate your physical health?," with responses recorded on a Likert scale from 1 (very poor) to 5 (very good). In terms of the mental health, we used the "Chinese Adolescents' Emotional and Behavioral Problems Simplified Scale," which has demonstrated high reliability and validity in a survey involving 4,727 students in Hunan Province, China (59). We assessed mental health across three dimensions: anxiety, depression, and social problems. Each dimension comprises 10 to 13 questions, with response options and scoring as follows: Never/Rarely (1), Sometimes (2), Often (3), and Most of the time (4). Notably, since most response options are negative indicators, we converted all responses to positive values for the calculation of mental health scores, thereby measuring positive levels of mental health.

In this study, we assessed the relative health status of the surveyed students. First, participants who rated their physical health as "good" or "very good" were classified as "healthy," while those with remaining ratings were classified as "unhealthy" (15). Second, for mental health, we calculated the average scores for each dimension across all questions. Participants with average scores below 3 were classified as "unhealthy," while those with scores above 3 were classified as "healthy."

3.2.2 Independent variables

Based on the multidimensional definitions of environmental factors influencing health in Healthy Cities theory and socioecological theory (including the natural, built, and social environments), along with extensive discussions on objective and subjective environments in neighborhood studies on adolescent health, we developed an analytical framework for examining the impact of neighborhood environments on health (Figure 3). Regarding the neighborhood environment, we referenced the classification of residential environment attributes into subjective and objective components in the neighborhood satisfaction model (60), and reviewed evaluation variables related to both objective environments and subjective perceptions in existing research. A total of 26 indicators were selected, covering aspects of the objective environment, subjective environment, and socioeconomic attributes (Table 1). The following sections will provide a detailed introduction to the variables for both objective and subjective environments.

3.2.2.1 Objective environment

Previous research on objective environment and adolescent health consistently highlights the significant health impacts of factors such as greening levels, road design elements, and built environment

1 https://www.openstreetmap.org/
2 https://lbs.amap.com/
3 https://lbsyun.baidu.com/
4 http://www.nesdc.org.cn/

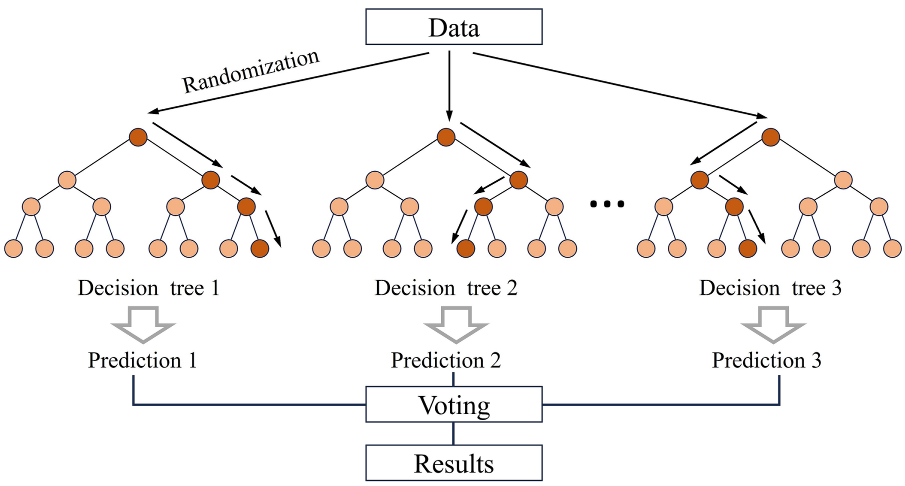

FIGURE 3
The process of random forest algorithm [adapted from Xu et al. (15)].

attributes. These factors influence adolescent health both directly and indirectly by shaping landscape quality, residential conditions, service accessibility, and transportation connectivity, ultimately impacting health behaviors and social interactions. Recent advancements in street view image semantic segmentation via machine learning have enhanced understanding of the built environment by measuring three-dimensional street visual elements, which have increasingly been applied in studies on adolescent health behaviors.

Based on previous studies and the widely used "5Ds" model in built environment and health research, we measured the objective environment using 11 variables across five dimensions. We created a circular buffer with 800-meter radius, commonly referred to as a 15-min pedestrian-scale neighborhood, within which residents can generally access essential service facilities. The natural environment is measured by NDVI (13, 15), reflecting adolescents' access to natural surroundings. Density is measured by intersection density (8, 25), reflecting the street network layout within the community. Diversity is measured by land use mix, reflecting the variety of functional facilities within the community (7, 25, 26). Street design is evaluated through the sky view index, greening view index, relative pedestrian width, and ratio of traffic safety facilities (61, 62), reflecting the three-dimensional visual conditions encountered by adolescents on streets. These indicators were determined by averaging the pixel ratio from street view images at each sampling point. Accessibility to transportation and facilities is measured by the distance to nearest bus stop, subway station, park or square, and sports facilities, reflecting adolescents' access to transportation, natural or open spaces, and recreational spaces in the neighborhood (7, 13, 20). These indicators were determined using the tool of "Find Closest Facilities" in ArcMap 10.8.1.

3.2.2.2 Subjective environment

Similarly, previous studies have demonstrated that the perceptions of natural, built, and social environments significantly impact adolescent health by fostering positive lifestyles and attitudes. Based on these studies, we measured the subjective environment using 9 variables across three dimensions. Community management is measured by perceived sanitary condition and property management quality, and community safety (11, 36, 37, 63), reflecting perceptions of community management quality and safety. Community image is measured by subjective air quality and noise quality, and perceived landscape environment (10, 34), reflecting perceptions of the neighborhood's physical environment. Community capital is measured by sense of community belonging, neighborhood familiarity, and frequency of community events (6, 9, 38, 39), reflecting social support and interpersonal interactions within the community. All subjective environmental indicators were evaluated using a five-point Likert scale.

3.3 Method

The Random Forest (RF) model, introduced by Leo Breiman in 2001, is a decision tree-based machine learning algorithm, particularly effective at handling large datasets while minimizing the risk of overfitting (64). In classification tasks, as illustrated in Figure 4, the core principle involves repeatedly drawing M sample sets from the original dataset using the bootstrap resampling method, generating M decision trees that collectively form a random forest. At each tree node, a random subset of n features is selected from the total of N features, and the feature that minimizes the Gini index is chosen to split the node. Each tree is fully grown, and the ensemble of M trees provides the final classification result, which is determined by majority voting across all trees.

In this study, we utilized the "Random Forest "package in Python 3.6, Jupyter Notebook 5.7.10. The model construction and validation process involves two main steps. First, using the 'train_test_split' module randomly allocates 70% of the analysis samples to the training set for model building, while the remaining 30% are reserved as the test set to assess the model's performance. Second, to optimize the model and avoid issues of underfitting and overfitting, based on previous study (65), three key hyperparameters are fine-tuned. The search ranges for these hyperparameters are as follows: max_depth ranging from 3 to 7 (step size of 1); n_estimators ranging from 100 to

TABLE 1 Description of variables.

Variables		Description	Mean (standard deviation) or proportion
Objective environment	**Natural environment**		
	NDVI	The mean of NDVI within 0.8 km buffer	0.40 (0.05)
	Density		
	Intersection density (number/km^2)	Number of road intersections / buffer area	19.47 (6.81)
	Diversity		
	Land use mix	$\text{Land use mix}_i = -\frac{1}{\ln A}\sum_{j=1}^{A} p_{ij} \ln p_{ij}$ Where p_{ij} refers to the proportion of the j-th type of POI within unit i relative to the total number of POIs in that unit. A refers to the number of POI types in the unit.	0.74 (0.05)
	Street design		
	Sky view index (%)	The mean of sky pixel ratio within 0.8 km buffer	48.85 (4.02)
	Greening view index (%)	The mean of green plants pixel ratio within 0.8 km buffer	12.14 (2.59)
	Relative pedestrian width	The mean ratio of pedestrian pathways to roads within 0.8 km buffer	0.37 (0.88)
	Ratio of traffic safety facilities (%)	The mean of safety facilities ratio within 0.8 km buffer	0.81 (0.22)
	Distance to transit		
	Distance to bus stop (km)	Distance to the nearest bus stop	0.25 (0.18)
	Distance to subway station (km)	Distance to the nearest subway station	1.42 (0.81)
	Destination accessibility		
	Distance to sports facility (km)	Distance to the nearest sports facility	0.36 (0.35)
	Distance to park or square (km)	Distance to the nearest park or square	0.69 (0.51)

(Continued)

TABLE 1 (Continued)

Variables		Description	Mean (standard deviation) or proportion
Subjective environment	**Community management**		
	Perceived sanitary condition	1 (Very bad) to 5 (Very good)	3.74 (0.87)
	Perceived property management quality	1 (Very bad) to 5 (Very good)	3.50 (0.98)
	Community safety	1 (Very bad) to 5 (Very good)	4.01 (0.83)
	Community image		
	Subjective noise quality	1 (Very noise) to 5 (Very quiet)	3.50 (1.00)
	Subjective air quality	1 (Very bad) to 5 (Very good)	3.72 (0.88)
	Perceived landscape environment	1 (Very bad) to 5 (Very good)	3.51 (0.90)
	Community capital		
	Sense of community belonging	1 (Very weak) to 5 (Very strong)	3.49 (0.89)
	Neighborhood familiarity	1 (Incognizant) ~ 5 (Knows each other)	2.29 (0.97)
	Frequency of community events	1 (None/very few) ~ 5 (Frequently)	2.59 (1.10)
Socioeconomic attributes	Age	The age of surveyed students	11.02 (2.18)
	Gender	Male = 0, Female = 1	0 = 52.77%, 1 = 47.23%
	Household registration	Non-local household registration =0, Local household registration = 1	0 = 36.97%, 1 = 63.03%
	Household income level (RMB)	Yearly household income: <50,000 = 1, 50,000–150,000 = 2, 150,000-250,000 = 3, > 250,000 = 4	2.29(0.93)
	Housing area(m^2)	Housing area of surveyed students	101.11 (53.01)
	Car ownership status	Without private vehicle = 0, With private vehicle = 1	0 = 16.01%, 1 = 83.99%

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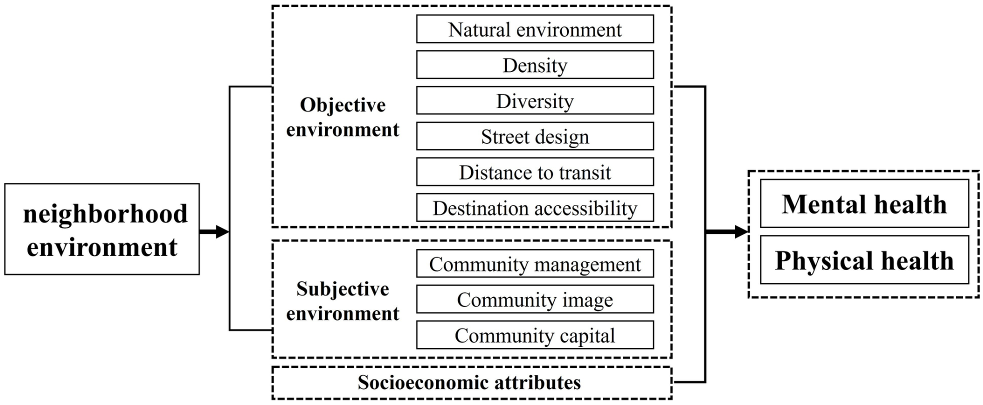

FIGURE 4
The framework for neighborhood environments on health.

500 (step size of 100); and max_features ranging from 1 to 5 (step size of 1). Grid SearchCV from Scikit-learn is used for grid search and five-fold cross-validation to evaluate 125 possible hyperparameter combinations and determine the optimal set that delivers the best model performance: max_depth is set to 3, n_estimators is set to 100, max_features is set to 1.

4 Results

4.1 Model performance

To assess the suitability of the Random Forest model for this study, we trained and tested three commonly used machine learning models: RF, XGBoost, and LightGBM. The performance of these models is evaluated using commonly used metrics in supervised machine learning: Accuracy, Precision, Recall, and F1 scores. The value closer to 1 indicates better model performance (13, 15). As shown in Table 2, RF outperformed the other models in accuracy, recall, and F1 score. Although RF did not achieve the highest precision value among the models, it was very close to the maximum value. Overall, the Random Forest model demonstrated high accuracy, adaptability, and excellent predictive performance, making it effective for uncovering the complex nonlinear relationships between neighborhood environment and adolescent health. To further assess the robustness of the selected research units and study results, we constructed an 800-meter network buffer to measure the objective environment. The results indicate that the Random Forest model also exhibits strong robustness. Furthermore, the relative importance rankings of both subjective and objective environmental factors remained largely consistent. Specifically, with the exception of a few variables, the rankings of the top 12 factors remained stable across each control group.

4.2 Relative importance of predictors

Table 3 displays a comparison of the relative importance and rankings of all variables. Among the three types of independent variables, the objective environment has the greatest significance for both physical and mental health, with relative importance percentages of 51.03 and 53.30%, respectively. The subjective environment ranks next in importance, with its significance notably exceeding that of socioeconomic attributes. When comparing the relative importance rankings and percentages of various indicators, the following observations are made: (1) The greening view index, relative walking width, and ratio of traffic safety facilities in representing the three-dimensional environment of streets are comparable. (2) In contrast, the NDVI is more strongly associated with physical health, whereas intersection density, distance to bus stop, and community safety are more strongly associated with mental health.

In terms of physical health, the most significant variables in the neighborhood environment are sense of community belonging, distance to subway station and greening view index. The relative walking width, sky view index and land use mix are also closely associated with physical health. However, the relative importance of community safety and perceived sanitary condition is comparatively lower.

In terms of mental health, the most significant variables are distance to bus stop and subway station, sense of community belonging. Next in importance are intersection density, greening view index, and land use mix. Conversely, the relative importance of perceived landscape environment and distance to sports facility is comparatively lower.

Additionally, among socioeconomic attributes, housing area plays a significant role in influencing the physical health of adolescents, with its relative importance ranked 3rd for physical health and 2nd for mental health. Other personal socioeconomic attributes, such as gender and household registration, do not exhibit a significant impact on adolescent health.

4.3 Non-linear relationship

We visualize the non-linear relationships and threshold effects between various variables and adolescent physical and mental health using partial dependence plots. Additionally, we apply a fitting curve to smooth the effects of objective environmental factors and some

TABLE 2 Model performance metrics.

Model		Accuracy	Precision	Recall	F1 scores
Physical_health	Radom forest	**0.8771**	**0.8837**	**0.9917**	**0.9346**
	XGBoost	0.8570	0.8832	0.9660	0.9231
	LightGBM	0.8649	0.8822	0.9778	0.9275
Mental_health	Radom forest	**0.8157**	0.8210	**0.9910**	**0.8985**
	XGBoost	0.8030	0.8244	0.9670	0.8901
	LightGBM	0.7985	0.8203	0.9672	0.8877

TABLE 3 Relative importance of variables.

Variables	Physical health		Mental health	
	Relative importance (%)	Rank	Relative importance (%)	Rank
Objective environment	**51.03%**		**53.30%**	
NDVI	4.02%	11	2.39%	20
Intersection density	3.12%	17	5.75%	5
Land use mix	4.76%	7	5.72%	7
Sky view index	4.86%	6	4.03%	13
Greening view index	5.37%	4	5.73%	6
Relative pedestrian width	5.17%	5	5.29%	8
Ratio of traffic safety facilities	4.36%	8	4.40%	9
Distance to bus stop	3.66%	14	6.98%	1
Distance to subway station	7.84%	2	6.55%	3
Distance to sports facility	3.64%	15	2.32%	21
Distance to park or square	4.22%	10	4.14%	11
Subjective environment	**33.61%**		**32.92%**	
Perceived sanitary condition	2.02%	23	2.81%	19
Perceived property management quality	3.73%	13	3.09%	17
Community safety	1.97%	24	4.05%	12
Subjective noise quality	4.28%	9	4.16%	10
Subjective air quality	3.98%	12	3.49%	15
Perceived landscape environment	2.86%	19	2.18%	22
Sense of community belonging	9.08%	1	6.07%	4
Neighborhood familiarity	2.18%	22	3.68%	14
Frequency of community events	3.52%	16	3.38%	16
Socioeconomic attributes	**15.36%**		**13.78%**	
Age	0.72%	25	0.79%	25
Gender	3.10%	18	1.78%	23
Household registration	2.30%	21	0.56%	26
Household income level	2.80%	20	2.97%	18
Housing area	5.92%	3	6.66%	2
Car ownership status	0.53%	26	1.03%	24

socioeconomic attributes on health outcomes (66). Based on the relative importance ranking of factors influencing adolescent health, we individually analyze the top 12 most significant neighborhood environment variables.

4.3.1 Adolescent physical health

Figure 5 displays the partial dependence plots for the top 12 variables influencing adolescent physical health. In terms of the objective environment, the greening view index, ratio of traffic

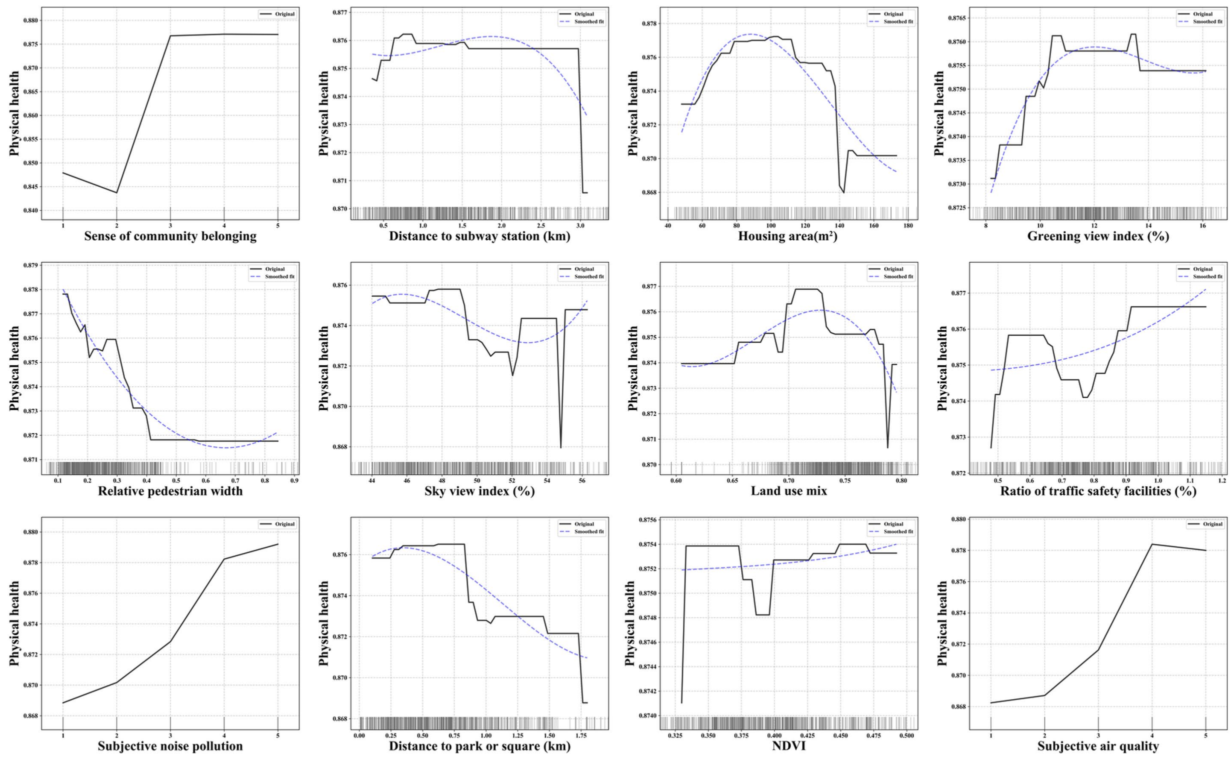

FIGURE 5
The non-linear association between key variables and adolescent physical health.

safety facilities and NDVI are positively associated with the probability of positive physical health status, with evident threshold effects. Specifically, the greening view index shows no significant effect once it exceeds approximately 14%, while ratio of traffic safety facilities and NDVI exhibit local low values around 0.8 and 0.38, respectively. Conversely, the relative walking width, distance to subway station and park or square are negatively associated with the probability of positive physical health status. Specifically, the relative walking width shows no significant effect once it exceeds approximately 0.4. Additionally, the sky view index and land use mix exhibit differentiated relationships with the probability of positive physical health status. Specifically, the sky view index leads to a "decrease–increase" trend in the probability, with a threshold at approximately 52%. The land use mix leads to an "increase–decrease" trend in the probability, with a threshold at approximately 0.71.

In terms of the subjective environment, the sense of community belonging, subjective noise quality and air quality are positively associated with the probability of positive physical health status. Specifically, the probability is maximized when sense of community belonging is rated as "normal," subjective noise quality is rated as "very quiet," and subjective air quality is rated as "good."

4.3.2 Adolescent mental health

Figure 6 displays the partial dependence plots for the top 12 variables affecting adolescent mental health. In terms of the objective environment, the intersection density is positively associated with the probability of positive mental health status. Conversely, the distance to park or square, distance to bus stop, relative walking width, and ratio of traffic safety facilities are negatively associated with the probability of positive mental health status. Specifically, the probability significantly decreases when distance to bus stop exceeds approximately 0.5 km. Additionally, the distance to subway station, land use mix and greening view index exhibit differentiated relationships with the probability of positive mental health status. Specifically, the distance to subway station and land use mix lead to an "increase–decrease" trend in the probability, with a threshold at approximately 1.2 km and 0.71. The greening view index leads to a "decrease–increase" trend in the probability, with a threshold at approximately 10%.

In terms of the subjective environment, the perceived sanitary condition, subjective quality pollution, and community safety are positively associated with the probability of positive mental health status. When these three factors are rated at the highest levels, the probability of mental health is maximized.

5 Discussion

This study, utilizing questionnaire data and multi-source urban spatial data, employs the Random Forest model to explore the non-linear relationships between neighborhood environments and adolescent health. It assesses the relative importance of both objective and subjective environmental factors on adolescent physical and mental health and examines the impact of various variables on health status. To our knowledge, this is the first study to thoroughly explore the non-linear associations between neighborhood environments and adolescent health from both subjective and objective perspectives. The

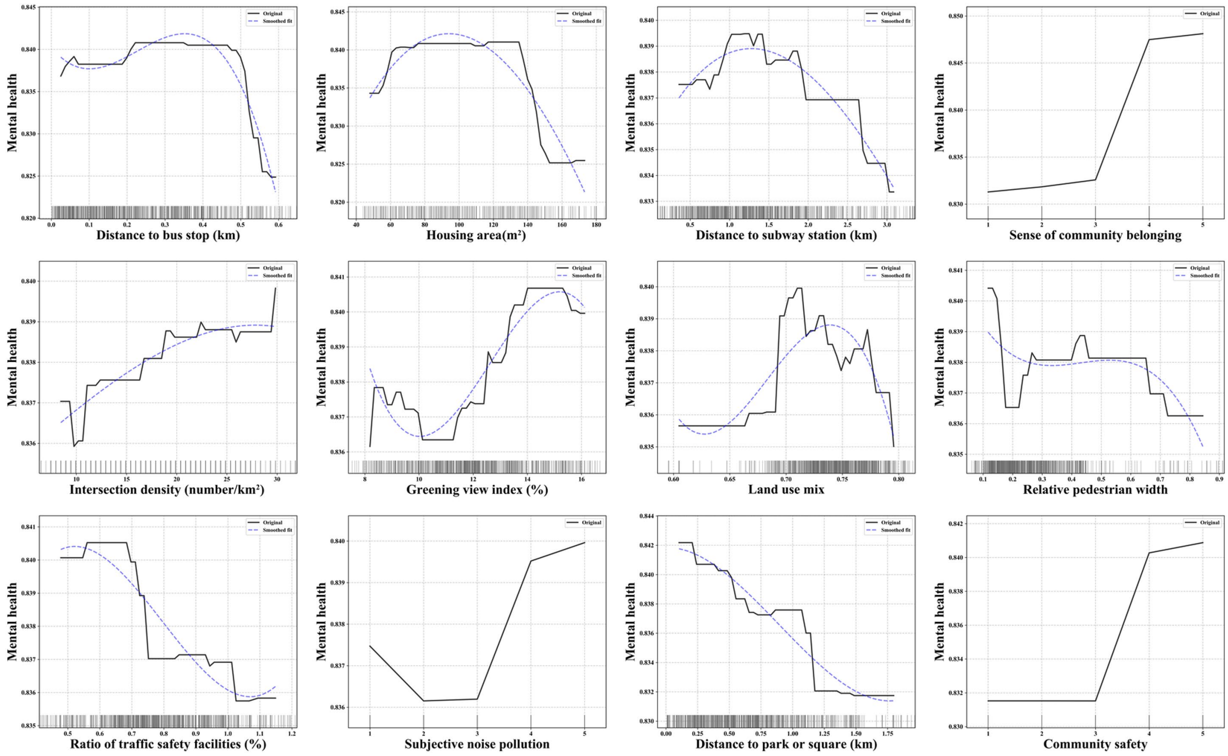

FIGURE 6
The non-linear association between key variables and adolescent mental health.

study enriches the perspectives and methods of research on neighborhood environments and adolescent health. Furthermore, it provides valuable insights for the planning of healthy communities, environmental interventions, and health promotion in specific dimensions among adolescents.

5.1 Contribution of the neighborhood environment to adolescent health

Compared to subjective environments, objective environments have a more significant impact on adolescent physical and mental health. This finding contrasts with existing research, which emphasizes the substantial influence of subjective environments on residents' health and older adults health (15, 67, 68), considering them as crucial predictors of health status. Unlike adults, who possess fully developed judgment and cognitive abilities, adolescents are still undergoing developmental changes, and their mental and cognitive faculties are not yet fully mature. Therefore, their health status is more directly influenced by objective material conditions than by perceptions of social environment (e.g., neighborhood relationships, facility conditions and community image).

Additionally, we observed notable differences in the contribution of specific key variables between physical and mental health. For instance, NDVI plays a more significant role in physical health. One possible explanation is that vegetation coverage directly reflects the air quality, heat, humidity conditions (e.g., local heat island effects), and opportunities for natural contact, which are closely associated with adolescents' respiratory and cardiovascular health (69), thereby having a more pronounced impact on physical health. In contrast, distance to bus stop and community safety are more influential for mental health. One possible explanation is that the distance to bus stop reflects the convenience of accessing social places, which plays a crucial role in the development of adolescents' independent social capabilities and participation in activities. Similarly, during the adolescent mental development stage, fostering independent travel abilities also contributes to enhancing self-efficacy. Environmental psychology theory posits that a safe and comfortable environment can reduce anxiety and stress (70), thereby enhancing personal well-being and a sense of security. Similarly, for adolescents, the security level of the neighborhood environment (e.g., the frequency of criminal or violent incidents) indirectly influences patterns of social interaction and emotional stability, which may lead to increased anxiety and depression (63, 71, 72).

5.2 The impact of objective environment on adolescent health

5.2.1 Non-linear relationship between the objective environment and adolescent health

The presence of non-linear relationships and threshold effects between key objective environmental variables and adolescent physical and mental health is notable. For instance, the land use mix leads to an "increase–decrease" trend in the probability of adolescent health. An appropriate level of land use mix reflects the diversity of public facilities, potentially reducing the need for long commutes and promoting active travel modes (e.g., walking and cycling) (73, 74), thereby enhancing physical health. Furthermore, social interactions within diverse public spaces can facilitate expansion of social

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networks, and the development of self-confidence. However, an excessive degree of land use mix often leads to high-frequency, prolonged population activities within the community, creating a bustling neighborhood atmosphere that may negatively impact both sleep quality and academic performance.

The distance to park or square is negatively associated with physical and mental health, while the NDVI is positively associated with physical health. This observation aligns with the biophilia hypothesis, which describes humans' intrinsic connection to nature and an innate tendency for outdoor exploration (75). Adolescents foster positive health outcomes through participation in physical activities, nature exposure, and social interactions within natural or open spaces (6, 28, 29). Furthermore, high-quality outdoor environments (e.g., good air circulation and low noise levels) benefit respiratory and physical health (21, 22). The relatively smooth curve observed for NDVI suggests that the health-promoting effects of nature are more evident in well-maintained, landscaped natural and open spaces.

The probability significantly decreases when distance to bus stop exceeds approximately 0.5 km. The 0.5 km radius around a bus stop is generally sufficient to meet residents' travel needs and is a fundamental feature of a 5-min pedestrian-scale neighborhood (76). Therefore, the distance may not directly affect adolescents' mood through promoting physical activity. However, when bus stops are located farther than 0.5 km, transportation inconvenience restricts adolescents' opportunities and willingness to engage in outdoor social activities. This reduced accessibility may foster feelings of anxiety and social isolation, ultimately exerting a negative impact on mental health.

The relative pedestrian width is negatively associated with physical and mental health. In urban road design, sidewalk width is often closely related to the road classification. As a result, wider sidewalks are typically found along primary and secondary arterial roads, which are less likely to be chosen for active commuting by residents (77). For instance, as demonstrated in this study, relative pedestrian width exceeding 0.4 no longer shows a significant impact on physical health. While wider pedestrian spaces provide opportunities for social interaction (e.g., certain sidewalk widths may promote mental health), the higher traffic flow on major roads often presents perceived safety risks and psychological stress for adolescents when walking or crossing these roads.

The intersection density is positively associated with mental health. Communities with higher intersection density generally feature a more diverse distribution of facilities and more active interpersonal interaction patterns (e.g., with more flexible land use layouts). Consequently, in such high-access environments, adolescents can more easily and freely access social activity locations. The social interaction opportunities provided help alleviate stress, improve life satisfaction, and foster a sense of community belonging.

The sky view index leads to a "decrease–increase" trend in the probability of physical health. Low levels of sky openness create a sense of spatial enclosure, resulting in visual interference with traffic-related travel activities on the streets, thereby reducing adolescents' willingness to engage in active travel. However, similar to existing studies, as the spatial view gradually opens up, active physical activities such as walking and cycling are more likely to occur on the streets (78, 79), thereby promoting individuals' physical fitness, cardiovascular health, and overall well-being.

5.2.2 Differences in the impact of objective environment on adolescent physical and mental health

It is noteworthy that some variables exhibit significant differences in their impact on physical versus mental health. Firstly, compared to physical health, the distance to subway station exhibits a clear trend of initially increasing and then decreasing. At an optimal proximity to the subway station (approximately 1.2 km), adolescents can conveniently access entertainment, sports, and recreational spaces through the "subway +" travel mode, which in turn enhances social connections, reduces feelings of loneliness, and improves life satisfaction. However, the distribution of subway stations reflects urban location differences and functional layout needs, with demand primarily concentrated on long-distance commuting rather than daily short trips, thus failing to significantly promote travel modes that support physical activity. Furthermore, as the distance to the subway station increases, the probabilities of both physical and mental health decline. On one hand, this result suggests that greater distances from transportation (including bus stops and subway stations) limit opportunities for social participation, leading to "social isolation." On the other hand, increased commuting time reduces opportunities for active commuting to school and outdoor physical activities, resulting in an overall decrease in adolescents' physical activity, which negatively impacts physical health. This result confirms that, beyond the positive effects of transportation stations within a fixed proximity (7, 13), excessive distance may even have negative effects.

Secondly, the ratio of traffic safety facilities is positively associated with physical health, while negatively associated with mental health. Well-established traffic safety features (e.g., traffic lights, barriers, curbs) regulate pedestrian spaces and behaviors on streets (80), which reduces the risk of injury or traffic accidents for adolescents and encourages them to actively choose walking, cycling, and other modes of participation in street activities. However, an excessive number of traffic safety facilities can introduce environmental warnings, visual complexity, and a sense of safety dependence. On one hand, this may cause confusion among adolescents about the external environment and a sense of helplessness regarding potential dangers. On the other hand, the overly "formal" atmosphere created by these facilities hinders adolescents from developing an exploratory desire based on the complexity and diversity of the environment.

Thirdly, compared to physical health, the greening view index significantly induces a "decrease–increase" trend in mental health within certain intervals. A possible explanation is that in areas with low levels of street greening, adolescents are more likely to feel mentally oppressed or uncomfortable (e.g., high levels of spatial construction intensity) and unsafe (e.g., vast open spaces) due to the lack of natural exposure, which can lead to negative emotions. As the level of greenery increases (particularly after exceeding 10%), both the physical and mental health of adolescents gradually improve. This further demonstrates that, in addition to the proximity and coverage of green spaces within neighborhoods, well-visible green spaces on streets can also promote health through environmental contact and activity (expressed through active commuting behaviors) (62, 81). However, excessively high levels of green visibility imply excessive obstruction of street space and a lack of construction activity, which leads to fewer adolescents engaging in physical activities or social interactions in these areas.

5.3 The impact of subjective environment on adolescent health

We found that the subjective environment typically has a beneficial impact on promoting adolescent health. For instance, among the key variables related to community management, such as community safety is positive associated with adolescent mental health. Poor maintenance of facilities, littering, and other signs of environmental disorder can lead to increased concerns about public safety and crime (71, 72). In contrast, a well-maintained and safe community environment enhances adolescents' sense of security and comfort during outdoor activities, which can alleviate potential sleep difficulties and reduce life stress (6).

Among the key variables related to community image, a quieter noise environment is beneficial to physical and mental health. Previous studies have indicated that urban traffic noise leads to sleep disturbances (82). Similarly, exposure to high levels of noise (including traffic and activity noise) can induce stress responses in adolescents, potentially affecting academic performance and sleep quality. Air quality can directly affects respiratory and cardiovascular health (69). Exposure to low levels of air pollution (e.g., NO_2, $PM_{2.5}$), is more likely to lead to physiological issues such as insomnia and cardiovascular diseases during adolescence (6, 23).

Among the key variables related to community capital, sense of community belonging positively influences both adolescent physical and mental health. Existing research indicates that social cohesion among neighbors helps alleviate psychological stress and enhances social connections in adults (83, 84). Similarly, a supportive and emotionally connected neighborhood environment promotes positive health behaviors and psychological well-being in adolescents (40, 85).

5.4 Limitations

This study has two limitations due to the study area and sample constraints. First, due to the sample size of the survey data, it is challenging to control for geographic environmental differences that may arise from residential self-selection (16). For instance, parents of students living in commercial properties or rental accommodations might choose residences with better scenic environments and amenities based on their economic status and social position. Second, although we explored the optimal impact range of the built environment on adolescent physical and mental health, the threshold effects of the built environment may differ under varying regional conditions. Therefore, future research should aim to enhance the generalizability of the findings by conducting comparative studies across different cities and increasing sample size. Nonetheless, considering the challenges of data acquisition, the non-linear and threshold effects of neighborhood environments highlighted in this study offer valuable insights for adolescent-friendly community planning, construction, and management, particularly for large cities along the southwestern border of China.

6 Conclusion

This study, leveraging survey data, multi-source urban spatial data, and machine learning techniques, examines the relative importance of subjective and objective environmental factors on adolescent physical and mental health, and analyzes the non-linear relationships between various environmental variables and health status. The findings reveal that: (1) Objective environments exert a greater influence on adolescent physical and mental health compared to subjective environments. (2) Within objective environments, the relationship between different variables and adolescent health is typically non-linear, displaying threshold effects. Notably, the distance to subway station, ratio of traffic safety facilities, and greening view index have differing impacts on physical and mental health. (3) Within subjective environments, key factors related to community management, community image, and community capital generally positively influence adolescent health.

Based on the above conclusions, this study explores three aspects of interventions in the neighborhood environment (including both subjective and objective elements), and aims to provide policy recommendations for policymakers, planners, and community managers in planning and managing of healthy communities. Firstly, in urban planning and the layout of community facilities, policymakers and planners should consider flexible facility models, with an emphasis on the rational arrangement of landscape spaces, open spaces, and transportation facilities. For instance, considering the health-promoting effects of green landscapes and open spaces, the construction of community parks, gardens, and playgrounds should be prioritized (86). A distance exceeding 450–500 meters from bus stations has been associated with reduced adolescent health levels. Therefore, their layout should ensure a service radius of 500 meters within the 5-min pedestrian-scale neighborhood. Secondly, in the renovation of community street microenvironments, planners should consider the nonlinear impacts and potential threshold effects of three-dimensional spatial boundaries on adolescent health. For instance, excessively high greenery coverage (over 14%) no longer significantly impacts physical and mental health, while low sky openness (below 52%) is detrimental to health. Therefore, urban planners should adopt refined spatial strategies in street renovation and optimization for these specific environmental elements. Thirdly, community management efforts should focus on enhancing a positive community atmosphere. Given the general health-promoting effects of the neighborhood's perceived environment on adolescent health, policymakers and community managers should focus not only on improving the provision of "hardware" such as landscape environments, sanitation conditions, and security facilities but also on fostering a supportive "software" atmosphere, including social cohesion, networks, and support.

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 to participate in this study was provided by the participants' legal guardian/next of kin.

Author contributions

JS: Conceptualization, Data curation, Methodology, Software, Writing – original draft, Writing – review & editing. ZX: Conceptualization, Formal analysis, Funding acquisition, Resources, Writing – review & editing. PB: Writing – review & editing, Formal analysis, Funding acquisition.

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Conflict of interest

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References

1. Pan X-F, Wang L, Pan A. Epidemiology and determinants of obesity in China. *Lancet Diabetes & Endocrinol*. (2021) 9:373–92. doi: 10.1016/S2213-8587(21)00045-0

2. Zhu Z, Yang Y, Kong Z, Zhang Y, Zhuang J. Prevalence of physical fitness in Chinese school-aged children: findings from the 2016 physical activity and fitness in China—the youth study. *J Sport Health Sci*. (2017) 6:395–403. doi: 10.1016/j.jshs.2017.09.003

3. Li F, Cui Y, Li Y, Guo L, Ke X, Liu J, et al. Prevalence of mental disorders in school children and adolescents in China: diagnostic data from detailed clinical assessments of 17,524 individuals. *J Child Psychol Psychiatry*. (2022) 63:34–46. doi: 10.1111/jcpp.13445

4. Polanczyk GV, Salum GA, Sugaya LS, Caye A, Rohde LA. Annual research review: a meta-analysis of the worldwide prevalence of mental disorders in children and adolescents. *J Child Psychol Psychiatry*. (2015) 56:345–65. doi: 10.1111/jcpp.12381

5. UNICEF China. (2020). Population status of adolescents in China in 2020: facts and figures. Available at: https://www.unicef.cn/en/reports/population-status-adolescents-china-2020 (Accessed August 28, 2024).

6. Daniels K, Lê-Scherban F, Auchincloss AH, Moore K, Melly S, Razzaghi H, et al. Longitudinal associations of neighborhood environment features with pediatric body mass index. *Health Place*. (2021) 71:102656. doi: 10.1016/j.healthplace.2021.102656

7. Liang J, Huang S, Bao W, Pu Y, Liu M, Yang X, et al. Longitudinal relationship between built environment and physical fitness in Chinese children and adolescents: findings from the COHERENCE study. *Build Environ*. (2025) 267:112216. doi: 10.1016/j.buildenv.2024.112216

8. Lin L. Leisure-time physical activity, objective urban neighborhood built environment, and overweight and obesity of Chinese school-age children. *J Transp Health*. (2018) 10:322–33. doi: 10.1016/j.jth.2018.05.001

9. Brons ME, Helbich M, Bolt G, Visser K, Stevens GWJM. Time trends in associations between neighbourhood and school characteristics and mental health problems among Dutch adolescents. *Health Place*. (2023) 84:103140. doi: 10.1016/j.healthplace.2023.103140

10. Buttazzoni A, Dean J, Minaker L. Urban design and adolescent mental health: a qualitative examination of adolescent emotional responses to pedestrian-and transit-oriented design and cognitive architecture concepts. *Health Place*. (2022) 76:102825. doi: 10.1016/j.healthplace.2022.102825

11. Sandy R, Tchernis R, Wilson J, Liu G, Zhou X. Effects of the built environment on childhood obesity: the case of urban recreational trails and crime. *Econ Hum Biol*. (2013) 11:18–29. doi: 10.1016/j.ehb.2012.02.005

12. Yang H, He D, Lu Y, Ren C, Huang X. Disentangling residential self-selection from the influence of built environment characteristics on adiposity outcomes among undergraduate students in China. *Cities*. (2021) 113:103165. doi: 10.1016/j.cities.2021.103165

13. Chen Y, Liu Y, Grekousis G, Qian Z, Vaughn MG, Bingheim E, et al. Examining the non-linear association between the built environment around residence and the risk of obesity among children and adolescents at different school stages in Guangzhou and Shenzhen, China. *Cities*. (2024) 145:104674. doi: 10.1016/j.cities.2023.104674

14. Chen Y, Zhang X, Grekousis G, Huang Y, Hua F, Pan Z, et al. Examining the importance of built and natural environment factors in predicting self-rated health in older adults: An extreme gradient boosting (XGBoost) approach. *J Clean Prod*. (2023) 413:137432. doi: 10.1016/j.jclepro.2023.137432

15. Xu J, Ma J, Tao S. Examining the nonlinear relationship between neighborhood environment and residents' health. *Cities*. (2024) 152:105213. doi: 10.1016/j.cities.2024.105213

16. Yang L, Ao Y, Ke J, Lu Y, Liang Y. To walk or not to walk? Examining non-linear effects of streetscape greenery on walking propensity of older adults. *J Transp Geogr*. (2021) 94:103099. doi: 10.1016/j.jtrangeo.2021.103099

17. Tsouros AD. Twenty-seven years of the WHO European Healthy Cities movement: a sustainable movement for change and innovation at the local level. *Health Promo Intern*. (2015) 30:i3–i7. doi: 10.1093/heapro/dav046

18. Bronfenbrenner U. The ecology of human development: Experiments by nature and design. Cambridge: Harvard University Press (1979).

19. Sallis JF, Owen N, Fisher EB. Ecological models of health behavior.In: eds. K. Glanz, B. K. Rimer and K. Viswanath *Health Behavior: Theory, Research, and Practice 5th ed*. San Francisco, CA: Jossey-Bass. (2015) 43–64.

20. Husain S, Morales KH, Williamson AA, Mayne SL, Fiks AG, Basner M, et al. The neighborhood environment and sleep health in adolescents. *Sleep Health*. (2023) 9:512–8. doi: 10.1016/j.sleh.2023.05.010

21. Liang J, Yang R, Liu M, Pu Y, Bao W, Zhao Y, et al. Urban green, blue spaces and their joint effect are associated with lower risk of emotional and behavior problem in children and adolescents, a large population-based study in Guangzhou, China. *Environ Res*. (2024) 240:117475. doi: 10.1016/j.envres.2023.117475

22. Mavoa S, Lucassen M, Denny S, Utter J, Clark T, Smith M. Natural neighbourhood environments and the emotional health of urban New Zealand adolescents. *Landsc Urban Plan*. (2019) 191:103638. doi: 10.1016/j.landurbplan.2019.103638

23. Wies B, Valls I, Fernandes A, Ubalde-López M, Rocabois A, Vrijheid M, et al. Urban environment and children's health: An umbrella review of exposure response functions for health impact assessment. *Environ Res*. (2024) 263:120084. doi: 10.1016/j.envres.2024.120084

24. Lozano PM, Bobb JF, Kapos FP, Cruz M, Mooney SJ, Hurvitz PM, et al. Residential density is associated with BMI trajectories in children and adolescents: findings from the moving to health study. *AJPM Focus*. (2024) 3:100225. doi: 10.1016/j.focus.2024.100225

25. Duncan DT, Sharifi M, Melly SJ, Marshall R, Sequist TD, Rifas-Shiman SL, et al. Characteristics of walkable built environments and bmi z-scores in children: evidence from a large electronic health record database. *Environ Health Perspect*. (2014) 122:1359–65. doi: 10.1289/ehp.1307704

26. Schwartz BS, Stewart WF, Godby S, Pollak J, DeWalle J, Larson S, et al. Body mass index and the built and social environments in children and adolescents using electronic health records. *Am J Prev Med*. (2011) 41:e17–28. doi: 10.1016/j.amepre.2011.06.038

27. Caryl F, McCrorie P, Olsen JR, Mitchell R. Use of natural environments is associated with reduced inequalities in child mental wellbeing: a cross-sectional analysis using global positioning system (GPS) data. *Environ Int*. (2024) 190:108847. doi: 10.1016/j.envint.2024.108847

28. Moll A, Collado S, Staats H, Corraliza JA. Restorative effects of exposure to nature on children and adolescents: a systematic review. *J Environ Psychol*. (2022) 84:101884. doi: 10.1016/j.jenvp.2022.101884

29. Tillmann S, Tobin D, Avison W, Gilliland J. Mental health benefits of interactions with nature in children and teenagers: a systematic review. *J Epidemiol Community Health*. (2018) 72:958–66. doi: 10.1136/jech-2018-210436

30. Roberts S, Arseneault L, Barratt B, Beevers S, Danese A, Odgers CL, et al. Exploration of NO and PM air pollution and mental health problems using high-resolution data in London-based children from a UK longitudinal cohort study22.5. *Psychiatry Res*. (2019) 272:8–17. doi: 10.1016/j.psychres.2018.12.050

31. Newbury JB, Arseneault L, Beevers S, Kitwiroon N, Roberts S, Pariante CM, et al. Association of air pollution exposure with psychotic experiences during adolescence. *JAMA Psychiatry*. (2019) 76:614–23. doi: 10.1001/jamapsychiatry.2019.0056

32. Weden MM, Carpiano RM, Robert SA. Subjective and objective neighborhood characteristics and adult health. *Soc Sci Med*. (2008) 66:1256–70. doi: 10.1016/j.socscimed.2007.11.041

33. Zhang L, Zhou S, Kwan M-P. A comparative analysis of the impacts of objective versus subjective neighborhood environment on physical, mental, and social health. *Health Place*. (2019) 59:102170. doi: 10.1016/j.healthplace.2019.102170

34. Wang J, Wang M, Lau PWC, Ainsworth BE, He G, Gao Y. Physical activity as a mediator of the associations between perceived environments and body mass index in Chinese adolescents. *Health Place*. (2018) 54:37–42. doi: 10.1016/j.healthplace.2018.09.004

35. Vanhelst J, Béghin L, Salleron J, Ruiz JR, Ortega FB, De Bourdeaudhuij I, et al. A favorable built environment is associated with better physical fitness in European adolescents. *Prev Med*. (2013) 57:844–9. doi: 10.1016/j.ypmed.2013.09.015

36. Patalay P, Fitzsimons E. Correlates of mental illness and wellbeing in children: are they the same? Results from the UK millennium cohort study. *J Am Acad Child Adolesc Psychiatry*. (2016) 55:771–83. doi: 10.1016/j.jaac.2016.05.019

37. Putra IGNE, McInerney AM, Robinson E, Deschênes SS. Neighbourhood characteristics and socioeconomic inequalities in child mental health: cross-sectional and longitudinal findings from the growing up in Ireland study. *Health Place*. (2024) 86:103180. doi: 10.1016/j.healthplace.2024.103180

38. Cheng Y, Li X, Lou C, Sonenstein FL, Kalamar A, Jejeebhoy S, et al. The association between social support and mental health among vulnerable adolescents in five cities: findings from the study of the well-being of adolescents in vulnerable environments. *J Adolesc Health*. (2014) 55:S31–8. doi: 10.1016/j.jadohealth.2014.08.020

39. Huang Y, Lu J, Širůček J. The associations between social environment and adolescents' psychosomatic health: An ecological perspective. *Front Psychol*. (2023) 14:1141206. doi: 10.3389/fpsyg.2023.1141206

40. Lima J, Caughy M, Nettles SM, O'Campo PJ. Effects of cumulative risk on behavioral and psychological well-being in first grade: moderation by neighborhood context. *Soc Sci Med*. (2010) 71:1447–54. doi: 10.1016/j.socscimed.2010.06.022

41. Ma J, Klein S. Does race/ethnicity moderate the associations between neighborhood and parenting processes on early behavior problems? *J Child Fam Stud*. (2018) 27:3717–29. doi: 10.1007/s10826-018-1200-7

42. Mueller MAE, Flouri E, Kokosi T. The role of the physical environment in adolescent mental health. *Health Place*. (2019) 58:102153. doi: 10.1016/j.healthplace.2019.102153

43. Ettema D, Schekkerman M. How do spatial characteristics influence well-being and mental health? Comparing the effect of objective and subjective characteristics at different spatial scales. *Travel Behav Soc*. (2016) 5:56–67. doi: 10.1016/j.tbs.2015.11.001

44. Godhwani S, Jivraj S, Marshall A, Bécares L. Comparing subjective and objective neighbourhood deprivation and their association with health over time among older adults in England. *Health Place*. (2019) 55:51–8. doi: 10.1016/j.healthplace.2018.10.006

45. Lin L, Moudon AV. Objective versus subjective measures of the built environment, which are most effective in capturing associations with walking? *Health Place*. (2010) 16:339–48. doi: 10.1016/j.healthplace.2009.11.002

46. Gomm S, Bernauer T. Are actual and perceived environmental conditions associated with variation in mental health? *Environ Res*. (2023) 223:115398. doi: 10.1016/j.envres.2023.115398

47. Gale CR, Dennison EM, Cooper C, Sayer AA. Neighbourhood environment and positive mental health in older people: the hertfordshire cohort study. *Health Place*. (2011) 17:867–74. doi: 10.1016/j.healthplace.2011.05.003

48. Ding D, Sallis JF, Kerr J, Lee S, Rosenberg DE. Neighborhood environment and physical activity among youth a review. *Am J Prev Med*. (2011) 41:442–55. doi: 10.1016/j.amepre.2011.06.036

49. Chen Y, Liu Y. Which risk factors matter more for psychological distress during the COVID-19 pandemic? An application approach of gradient boosting decision trees. *Int J Environ Res Public Health*. (2021) 18:5879. doi: 10.3390/ijerph18115879

50. Zijlema W, Cerin E, Cirach M, Bartoll X, Borrell C, Dadvand P, et al. Cities and mental health: the role of the built environment, and environmental and lifestyle factors in Barcelona. *Environ Pollut*. (2024) 346:123559. doi: 10.1016/j.envpol.2024.123559

51. Wang X, Shao C, Yin C, Guan L. Disentangling the comparative roles of multilevel built environment on body mass index: evidence from China. *Cities*. (2021) 110:103048. doi: 10.1016/j.cities.2020.103048

52. Yin C, Cao J, Sun B. Examining non-linear associations between population density and waist-hip ratio: An application of gradient boosting decision trees. *Cities*. (2020) 107:102899. doi: 10.1016/j.cities.2020.102899

53. Tao T, Wu X, Cao J, Fan Y, Das K, Ramaswami A. Exploring the nonlinear relationship between the built environment and active travel in the twin cities. *J Plan Educ Res*. (2020) 43:637–52. doi: 10.1177/0739456X20915765

54. Yin C, Cao J, Sun B, Liu J. Exploring built environment correlates of walking for different purposes: evidence for substitution. *J Transp Geogr*. (2023) 106:103505. doi: 10.1016/j.jtrangeo.2022.103505

55. Guo L, Yang S, Peng Y, Yuan M. Examining the nonlinear effects of residential and workplace-built environments on active travel in short-distance: a random forest approach. *Int J Environ Res Public Health*. (2023) 20:1969. doi: 10.3390/ijerph20031969

56. Kunming Bureau of Statistics. (2024). Bulletin of key statistics for the permanent resident population of Kunming in 2023. Available at: https://tjj.km.gov.cn/upload/resources/file/2024/04/08/3956737.doc [Accessed August 28, 2024].

57. Kunming Bureau of Statistics. (2023). Kunming statistical yearbook. Available at: https://www.km.gov.cn/c/2024-02-19/4659502.shtml [Accessed August 28, 2024].

58. The Pediatric Brain Foundation. (2023). Child cognitive development: essential milestones and strategies. Available at: https://pediatricbrainfoundation.org/child-cognitive-development/ [Accessed October 31, 2024].

59. Shen M, Hu M, Sun Z. Development and validation of brief scales to measure emotional and behavioural problems among Chinese adolescents. *BMJ Open*. (2017) 7:e012961. doi: 10.1136/bmjopen-2016-012961

60. Amérigo M, Aragonés JI. A theoretical and methodological approach to the study of residential satisfaction. *J Environ Psychol*. (1997) 17:47–57. doi: 10.1006/jevp.1996.0038

61. Wang X, Liu Y, Zhu C, Yao Y, Helbich M. Associations between the streetscape built environment and walking to school among primary schoolchildren in Beijing. *China J Transport Geography*. (2022) 99:103303. doi: 10.1016/j.jtrangeo.2022.103303

62. Wu F, Li W, Qiu W. Examining non-linear relationship between streetscape features and propensity of walking to school in Hong Kong using machine learning techniques. *J Transp Geogr*. (2023) 113:103698. doi: 10.1016/j.jtrangeo.2023.103698

63. Zhang Y, Zhao J, Mavoa S, Fenaughty J, Clark TC, Crengle S, et al. Impacts of sociodemographic factors, identities and neighbourhood safety on the relationship between urban green space and adolescent mental well-being: findings from Tāmaki Makaurau Auckland, Aotearoa New Zealand. *SSM - Population Health*. (2024) 25:101603. doi: 10.1016/j.ssmph.2024.101603

64. Breiman L. Random forests. *Mach Learn*. (2001) 45:5–32. doi: 10.1023/A:1010933404324

65. Liu Y, Li Y, Yang W, Hu J. Exploring nonlinear effects of built environment on jogging behavior using random forest. *Appl Geogr*. (2023) 156:102990. doi: 10.1016/j.apgeog.2023.102990

66. Cleveland WS. Robust locally weighted regression and smoothing scatterplots. *J Am Stat Assoc*. (1979) 74:829–36. doi: 10.1080/01621459.1979.10481038

67. Guo Y, Liu Y, Lu S, Chan OF, Chui CHK, Lum TYS. Objective and perceived built environment, sense of community, and mental wellbeing in older adults in Hong Kong: a multilevel structural equation study. *Landsc Urban Plan*. (2021) 209:104058. doi: 10.1016/j.landurbplan.2021.104058

68. Kwan M-P. The limits of the neighborhood effect: contextual uncertainties in geographic, environmental health, and social science research. *Ann Am Assoc Geogr*. (2018) 108:1482–90. doi: 10.1080/24694452.2018.1453777

69. Mayntz SP, Rosenbech KE, Mohamed RA, Lindholt JS, Diederichsen ACP, Frohn LM, et al. Impact of air pollution and noise exposure on cardiovascular disease incidence and mortality: a systematic review. *Heliyon*. (2024) 10:e39844. doi: 10.1016/j.heliyon.2024.e39844

70. Kaplan R, Kaplan S. The experience of nature: A psychological perspective. New York: Cambridge University Press (1989).

71. Collins RE. Addressing the inconsistencies in fear of crime research: a meta-analytic review. *J Crim Just*. (2016) 47:21–31. doi: 10.1016/j.jcrimjus.2016.06.004

72. Foster S, Giles-Corti B. The built environment, neighborhood crime and constrained physical activity: An exploration of inconsistent findings. *Prev Med*. (2008) 47:241–51. doi: 10.1016/j.ypmed.2008.03.017

73. Lun Y, Wang H, Liu Y, Wang Q, Liu T, Han Z. Comparison of the impact of school environment on body mass index, physical fitness, and mental health among Chinese adolescents: correlations, risk factors, intermediary effects. *Landsc Urban Plan*. (2024) 251:105151. doi: 10.1016/j.landurbplan.2024.105151

74. Tewahade S, Li K, Goldstein RB, Haynie D, Iannotti RJ, Simons-Morton B. Association between the built environment and active transportation among U.S. adolescents. *J Transp Health*. (2019) 15:100629. doi: 10.1016/j.jth.2019.100629

75. Akpinar A. How is high school greenness related to students' restoration and health? *Urban For Urban Green*. (2016) 16:1–8. doi: 10.1016/j.ufug.2016.01.007

76. Ministry of Housing and Urban-Rural Development of the People's Republic of China. (2018). Standard for urban residential area planning and design. Available at: https://www.mohurd.gov.cn/gongkai/zhengce/zhengcefilelib/201811/20181130_238590.html [Accessed October 31, 2024].

77. Zhong Q, Li B, Chen Y. How do different urban footpath environments affect the jogging preferences of residents of different genders? Empirical research based on trajectory data. *Int J Environ Res Public Health*. (2022) 19:14372. doi: 10.3390/ijerph192114372

78. An Z, Liuyi S, Fan Z. Perception of pleasure in the urban running environment with street view images and running routes. *J Geogr Sci*. (2022) 32:2624–40. doi: 10.1007/s11442-022-2064-8

79. Yang W, Chen H, Li J, Guo W, Fei J, Li Y, et al. How does visual environment affect outdoor jogging behavior? Insights from large-scale city images and GPS trajectories. *Urban For Urban Green*. (2024) 95:128291. doi: 10.1016/j.ufug.2024.128291

80. Jiang H, Dong L, Qiu B. How are macro-scale and micro-scale built environments associated with running activity? The application of strava data and deep learning in inner London. *ISPRS Int J Geo Inf*. (2022) 11:504. doi: 10.3390/ijgi11100504

81. Lu Y, Sarkar C, Xiao Y. The effect of street-level greenery on walking behavior: evidence from Hong Kong. *Soc Sci Med*. (2018) 208:41–9. doi: 10.1016/j.socscimed.2018.05.022

82. Guo M, Ni MY, Shyu R-J, Ji JS, Huang J. Automated simulation for household road traffic noise exposure: application and field evaluation in a high-density city. *Comput Environ Urban Syst*. (2023) 104:102000. doi: 10.1016/j.compenvurbsys.2023.102000

83. Christakis NA, Fowler JH. Social contagion theory: examining dynamic social networks and human behavior. *Stat Med*. (2013) 32:556–77. doi: 10.1002/sim.5408

84. Erdem Ö, Lenthe FJV, Prins RG, Voorham TAJJ, Burdorf A. Socioeconomic inequalities in psychological distress among urban adults: the moderating role of neighborhood social cohesion. *PLoS One*. (2016) 11:e0157119. doi: 10.1371/journal.pone.0157119

85. Novak D, Kawachi I. Influence of different domains of social capital on psychological distress among Croatian high school students. *Int J Ment Heal Syst*. (2015) 9:18. doi: 10.1186/s13033-015-0010-1

86. Ministry of Housing and Urban-Rural Development of the People's Republic of China. (2023). Guidelines for the construction of child-friendly spaces in cities. Available at: https://www.mohurd.gov.cn/gongkai/zhengce/zhengcefilelib/202308/20230824_773739.html [Accessed October 31, 2024].

87. van Wee B, Handy S. Key research themes on urban space, scale, and sustainable urban mobility. *Int J Sust Transport*. (2016) 10:18–24. doi: 10.1080/15568318.2013.820998

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Exploring urban–rural inequities in older adults life expectancy: a case study in Zhejiang, China for health equity

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This study investigates the inequities in life expectancy among individuals aged 65 and above in urban and rural areas of Zhejiang Province, China, with a primary focus on promoting health equity among the older adults population. The objective is to analyze the trends and factors contributing to the urban–rural gap in life expectancy and to propose strategies for reducing this disparity. Data from the 2010 and 2020 statistical records and census data were analyzed using cohort life tables and gray correlation analysis. Results indicate an overall increase in life expectancy among the older adults, with a more pronounced improvement in rural areas, thereby narrowing the urban–rural gap from 1.53 years in 2010 to 1 year in 2020. Income inequality emerges as the primary factor influencing life expectancy, followed by educational attainment, with variations across different age groups and gender. This underscores the importance of tailored interventions that consider the specific needs of older adults individuals in diverse geographical areas and age brackets to extend life expectancy and promote health equity. By tackling these unfair differences, health equity can be ensured and the overall well-being of the older population in both urban and rural areas can be improved.

KEYWORDS

the older adults, life expectancy, urban–rural inequities, health inequities, social, determinants of health

1 Introduction

Health equity, defined as the endeavor to reduce avoidable disparities in health and its determinants—encompassing not only healthcare but also broader factors—among groups of people characterized by varying levels of underlying social advantage or privilege (1). Societal-level inequality inherently harms the entire population (2), and these inequalities can be reflected in the life expectancy of populations in different regions. According to the data disclosed in the World Health Statistics Report (2023) published by the World Health Organization, global life expectancy jumped from 46.5 to about 73.0 years from 1950 to 2019. It is projected that by 2048, the average global life expectancy is expected to reach 77.0 years (3). China's National Health and Wellness Commission released the Healthy China Initiative (2019–2030), which explicitly sets specific target values for China's life expectancy to reach 77.7 years in 2022, and aims to reach 79.0 years by 2030 (4). Throughout the Yangtze River Delta (YRD) region, many health policies have also been proposed individually. By analyzing Zhejiang's practices in the context of the YRD, we can gain insight into the factors affecting life expectancy and identify opportunities for collaboration and improvement. In Zhejiang Province, particular attention has been paid to reducing the gap between urban and rural life expectancy, as reflected in the province's specific development strategies. Guided by the "Eight-eight Strategy," which clearly states that the goal of Zhejiang Province is to achieve a life expectancy of 82.4 years by 2027 (5), this strategy emphasizes urban–rural integration, by investing in rural infrastructure, medical facilities and education, in order to promote the sustainable development of society. It can be seen that, along with the policy orientation, the attention from society and academia towards the measurement indicators and influencing factors of healthy life expectancy has also increased (6).

Life expectancy serves as a crucial indicator of population health and social development, and it has witnessed a general increase in recent years due to advancements in medical technology, living conditions, and public health policies. However, this increase is not solely linear; rather, it is influenced by a variety of factors leading to diverse outcomes. Despite the overall increasing trend in global life expectancy, significant inequalities persist among different countries, regions, and races (7, 8), largely influenced by disparate living habits, cultural practices, and socioeconomic status (9). Furthermore, the unique characteristics of groups affected by social determinants of health, including territorial factors, gender differences and disability status, significantly shape their access to healthcare resources and quality of life, thereby influencing their life expectancy in profound ways. For instance, in certain less developed regions, life expectancy remains lower due to issues such as resource scarcity and poverty (10). Moreover, significant disparities in life expectancy exist between urban and rural areas (11, 12). Rural residents tend to have lower life expectancy than urban residents due to relatively inadequate social and medical conditions and differences in living environments (13). Nevertheless, the urban–rural gap is gradually narrowing with the enhancement of economic and medical conditions in rural areas (14, 15). Gender differences should not be overlooked. Generally, female life expectancy exceeds that of males in most countries and regions (16), except for a few of the world's poorest nations (17). Nonetheless, gender differences are somewhat mitigated by a combination of various factors, potentially resulting in subsequent alterations in their correlation with life expectancy (18). In addition, the analysis showed significant differences in life expectancy based on disability, with years lost to disability being a linear function of life expectancy at birth (19). Older adults individuals face an increasing risk of disability (20). Each of these factors has a significant impact on social groups, and in more detail, territory differences that generate geographic and cultural differences in access to health services, gender differences that may affect health outcomes from an innate perspective, and disabilities that can affect quality of life by limiting mobility and social participation, all further exacerbate these inequalities. Presently, greater research emphasis is placed on investigating the specific factors influencing life expectancy. Particularly, socio-public factors such as socio-economic development, health expenditures, and health services have been identified as significant determinants affecting life expectancy (21–24). It is noteworthy that environmental factors, including carbon emissions and energy, have garnered considerable attention (25–27). Additionally, personal factors such as income level, education level, and health behaviors are deemed to be closely intertwined with life expectancy (28–31). Nonetheless, there remains a dearth of current research on the precise degree of correlation between these social factors and life expectancy among the older adults population, delineating primary and secondary factors. Considering that social roles are in a state of continual flux, the influence of these factors on the life expectancy of the older adults population may adopt a more intricate and multifaceted stance. Hence, there is an urgent need for further in-depth studies and research.

With societal progress and advancements in medical technology, the current focus on increasing population life expectancy has shifted towards reducing mortality rates among the older adults (32). Zhejiang Province is among the provinces experiencing relatively high levels of aging. Additionally, Zhejiang Province experiences the phenomenon of "urban–rural inversion" in aging. According to the results of the seventh population census, in 2020, the proportion of individuals aged 65 and above in urban areas of Zhejiang Province was 10.32%, compared to 20.90% in rural areas, reflecting a difference of approximately 10.6 percentage points (33). The degree of aging in rural areas is much higher than that in urban areas, and some studies predict that this phenomenon will further intensify (34). In contrast to inverted ageing, the coexistence of urban and rural systems has resulted in urban residents generally having better access to health care (35). However, differences in health outcomes between urban and rural residents are more likely to be due to the social determinants of health rather than just the availability of health care services. In the current society, resource allocation is usually more skewed towards urban areas, these phenomena appear to be inevitable consequences of urbanization, which also results in rural residents often facing significant challenges due to reasons such as lower socioeconomic status, limited education, and inadequate social support networks. This suggests that the health needs of a significant portion of the rural older adults population may have been overlooked to some extent, highlighting a substantial inequity between urban and rural regions (36), posing significant challenges to societal sustainability. Thus, investigating inequities in life expectancy and its determinants among urban and rural older adults populations in Zhejiang Province can offer a scientific foundation for the government to devise more precise geriatric health policies. This, in turn, can help bridge the urban–rural gap and foster social equity, ultimately promoting sustainable societal development in Zhejiang Province.

The main objectives of this study are as follows: (1) Constructing a life table and measuring life expectancy using data from the Sixth and Seventh Population Census of Zhejiang Province, the database of the Zhejiang Provincial Health and Health Commission, and data published by the Zhejiang Provincial Bureau of Statistics; (2) Calculating the degree of correlation between life expectancy and the specific characteristics of the population in different regions (urban and rural) that are related to differences in life expectancy, using a gray correlation analysis method. (3) Analyzing changes in life expectancy and its influencing factors based on the study results for the years 2010 and 2020, including horizontal analysis of time trends and vertical comparison of urban and rural geographic differences; (4) Analyze key gender differences in life expectancy factors, to inform ageing health policies promoting social equity and sustainable development.

2 Materials and methods

2.1 Study design

This section outlines the detailed plan and methodology employed in the study. It begins with a visual representation of the study design, specifically a descriptive study, in the form of a mind map. This mind map provides a concise overview of the research process, including the background of the study, data sources, research methodology and analysis, and steps for the purpose of the study. As shown in Figure 1.

2.2 Materials

The calculation of life expectancy in this study requires data on the survival and death of the older adults population aged 65 years or older, categorized by age group and region. The study sample consists of individuals from Zhejiang Province, China, who were aged 65 and above during the periods covered by the sixth population census (2010) and the seventh population census (2020). These data are primarily sourced from these two censuses and are calibrated using information provided by the Zhejiang Provincial Bureau of Statistics (SPBS) and the Zhejiang Provincial Center for Disease Control and Prevention (CDC), as detailed in Table 1. Additionally, this study adhered to international standards by defining the age of the older adults population as 65 years old to ensure result generalizability and comparability. To maintain data consistency, urban administrative divisions comprising "city" and "town" were consolidated into the urban category, while rural areas retained their original administrative divisions. This approach facilitates a more accurate analysis of disparities between urban and rural areas and their impact on older adults population life expectancy.

The data on influencing factors required for this study primarily originate from the sixth population census of Zhejiang Province in 2010, the seventh population census in 2020, the Zhejiang Provincial Bureau of Statistics, and the statistical yearbook. These variables encompass three levels: social, economic, and personal. These include social welfare, income, education, health status, gender, and whether the older adults lives alone. Specifically, the social dimension includes "social welfare," which in our study refers to social security programs such as retirement pensions, unemployment insurance, and minimum living allowances, measured as a proportion of the total population. The economic dimension encompasses "income" calculated as the average income of the study population across various age groups. The personal dimension spans "education" measured by the duration of educational attainment. The "health status" primarily referring to an individual's capacity to live independently and categorized into "healthy" and "unhealthy" based on survey data from the censuses. And "whether the older adults lives alone" determined by the household population size in the survey. These factors, which are well-established in previous studies (21–31) as being correlated with life expectancy, were selected for analysis to determine the specific degree of association with life expectancy and identify primary and secondary factors.

2.3 Methods

2.3.1 The period life table

This study employed the construction of period life tables to measure life expectancy. The life table is a statistical model compiled based on the probability of death at each age, noted for its ease of

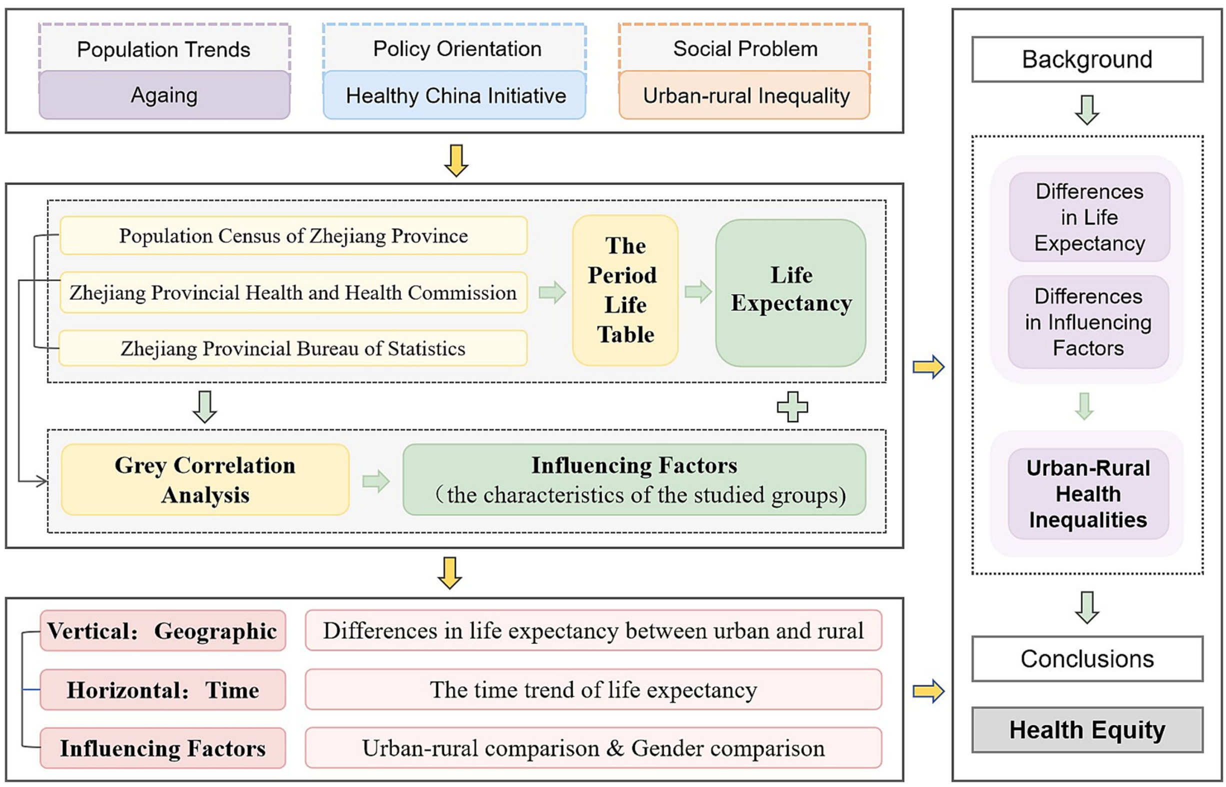

FIGURE 1
Study design.

TABLE 1 Survivors and deaths of the older adults population aged 65 and above in urban and rural areas of Zhejiang Province in 2010 and 2020 (persons).

Year	Area		Life expectancy of age groups (persons)					
			65–69	70–74	75–79	80–84	85–89	90—
2010	Urban	h_x[a]	744,586	611,953	531,544	305,261	135,766	43,830
	Rural	d_x[b]	7,526	11,978	18,488	20,854	16,401	9,437
2020	Urban	h_x	776,071	708,890	635,604	374,445	165,058	48,667
	Rural	d_x	12,183	20,167	30,070	33,081	25,033	13,288

[a] h_x =number of survivors at age x.
[b] d_x =number of death at age x.

production, intuitiveness, and simplicity (37). The life table examines the survival of individuals born in the same period at different ages (38). It can be divided into the Cohort Life Table and the Period Life Table. The latter conducts a cross-sectional analysis of the life process by assuming the current age-specific probability of death throughout life to measure life expectancy. This latter approach calculates the average number of years of survival for the same group of people, considering the current probability of dying at the current age (5). In this study, 65 years of age were utilized as the starting point for the older adults age group, with a subsequent age interval of 5 years. The final age group comprised individuals aged >90 years, while the remaining age groups were divided based on a 5-year criterion. Compilation followed the methodology outlined in prior studies (5, 39).

The number of survivors h_x(where x represents age) and deaths d_x by age group, as per the data published by the respective statistical offices, are displayed in Table 1. The fundamental data for computing the period life table is the mortality rate m_x for each age group, serving as the basis for deriving all other indicators (40). This ratio, calculated by the formula, represents the number of deaths relative to the number of survivors:

$$m_x = d_x / h_x$$

The probability of death q_x represents the likelihood that individuals who have reached age x will die before reaching age $x + n$, assuming a uniform distribution of deaths within the age interval. This probability is calculated using this formula:

$$q_x = \frac{nd_x}{h_x} = (2 \times n \times m_x) / (2 + n \times m_x)$$

The number of survivors l_x refers to the count of individuals within each age group who have survived, typically beginning with the first group $m_x = 10,000$:

$$l_x = l_{x-1} - D_x$$

The number of life table deaths D_x represents the individuals in each age group expected to die among the number of survivors l_x, based on the prevailing probability of death q_x. It is calculated using the formula:

$$D_x = q_x \times l_x$$

Survivor years L_x represent the cumulative number of years survived by each age group, with the number of survivors l_x aged 65 serving as the baseline:

$$L_x = \begin{cases} (l_x + l_{x+n}) \times n / 2 \\ l_x / m_x, x = Highest\ age\ group \end{cases}$$

Total survivor years T_x represent the cumulative survivor years from age x to the maximum age, where the maximum age is denoted as ω:

$$T_x = \sum_{x}^{\omega} L_x, L_\omega$$

Finally, calculating life expectancy E_x:

$$E_x = T_x / l_x$$

2.3.2 Grey correlation analysis

Gray correlation analysis is a scientific method used for quantitatively describing and comparing the developmental dynamics of system changes. Its primary purpose is to calculate the correlation degree of each factor and identify the key factors influencing the independent variable based on ranking (41). Following the steps of gray correlation analysis, the calculated results are categorized into different years, regions, and age groups, corresponding to the gray correlation. Based on the correlation degree calculated from the aforementioned grouping, which indicates the correlation strength of each factor with the reference variable, the variables closely related to the reference variable are determined. Additionally, the magnitude of the data resulting from the relationship between each factor and the reference variable was ranked to precisely convey the influence of each factor on life expectancy, facilitating the identification of primary and secondary factors driving changes in the dependent variable.

In this paper, calculations were conducted following the methods outlined by Zhao (42). Firstly, the analytical series were identified, and the selected variables were categorized into one dependent factor and several independent factors. The series containing the dependent variable served as the reference series $\{x_0\}$, while those containing the independent variables constituted the comparative series $\{x_m\}$. Secondly, the variables' series were normalized, and the initial data point of each series was used to normalize the subsequent data points, thereby transforming them into comparable data series.

Subsequently, the difference series was derived using the following formula:

$$\Delta m(n) = |x_0(n) - x_m(n)|$$

Maximum Difference:

$$A = \max(m)\max(n)\Delta m(n) = \max(m)\max(n)|x_0(n) - x_m(n)|$$

Minimum Difference:

$$B = \min(m)\min(n)\Delta m(n) = \min(m)\min(n)|x_0(n) - x_m(n)|$$

Next, the gray correlation coefficient is calculated by dividing the sum of A and B by the sum of $\Delta m(n)$ and A:

$$\eta_m(n) = \frac{\min(m)\min(n)\begin{vmatrix} x_0(n) - \\ x_m(n) \end{vmatrix} + \phi Max(m)\max(n)\begin{vmatrix} x_0(n) - \\ x_m(n) \end{vmatrix}}{|x_0(n) - x_m(n)| + \phi Max(m)\max(n)|x_0(n) - x_m(n)|}$$

Finally, the gray correlation is obtained by averaging the gray correlation coefficients of each column:

$$S_m = \frac{1}{t}\sum_{n=1}^{t}\eta_m(n)$$

3 Results

3.1 Life expectancy

In this study, we utilized EXCEL software to prepare and compute life tables using census data, thereby deriving the life expectancy of the older adults population aged 65 and above in both urban and rural areas of Zhejiang Province for the years 2010 and 2020, as depicted in Table 2, respectively. The calculated results are stratified by various years, regions, and age groups, offering a more comprehensive depiction of life expectancy among the older adults population. Based on the life table calculation results, notable trends emerge: firstly, the life expectancy of both urban and rural older adults populations in Zhejiang Province has markedly risen over the decade spanning from 2010 to 2020, aligning with anticipated trajectories and conforming to the principles of social development and advancement. Additionally, the hierarchy of "urban older adults population > rural" in terms of life expectancy persists. This pattern is evident not only across the entirety but also within all age brackets of both urban and rural locales. Conversely, while an urban–rural disparity persists, it has notably diminished over the course of the decade, corroborating the conclusions drawn by numerous scholars (14, 15). This suggests that Zhejiang Province has made strides in mitigating the urban–rural divide and enhancing the health outcomes of the rural older adults population.

In addition, in order to more visually reveal the significant differences in life expectancy that exist between urban and rural areas and over different time spans in Zhejiang Province, we have also plotted the following figures. Figure 2 shows life expectancy in 2010 and 2020, with Panel (C) highlighting the reduction in urban–rural differences over time. Figure 3 depicts changes in the older adults population, distinguishing between urban and rural areas, and indicates an increase in life expectancy from 2010 to 2020. Lastly, Figure 4 compares the added value of life expectancy for urban older adults aged 65+ across all age groups from 2010 to 2020, between urban and rural settings.

TABLE 2 Life expectancy of the older adults population aged 65 and above in urban and rural areas of Zhejiang Province in 2010 and 2020 (years).

Year	Area	Life expectancy of age groups (years)					
		65–69	70–74	75–79	80–84	85–89	90—
2010	Urban	19.71	15.60	11.95	8.75	6.33	4.64
	Rural	17.43	13.65	10.35	7.46	5.27	3.66
2020	Urban	22.08	17.75	13.75	10.24	7.57	5.54
	Rural	20.57	16.49	12.66	9.36	6.87	4.99

3.2 Factors

Correlations among various influencing factors were determined through gray correlation analysis (Table 3), and the resultant calculations were stratified across different years, regions, and age groups. A higher correlation value (closer to 1) indicates a stronger relationship with the reference variable.

In urban areas in 2010, income, educational attainment, and health status exhibited a notably strong correlation with life expectancy. Their correlations, surpassing 0.8 across all age groups, underscore the critical significance of these factors for the urban older adults population (30). Health status also demonstrates a strong correlation, albeit slightly lower than that of education and income. Conversely, in rural areas, the 2010 data reveal notably elevated correlations between income status, educational attainment, and life expectancy, surpassing those observed in urban areas. Although the correlation for health in rural areas is relatively modest, it still exceeds 0.7. The urban–rural disparity in welfare is most pronounced, particularly among older age groups, wherein the gap notably widens with advancing age. Furthermore, the correlation of non-living alone status is consistently the lowest across all age groups in both urban and rural areas, diminishing notably with increasing age. In particular, the correlation decreases significantly among those aged 70 and over, for example from 0.764 in the 65–69 age group to 0.333 in the 90 and over age group in urban areas.

In 2020, the correlation for income in urban areas has diminished slightly but still maintains a high level exceeding 0.8. Similarly, the correlation for educational attainment experiences a slight decrease yet remains significant, indicative of the enduring impact of education on individuals' health and socioeconomic status (29). Conversely, the correlation for health status has strengthened, persisting above the 0.9 threshold for the 65-year age group.

Table 4 presents gender comparisons of the correlation between influencing factors and the life expectancy of older adults people over 65 years old, across all age groups in both urban and rural areas of Zhejiang Province, for the years 2010 and 2020. Income stands out as the top factor for both males (M) and females (F), highlighting its crucial role. Education is significant, especially in rural areas in 2020. Health status is also key, with a slightly higher impact on males. Welfare and non-solitary status have lesser associations, gender differences in these factors' impact are minimal.

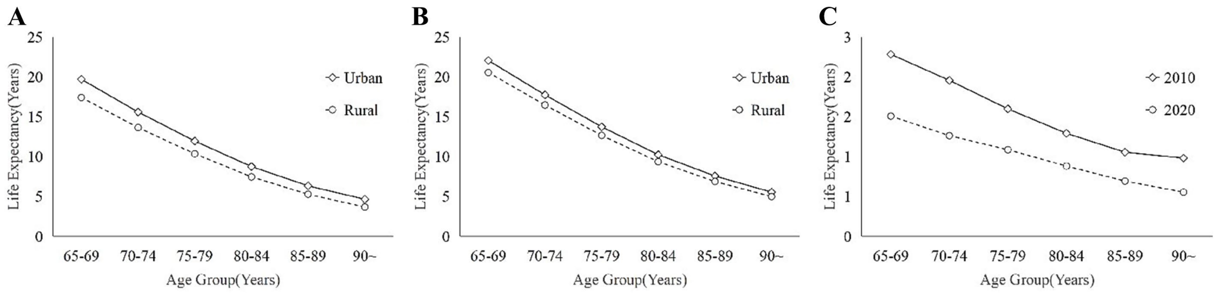

FIGURE 2
These illustrates the differences in life expectancy between urban and rural areas between different years: **(A)** 2010; **(B)** 2020; and **(C)** Urban–rural differences between 2010 and 2020.

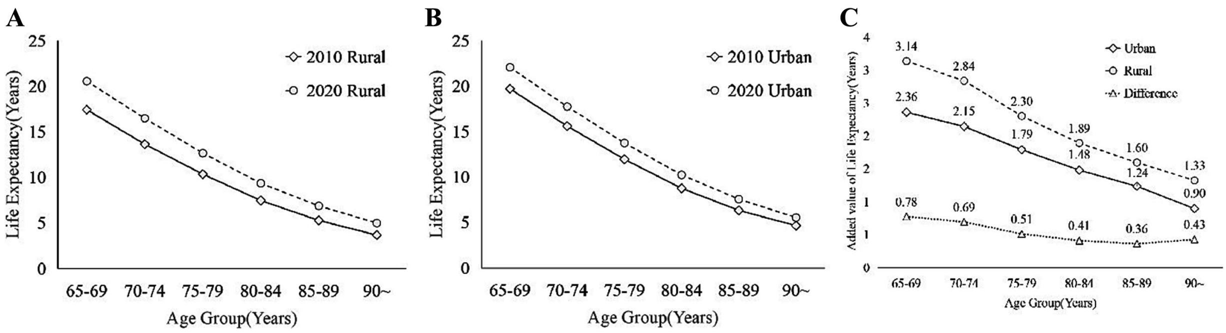

FIGURE 3
The difference of the older adults population in Zhejiang Province between 2010 and 2020 in different areas: **(A)** urban; **(B)** rural; **(C)** increase in life expectancy between 2010 and 2020.

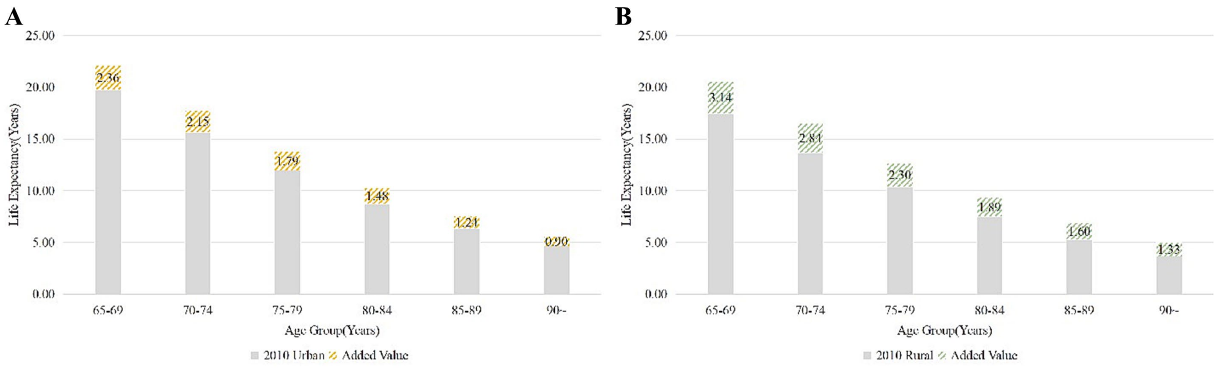

FIGURE 4
These illustrates the added value of life expectancy of urban older adults population aged 65 and above in Zhejiang Province at all age group, from 2010 to 2020: **(A)** Urban; **(B)** Rural.

4 Discussion

4.1 Differences in life expectancy between urban and rural

The life expectancy of the older adults population aged 65 and above in Zhejiang Province in 2010 by age group is shown in Figure 2A, which provides visual information on the health status and medical care level of the older adults population. It's noteworthy that the solid line in Figure 2C delineates the disparity in life expectancy between urban and rural older adults populations. Figure 2A illustrates that the life expectancy of the older adults population in urban generally exceeds that in rural, possibly attributable to superior medical facilities, living standards, and older adults care in urban areas (43). Nevertheless, it is observed that the disparities between urban and rural areas among different age groups of the older adults population exhibit varying characteristics. Specifically, Figure 2C depicts that the urban–rural disparities in life expectancy among the

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TABLE 3 Correlation degree of influencing factors on life expectancy of the older adults people over 65 in all age groups in urban and rural areas of Zhejiang Province in 2010 and 2020.

Year	Area	Age Groups	Degree of factors[1]				
			Welfare	Income	Education	Health Status	Non-living alone
2010	Urban	65–69	0.840	0.916	0.935	0.920	0.764
		70–74	0.751	0.851	0.898	0.862	0.583
		75–79	0.703	0.846	0.874	0.824	0.452
		80–84	0.691	0.861	0.858	0.803	0.375
		85–89	0.699	0.894	0.848	0.792	0.338
		90-	0.713	0.914	0.848	0.813	0.333
	Rural	65–69	0.741	0.973	0.953	0.921	0.756
		70–74	0.639	0.907	0.936	0.870	0.579
		75–79	0.573	0.877	0.920	0.834	0.458
		80–84	0.557	0.868	0.901	0.819	0.385
		85–89	0.562	0.892	0.887	0.811	0.345
		90–	0.576	0.917	0.895	0.819	0.338
2020	Urban	65–69	0.869	0.912	0.929	0.923	0.863
		70–74	0.769	0.849	0.868	0.864	0.663
		75–79	0.713	0.839	0.826	0.820	0.507
		80–84	0.689	0.858	0.803	0.797	0.406
		85–89	0.674	0.883	0.788	0.789	0.348
		90-	0.677	0.911	0.784	0.802	0.341
	Rural	65–69	0.797	0.951	0.929	0.923	0.829
		70–74	0.673	0.892	0.869	0.865	0.658
		75–79	0.612	0.866	0.831	0.827	0.512
		80–84	0.614	0.866	0.814	0.807	0.418
		85–89	0.604	0.887	0.803	0.803	0.355
		90–	0.617	0.906	0.803	0.817	0.349

[1]The higher the Degree of factors (closer to 1) the stronger the correlation.

older adults, from the age group of 65–69 to 85–89, exhibit a significant yet consistently diminishing trend, with the disparities tapering off in the age group of 90 and above. This trend may reflect advancements in rural areas concerning enhanced living conditions and improved medical care for the older adults (44).

Figure 2B illustrates the life expectancy of the older adults population in Zhejiang Province in 2020 for all age groups aged 65 and above, while the dotted line in Figure 2C further reveals the changes in the differences between urban and rural areas. Observing Figure 2B, it's evident that the life expectancy of the older adults population has generally risen. However, the consistent pattern persists whereby the life expectancy of urban older adults individuals surpasses that of their rural counterparts, aligning with research on the overarching urban–rural disparity in life expectancy in China (12), and globally (11, 45, 46). Upon juxtaposing Figures 2B,C, it's apparent that the gap in life expectancy between urban and rural areas for both younger and older adults individuals in 2020 exhibits a consistent trend of reduction and uniform narrowing in comparison to 2010.

The urban–rural disparities in life expectancy among the older adults population aged 65 and above in Zhejiang Province for 2010 and 2020 are examined using descriptive statistics based on the aforementioned data, with the findings presented in Table 5. Considering Figure 2C alongside, it's evident that the urban–rural disparity across all age groups was greater in 2010 compared to 2020. The average urban–rural difference was 1.53 years in 2010, and 1.00 years in 2020, indicating a 33.3% reduction. Concerning disparities among age groups, the urban–rural difference demonstrates a pattern of narrowing followed by widening. Notably, the widest gap is observed in the 65–69 age group, at 0.78 years, while the narrowest disparity is found in the 85–89 age group, at 0.36 years.

4.2 The time trend of life expectancy

Figure 3 illustrates the life expectancy of the older adults population of all ages in urban areas (A) and rural areas (B) for 2010 and 2020 is presented below, while Figure 3C illustrates the rise in life expectancy among the older adults population in urban and rural areas of Zhejiang Province from 2010 to 2020, alongside the urban–rural disparity. Overall, it's evident that the life expectancy of the older

TABLE 4 Gender comparisons of the correlation of influencing factors on life expectancy of the older adults people over 65 in all age groups in urban and rural areas of Zhejiang Province in 2010 and 2020.

Year	Area	Age groups	Degree of factors[1]									
			Welfare		Income		Education		Health status		Non-living alone	
			M[2]	F[3]	M	F	M	F	M	F	M	F
2010	Urban	65–69	0.584	0.496	0.788	0.566	0.778	0.765	0.772	0.658	0.758	0.701
		70–74	0.443	0.365	0.649	0.444	0.666	0.697	0.647	0.511	0.620	0.577
		75–79	0.364	0.337	0.626	0.466	0.588	0.682	0.574	0.444	0.543	0.514
		80–84	0.338	0.335	0.647	0.516	0.542	0.659	0.536	0.413	0.497	0.456
		85–89	0.339	0.333	0.716	0.590	0.527	0.585	0.516	0.397	0.476	0.398
		90-	0.333	0.333	0.762	0.647	0.531	0.542	0.545	0.428	0.463	0.348
	Rural	65–69	0.573	0.565	0.968	0.870	0.875	0.969	0.860	0.808	0.844	0.831
		70–74	0.444	0.467	0.888	0.669	0.814	0.984	0.778	0.708	0.745	0.741
		75–79	0.360	0.415	0.832	0.652	0.763	0.998	0.723	0.646	0.683	0.687
		80–84	0.333	0.399	0.793	0.679	0.725	0.938	0.696	0.627	0.643	0.637
		85–89	0.350	0.353	0.822	0.737	0.697	0.872	0.684	0.613	0.624	0.585
		90-	0.373	0.333	0.858	0.794	0.703	0.852	0.686	0.630	0.618	0.538
2020	Urban	65–69	0.628	0.619	0.765	0.711	0.794	0.732	0.792	0.698	0.776	0.716
		70–74	0.462	0.445	0.637	0.538	0.661	0.573	0.666	0.551	0.644	0.606
		75–79	0.394	0.368	0.625	0.501	0.578	0.500	0.588	0.470	0.562	0.552
		80–84	0.365	0.341	0.657	0.540	0.531	0.469	0.545	0.437	0.510	0.516
		85–89	0.341	0.333	0.702	0.604	0.496	0.455	0.529	0.429	0.494	0.472
		90-	0.333	0.338	0.760	0.684	0.485	0.446	0.543	0.451	0.489	0.412
	Rural	65–69	0.570	0.431	0.958	0.901	0.923	0.877	0.926	0.853	0.915	0.874
		70–74	0.540	0.427	0.907	0.780	0.861	0.782	0.869	0.758	0.846	0.807
		75–79	0.603	0.591	0.880	0.736	0.816	0.736	0.831	0.702	0.798	0.773
		80–84	0.506	0.540	0.876	0.748	0.791	0.724	0.809	0.677	0.769	0.742
		85–89	0.397	0.401	0.893	0.790	0.768	0.698	0.799	0.676	0.760	0.708
		90-	0.333	0.333	0.912	0.823	0.777	0.720	0.812	0.695	0.764	0.654

[1] The higher the Degree of factors (closer to 1) the stronger the correlation. [2] M = Male. [3] F = Female.

TABLE 5 Descriptive statistics of changes in life expectancy between 2010 and 2020 for urban and rural older adults populations in Zhejiang Province (years).

	2010	2020	D-value
Average	1.53	1.00	0.53
Standard Deviation	0.47	0.33	0.15
Median	1.45	0.98	0.47
Max	2.28	1.51	0.78
Min	0.98	0.55	0.36
Range	1.30	0.95	0.41

adults population of all ages has increased in both urban and rural areas between 2010 and 2020. This increase is closely associated with ongoing socio-economic development, advancements in medical technology, and enhancements in public health services (44).

In urban areas, while the growth in life expectancy of the older adults population is not as significant as in rural areas, there is a noticeable increase across all age groups, as shown in Figure 4A. In comparison to 2010, the most substantial rise in life expectancy in 2020 was observed in urban areas among the 65–69 age group, with an increase of approximately 2.36 years, whereas the smallest increase was noted among individuals aged 90 years and older, at around 0.90 years. An analysis of the rise in life expectancy across different age groups indicates a tendency for the increase to decelerate with advancing age.

Similarly, in rural areas, life expectancy shows an upward trend across all ages from 2010 to 2020, as shown in Figure 4B. Although it remains higher among the urban older adults population compared to rural areas. Additionally, Figure 3C illustrates that the increase in life expectancy is more notable among the older adults population compared to urban areas. The age groups exhibit distinct trends, with the most substantial increase in life expectancy observed in 2020 among the older adults population aged 65–69 years in rural areas compared to 2010, showing an increase of over 3 years to 3.14 years. The smallest increase in life expectancy is for those aged 90 years and above, with an increase of about 1.33 years. An examination of the rise in life expectancy across different ages reveals a tendency for fluctuation and deceleration with advancing age.

Regarding the disparities between urban and rural areas in the increase of life expectancy, as depicted in the calculation results, as shown in Figure 3C. These differences exhibit an initial narrowing followed by widening with age. Particularly, the highest disparity in life expectancy increase occurs in the 65–69 age group, reaching 0.76 years. Subsequently, from the 85–89 age group onwards, this difference progressively diminishes to 0.34 years, before ascending to 0.39 years in the 90 and above age group. Table 6 presents descriptive statistics concerning the increase in life expectancy among the older adults population aged 65 and above in urban and rural areas of Zhejiang Province in 2010 and 2020, respectively. Analysis of Table 5 indicates that over a decade of development, life expectancy among the older adults population in urban areas rose by an average of 1.65 years, compared to a 2.18-year increase in rural areas. This difference signifies a substantially greater increase in life expectancy in rural areas, the gap between urban and rural areas is gradually narrowing, consistent with findings from established studies (14, 15). This trend can be attributed to the equitable allocation of medical resources, enhancements in the social security system, and ongoing improvements in the living environment (47). The cumulative impact of these favorable factors enabled rural older adults individuals to access more timely and efficient medical services, alleviate financial burdens, enhance living conditions, and adopt healthier lifestyles, consequently enhancing their quality of life and life expectancy (28, 30). This trend underscores the notable achievements of Zhejiang Province in fostering coordinated urban–rural development and enhancing the well-being of the older adults.

TABLE 6 Descriptive statistics of life expectancy of older adults population in Zhejiang Province between urban and rural (years).

	Urban	Rural
Average	1.65	2.18
Standard deviation	0.51	0.65
Median	1.64	2.10
Max	2.36	3.14
Min	0.90	1.33
Range	1.47	1.81

4.3 Urban–rural comparison of influencing factors in 2010, 2020

Utilizing the correlations calculated from the aforementioned groupings, major and minor factors are ranked to provide a more comprehensible overview (Figure 5). Comparative analysis of correlation values between 2010 and 2020 enables an assessment of the influence of these factors across various age groups, urban and rural settings, and temporal changes, facilitating an exploration of urban–rural inequities.

4.3.1 Welfare

From the results, this factor consistently falls within the range of 0.6 to 0.8, holding the fourth position in the rankings (Figure 5). Nonetheless, concerning specific correlation values, it does not exert an identical degree of influence on the life expectancy of the older adults population across different years and regions. The public welfare system may contribute to divergent mortality rates (48). In 2010, welfare correlation values were higher in urban areas compared to rural areas, indicating a stronger association between welfare and life expectancy among older adults population in urban settings. This phenomenon may be attributed to the superior social security system in urban areas, where older adults population are more reliant on welfare (49). In 2020, the welfare correlation experiences a slight decline in urban areas but registers a significant increase in rural areas, possibly attributable to the restructuring of social security policies in rural regions (50). In the 1950s, China implemented a free public healthcare program in urban areas, specifically targeting public sector employees and their family members, as part of a broader welfare system that aimed to provide comprehensive support to its citizens (51). The healthcare program was one aspect of the welfare system, which also included social insurance, unemployment benefits, pensions, and other forms of social protection. Notably, in 2016, China took a significant step towards achieving greater equity by extending welfare benefits, including healthcare, to rural residents on par with their urban counterparts (52). However, despite these efforts, the correlation between welfare protection and social security indicators remains higher in urban areas compared to rural areas, as evidenced by data from both 2010 and 2020 (53). This observation underscores the need for continued efforts to address the relatively low level of welfare protection in rural areas, ensuring that all citizens, regardless of their location, have access to comprehensive social protection and healthcare services.

4.3.2 Income

Based on the calculation results, this factor emerges as the primary influencer of life expectancy among the older adults population in both urban and rural areas, except for rural areas in 2010 (Figure 5), aligning with previous research (54). A study pointed out that the evidence linking income inequality to population health status has primarily been observed at a broad geographic scale (55), a phenomenon likely observable in the provincial context of this study. In 2010, the urban older adults exhibited a strong correlation with income, suggesting that income played a pivotal role in meeting their fundamental needs and exerting a significant influence on life expectancy (56). Nevertheless, as society rapidly advances and progresses, the variety and complexity of factors impacting life expectancy are expanding and evolving. Amidst the intricate interplay and moderating influences of these factors (30), the correlation between income and life expectancy exhibits a subtle downward trajectory. This transition mirrors the diverse repercussions of social advancement and may indicate a more intricate and uncertain trajectory for the relationship between life expectancy and income in the future (36). The comparatively lower income correlation in rural areas in 2010 could stem from the relatively underdeveloped economic conditions in rural regions, a phenomenon observed in a study conducted in South Korea, which highlighted the likelihood of rural residents experiencing lower socio-economic status and enduring multidimensional poverty compared to their urban counterparts (57). Nonetheless, by 2020, there is a significant increase in income correlation alongside economic growth and rising income levels among rural residents. However, despite the 2020 increase, income correlation in rural areas remains lower than in urban areas due to the economic disparity between urban and rural regions.

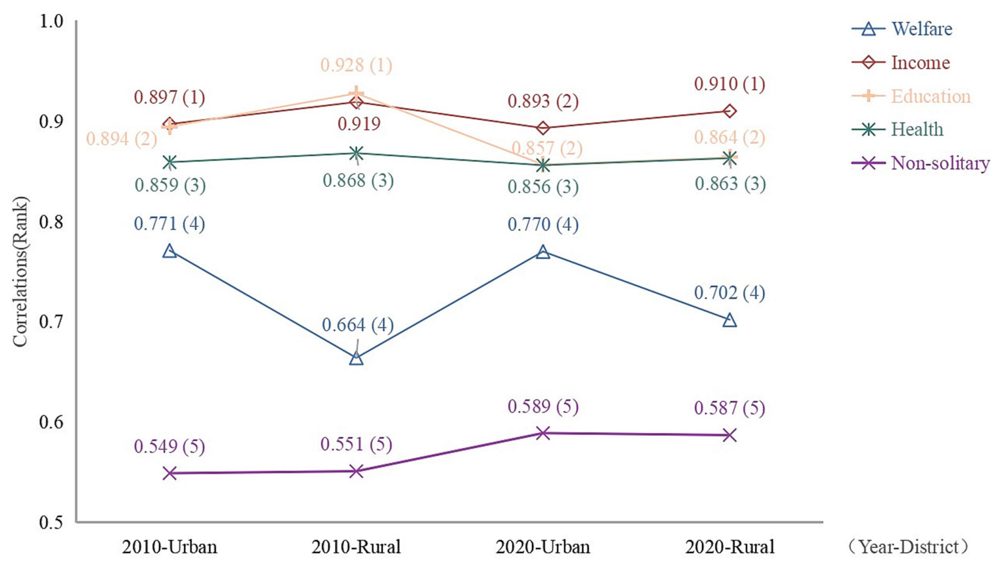


FIGURE 5
Ranking of the average value of the correlation between urban and rural elements in Zhejiang Province in 2010 and 2020.

4.3.3 Education

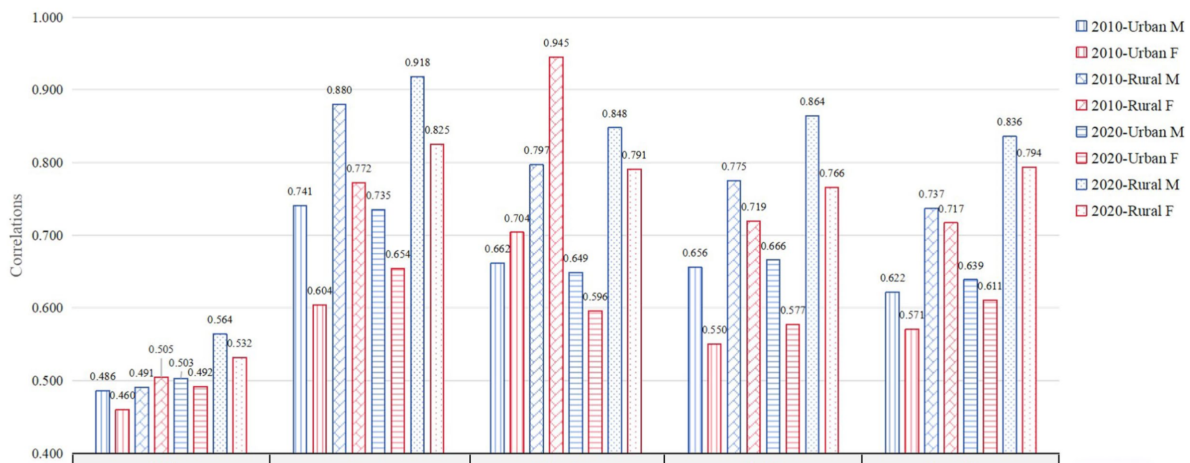
Based on the findings, it seems that educational attainment plays a secondary role in influencing life expectancy among both urban and rural older adults populations (Figure 5), consistent with established research indicating its significance (58). Nevertheless, it's noteworthy that the correlation was notably higher in 2010 than in 2020 for both urban and rural areas, and the disparity between urban and rural correlations was more pronounced in 2010 than in 2020. This shift may be attributed to the increased emphasis on and promotion of basic education for the older adults population in Zhejiang Province in recent years, resulting in a general improvement in education levels among both urban and rural older adults populations, particularly in rural areas (34). Consequently, this has reduced the disparity in educational attainment between urban and rural older adults populations and has fostered greater homogeneity within the population, resulting in a slight decline in the level of association. Overall, the degree of educational association remains substantial in both urban and rural areas in both 2010 and 2020. Notably, in rural areas in 2010, the correlation between educational attainment and life expectancy reached as high as 0.929. This may be due to the relative lack of educational resources in rural areas in 2010, which has led to a low emphasis on knowledge. Similar conclusions were reached in a study of healthy life expectancy among the older adults in China, which revealed through a careful social stratification analysis that only a minority of groups in rural areas had good access to education, further exacerbating inequalities in educational attainment among the population (56). These findings underscore the crucial role of education in shaping the life expectancy of the older adults population, as education levels influence individuals' career paths, income levels, and social standing (59), enhance cognitive abilities and decision-making skills, consequently promoting health and positively impacting life expectancy (60).

4.3.4 Health status

Health status consistently occupies a mid-level position (Figure 5), with its correlation to life expectancy exhibiting a similar pattern across different years in both urban and rural areas. This is likely attributable to Zhejiang Province's status as one of China's most developed provinces, prioritizing the health status of its residents and ensuring equitable distribution of medical resources between urban and rural areas. To be specific, in both 2010 and 2020, rural areas exhibit slightly higher health status correlations compared to urban areas. This reflects the fact that urban areas are relatively balanced in terms of healthcare resources and services, while rural areas are slightly less well-equipped in this regard (61). Nonetheless, it's noteworthy that the correlation decreased in 2020 compared to 2010. This could be attributed to ongoing advancements in medical infrastructure in recent years, coupled with increased government investment in the healthcare sector. As medical resources continue to improve and optimize, the risk of reduced life expectancy among the urban and rural older adults populations due to inadequate healthcare resources is gradually diminishing, prompting a greater focus on healthy living practices (62). This clearly demonstrates that Zhejiang Province's initiatives to enhance healthcare and boost investment in health are yielding favorable outcomes, ensuring robust health and life expectancy among both urban and rural older adults populations.

4.3.5 Residential status: non-living alone

The correlation between non-living alone and life expectancy appears relatively low in both urban and rural areas, ranking at the bottom of the list (Figure 5). This suggests that the mode of residence may have a relatively minor impact on the life expectancy of the older adults population, or its influence is less significant compared to other factors. On the one hand, with urbanization accelerating, the older adults population in urban areas may prefer independent living or residing in care facilities; on the other hand, the older adults population in rural regions may adhere to traditional living arrangements with



	Welfare	Income	Education	Health	Non-solitary
	Correlations(Rank)	Correlations(Rank)	Correlations(Rank)	Correlations(Rank)	Correlations(Rank)
2010-Urban M	0.486(5)	0.741(1)	0.662(2)	0.656(3)	0.622(4)
2010-Urban F	0.460(5)	0.604(2)	0.704(1)	0.550(4)	0.571(3)
2010-Rural M	0.491(5)	0.880(1)	0.797(2)	0.775(3)	0.737(4)
2010-Rural F	0.505(5)	0.772(2)	0.945(1)	0.719(3)	0.717(4)
2020-Urban M	0.503(5)	0.735(1)	0.649(3)	0.666(2)	0.639(4)
2020-Urban F	0.492(5)	0.654(1)	0.596(3)	0.577(4)	0.611(2)
2020-Rural M	0.564(5)	0.918(1)	0.848(3)	0.864(2)	0.836(4)
2020-Rural F	0.532(5)	0.825(1)	0.791(3)	0.766(4)	0.794(2)

FIGURE 6
Gender comparison of influencing factors on life expectancy for older adults people over 65 in Zhejiang Province.

family members due to entrenched family values and customs. The companionship and care provided by family members play an irreplaceable and crucial role in fulfilling the emotional needs of the older adults population (34). Consequently, the disparity in non-living alone associations between urban and rural areas may fluctuate between 2010 and 2020. This trend hinges on shifts in social structures, familial dynamics, and residential preferences across diverse regions, often constrained by individuals' abilities and opportunities to make choices (63). However, by 2020, the correlation with non-living alone had increased in both urban and rural areas, particularly in the former, resulting in a slight widening of the urban–rural disparity. This could be attributed to a rise in non-living alone arrangements accompanying shifts in family structures and increased empty-nesting in rural areas (64) (see Figure 5).

4.4 Gender comparison of influencing factors in different areas and years

Figure 6 shows the ranks and correlations of factors influencing life expectancy in Zhejiang Province for people over 65 years of age in different years (2010 and 2020) and in different regions (urban and rural), with comparisons for male and female, respectively.

From the results, it is clear that the welfare factor, both urban and rural, ranked lower in terms of association in both 2010 and 2020, with little gender difference. In contrast, the income factor has a significant impact on life expectancy in 2010 and 2020 for both males and females, ranking first in most cases in both urban and rural areas. For men in particular, the association is tops in both cases. At the same time, the education factor is also an important influence on life expectancy. For males, the effect is more pronounced in rural areas, probably because urban males usually have more resources and opportunities to compensate to some extent for the lack of education level. For females, the impact of education is more pervasive. Education has a significant impact on female life expectancy in both urban and rural areas. Meanwhile, health status does not have a strong impact, with all of its correlations ranked in the middle, and overall the gender differences are not significant. Residential status (non-living alone) ranks lower in the table, but also increases. This suggests that socializing or being accompanied has a positive impact on life expectancy in old age.

5 Conclusion

From the life table calculations, it is evident that the life expectancy of the older adults population in Zhejiang Province is on the rise, with a more pronounced increase observed in rural areas compared to urban areas, leading to a narrowing gap between the two regions. Nonetheless, rural areas still lag behind urban areas in terms of development, posing significant challenges to achieving sustainable societal progress. The findings from the gray correlation analysis indicate that economic income disparity serves as the primary determinant, with educational attainment acting as a secondary factor. Nonetheless, the correlation of each factor varies across different regions and age groups within the older adults population. Tackling these unfair differences is crucial not only for promoting social equity but also for fostering sustainable development, ensuring the well-being of current and future generations.

Consequently, targeted interventions for the older adults should be formulated on the basis of the data collected on various influencing factors and in the light of practical realities. For example, Zhejiang Province, at a press conference on the twentieth anniversary of the implementation of the "Eight-Eight Strategy," pointed to the highlight of "digital health care," which is aimed at building a new system of health care that is more convenient and more accessible in order to better serve all residents. However, it remains to be seen whether this initiative will be extended to rural areas to ensure that rural residents have access to the same medical services as their urban counterparts. In addition, in addition to external help, self-health awareness of the older adults is also very important, according to the research in this paper, it is known that the level of education is one of the main factors affecting life expectancy. It is suggested that geriatric education needs to be strengthened, especially in rural areas, to increase the awareness of health issues among the older adults, which enables them to better monitor their health status. Furthermore, given the high correlation between socioeconomic status and life expectancy identified in this study, policies addressing socioeconomic disparities should also be prioritized. This may involve providing financial support and access to social services for economically disadvantaged individuals and families, especially in rural areas. In summary, these initiatives also require the concerted efforts of the Government and all sectors of society in an effort to reduce urban–rural inequities.

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

YggC: Conceptualization, Supervision, Validation, Writing – original draft. XF: Conceptualization, Data curation, Formal analysis, Writing – original draft. SS: Methodology, Resources, Visualization, Writing – original draft. YgC: Investigation, Visualization, Writing – review & editing. ZP: Project administration, Writing – review & editing. ZC: Project administration, Writing – review & editing. HZ: Validation, Writing – review & editing. ML: Validation, Writing – review & 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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References

1. Braveman P. Health disparities and health equity: concepts and measurement. *Annu Rev Public Health*. (2006) 27:167–94. doi: 10.1146/annurev.publhealth.27.021405.102103

2. Woolf SH, Johnson RE, Fryer GE Jr, Rust G, Satcher D. The health impact of resolving racial disparities: an analysis of US mortality data. *Am J Public Health*. (2004) 94:2078–81. doi: 10.2105/AJPH.94.12.2078

3. World Health Organization. Available at: https://www.who.int/publications/i/item/9789240074323 (accessed March 16, 2024).

4. The State Council of the People's Republic of China. Available at: https://www.gov.cn/xinwen/2019-07/15/content_5409694.htm (Accessed March 16, 2024).

5. Health Commission of Zhejiang Province. Available at: https://wsjkw.zj.gov.cn/art/2023/4/25/art_1229123468_5105599.html (accessed March 16, 2024).

6. Dong H. Analysis on spatial-temporal changes of healthy life expectancy of elderly population in China. Changsha, Hunan: Central South University of Economics and Law (2021).

7. Bilal U, Hessel P, Perez-Ferrer C, Michael YL, Alfaro T, Tenorio-Mucha J, et al. Life expectancy and mortality in 363 cities of Latin America. *Nat Med*. (2021) 27:463–70. doi: 10.1038/s41591-020-01214-4

8. Sandoval MH, Alvear Portaccio ME, Albala C. Life expectancy by ethnic origin in Chile. *Front Public Health*. (2023) 11:1147542. doi: 10.3389/fpubh.2023.1147542

9. Zheng XY, Xu XJ, Liu YY, Xu YJ, Pan SX, Zeng XY, et al. Age-standardized mortality, disability-adjusted life-years and healthy life expectancy in different cultural regions of Guangdong, China: a population-based study of 2005–2015. *BMC Public Health*. (2020) 20:1–20. doi: 10.1186/s12889-020-8420-7

10. Liao R, Hu L, Liao Q, Zhu T, Yang H, Zhang T. Analysis of death causes of residents in poverty-stricken areas in 2020: take Liangshan Yi autonomous prefecture in China as an example. *BMC Public Health*. (2022) 22:1–3. doi: 10.1186/s12889-022-12504-6

11. Prochaska JD, Jupiter DC, Horel S, Vardeman J, Burdine JN. Rural-urban differences in estimated life expectancy associated with neighborhood-level cumulative social and environmental determinants. *Prev Med*. (2020) 139:106214. doi: 10.1016/j.ypmed.2020.106214

12. Wu J, Kc S, Luy M. The gender gap in life expectancy in urban and rural China, 2013–2018. *Front Public Health*. (2022) 10:749238. doi: 10.3389/fpubh.2022.749238

13. Hu Z, Liu X, Liao W, Kang N, Ma L, Mao Z, et al. Prevalence and health-adjusted life expectancy among older adults with hypertension in Chinese rural areas. *Front Public Health*. (2022) 10:802195. doi: 10.3389/fpubh.2022.802195

14. Kim I. Contributions of the life expectancy gap reduction between urban and rural areas to the increase in overall life expectancy in South Korea from 2000 to 2019. *Int J Equity Health*. (2023) 22:141. doi: 10.1186/s12939-023-01960-0

15. Chen M, Canudas-Romo V. Urban–rural lifespan disparities and cause-deleted analysis: evidence from China. *BMJ Open*. (2022) 12:e050707. doi: 10.1136/bmjopen-2021-050707

16. Wu Y, Zheng H, Liu Z, Wang S, Liu Y, Hu S. Dementia-free life expectancy among people over 60 years old by sex, urban and rural areas in Jiangxi Province, China.

Int J Environ Res Public Health. (2020) 17:5665. doi: 10.3390/ijerph17165665

17. Cullen MR, Baiocchi M, Eggleston K, Loftus P, Fuchs V. The weaker sex? Vulnerable men and women's resilience to socio-economic disadvantage. *SSM-Population Health*. (2016) 2:512–24. doi: 10.1016/j.ssmph.2016.06.006

18. Lu M, Wang X, Shen K, Ji C, Li W. Change trend and gender differences in disability-free life expectancy among older adults in China, 2010–2020. *Front Public Health*. (2023) 11:1167490. doi: 10.3389/fpubh.2023.1167490

19. Danovi A, Olgiati S, D'Amico A. Living longer with disability: economic implications for healthcare sustainability. *Sustain For*. (2021) 13:4467. doi: 10.3390/su13084467

20. Liu H. Research on disability grading based on ICF functional framework: empirical evidence from Zhejiang Province. *China Front Public Health*. (2022) 9:616180. doi: 10.3389/fpubh.2021.616180

21. Anwar A, Hyder S, Mohamed Nor N, Younis M. Government health expenditures and health outcome nexus: a study on OECD countries. *Front Public Health*. (2023) 11:1123759. doi: 10.3389/fpubh.2023.1123759

22. Shi G, Wang D, Altuntaş M. Financial development and health outcomes: do financial globalization matter in selected Asian economies? *Front Public Health*. (2022) 10:843935. doi: 10.3389/fpubh.2022.843935

23. Lin FL, Wang MC. Longevity and economic growth in China and India using a newly developed bootstrap ARDL model. *Front Public Health*. (2020) 8:488497. doi: 10.3389/fpubh.2020.00291

24. Liu C, Hou X, Wang Q, Xu X, Wu B, Liu J. Impact of access to childhood health services on healthy life expectancy of the older population. *Front Public Health*. (2023) 11:1234880. doi: 10.3389/fpubh.2023.1234880

25. Saidmamatov O, Saidmamatov O, Sobirov Y, Marty P, Ruzmetov D, Berdiyorov T, et al. Nexus between life expectancy, CO2 emissions, economic development, water, and agriculture in Aral Sea basin: empirical assessment. *Sustain For*. (2024) 16:2647. doi: 10.3390/su16072647

26. Rjoub H, Odugbesan JA, Adebayo TS, Wong WK. Investigating the causal relationships among carbon emissions, economic growth, and life expectancy in Turkey: evidence from time and frequency domain causality techniques. *Sustain For*. (2021) 13:2924. doi: 10.3390/su13052924

27. Weitensfelder L, Moshammer H, Ataniyazova O. Energy consumption, energy distribution, and clean energy use together affect life expectancy. *Sustain For*. (2024) 16:678. doi: 10.3390/su16020678

28. Moga Rogoz AT, Sart G, Bayar Y, Gavriletea MD. Impact of economic freedom and educational attainment on life expectancy: evidence from the new EU member states. *Front Public Health*. (2022) 10:907138. doi: 10.3389/fpubh.2022.907138

29. Zhan Z, Tao R, Niaz MU, Kirikkaleli D. Do higher education and financial institutions improve health in China? A New Perspective. *Front Public Health*. (2022) 10:874507. doi: 10.3389/fpubh.2022.874507

30. Cohen SA, Nash CC, Byrne EN, Greaney ML. Income and rural–urban status moderate the association between income inequality and life expectancy in US census tracts. *J Health Popul Nutr*. (2023) 42:24. doi: 10.1186/s41043-023-00366-6

31. Fall AK, Migot-Nabias F, Zidi N. Empirical analysis of health assessment objective and subjective methods on the determinants of health. *Front Public Health*. (2022) 10:796937. doi: 10.3389/fpubh.2022.796937

32. Qiao XC. Comparison of changes and differences in health expectancies of the elderly in the nation and provinces. *Popul Econ*. (2023) 5:1–20.

33. Zhejiang Province Population Census Office. Zhejiang Province population census yearbook 2020. Beijing: China Statistics Press (2022).

34. Mu YT, Long F, Yuan X. Urban-rural differences and trends in healthy ageing of Chinese elderly: an analysis based on the life course and health equity perspective. *Popul Res*. (2023) 47:82–97.

35. Chan KW, Wei Y. Two systems in one country: the origin, functions, and mechanisms of the rural-urban dual system in China. *Eurasian Geogr Econ*. (2019) 60:422–54. doi: 10.1080/15387216.2019.1669203

36. Vafaei A, Rosenberg MW, Pickett W. Relationships between income inequality and health: a study on rural and urban regions of Canada. *Rural Remote Health*. (2010) 10:270–8. doi: 10.22605/RRH1430

37. Lawless JF. Statistical modeling and methods in life span data. Beijing: China Statistics Press (1998).

38. Chiang CL. Practical methods of statistical analysis. Fang Jiqian, trans. Beijing: Beijing Medical University Peking Union Medical College Joint Publishing House (1998).

39. Song J. Demographics. Beijing: People's University of China Press (2019).

40. Wang RA. Method of constructing abridged life table by reference to a standard table. *J Beijing Med Univ*. (1987) 19:399–400.

41. Cui L. Grey forecast technology and its application research (MA thesis). Nanjing, Jiangsu: Nanjing University of Aeronautics and Astronautics (2010).

42. Zhao R. Average life expectancy and its influencing factors in Hebei Province (MA thesis). Shijiazhuang, Hebei: Hebei University of Economics and Busines (2020).

43. Dye C. Health and urban living. *Science*. (2008) 319:766–9. doi: 10.1126/science.1150198

44. Choi MH, Moon MH, Yoon TH. Avoidable mortality between metropolitan and non-metropolitan areas in Korea from 1995 to 2019: a descriptive study of implications for the national healthcare policy. *Int J Environ Res Public Health*. (2022) 19:3475. doi: 10.3390/ijerph19063475

45. Liu Z, Zheng H, Wu Y, Wang S, Liu Y, Hu S. Self-rated healthy life expectancy changes in Jiangxi province of China by gender and urban–rural differences, 2013–2018. *Front Public Health*. (2021) 8:596249. doi: 10.3389/fpubh.2020.596249

46. Sudharsanan N, Ho JY. Rural–urban differences in adult life expectancy in Indonesia: a parametric g-formula–based decomposition approach. *Epidemiology*. (2020) 31:393–401. doi: 10.1097/EDE.0000000000001172

47. Jones GW, Pratomo D. Education in Indonesia: Trends, differentials, and implications for development. Contemporary demographic transformations in China, India and Indonesia. Springer: Basel, Switzerland (2016). p. 195–214.

48. Jian Y, Neas L, Messer LC, Gray CL, Jagai JS, Rappazzo KM, et al. Divergent trends in life expectancy across the rural–urban gradient and association with specific racial proportions in the contiguous USA 2000–2005. *Int J Public Health*. (2019) 64:1367–74. doi: 10.1007/s00038-019-01274-5

49. James W, Cossman JS. Long-term trends in black and white mortality in the rural United States: evidence of a race-specific rural mortality penalty. *J Rural Health*. (2017) 33:21–31. doi: 10.1111/jrh.12181

50. Hao L, Xu X, Dupre ME, Guo A, Zhang X, Qiu L, et al. Adequate access to healthcare and added life expectancy among older adults in China. *BMC Geriatr*. (2020) 20:1–5. doi: 10.1186/s12877-020-01524-9

51. Zhang X, Dupre ME, Qiu L, Zhou W, Zhao Y, Gu D. Urban-rural differences in the association between access to healthcare and health outcomes among older adults in China. *BMC Geriatr*. (2017) 17:1. doi: 10.1186/s12877-017-0538-9

52. Yip W, Fu H, Chen AT, Zhai T, Jian W, Xu R, et al. 10 years of health-care reform in China: progress and gaps in universal health coverage. *Lancet*. (2019) 394:1192–204. doi: 10.1016/S0140-6736(19)32136-1

53. Liu D, Xi J, Hall BJ, Fu M, Zhang B, Guo J, et al. Attitudes toward aging, social support and depression among older adults: difference by urban and rural areas in China. *J Affect Dis*. (2020) 274:85–92. doi: 10.1016/j.jad.2020.05.052

54. Huang GG, Chen TH, Chen G, Guo F. A study of elderly healthy life expectancy of China: a new examination from the subjective dimension. *Popul Dev*. (2021):74–84.

55. Wilkinson RG, Pickett KE. Income inequality and population health: a review and explanation of the evidence. *Soc Sci Med*. (2006) 62:1768–84. doi: 10.1016/j.socscimed.2005.08.036

56. Liu M, Zhang M, Zhou J, Song N, Zhang L. Research on the healthy life expectancy of older adult individuals in China based on intrinsic capacity health standards and social stratification analysis. *Front Public Health*. (2024) 11:1303467. doi: 10.3389/fpubh.2023.1303467

57. Kim HJ, Park JY, Go NN, Jin NY, Kim JE. A study of the urban-rural poverty gap by applying definition of multidimensional poverty to Korean welfare panel data, 2005-2011. *Health Soc Welf Rev*. (2014) 34:5–1. doi: 10.15709/hswr.2014.34.1.5

58. Baker DP, Leon J, Smith Greenaway EG, Collins J, Movit M. The education effect on population health: a reassessment. *Popul Dev Rev*. (2011) 37:307–32. doi: 10.1111/j.1728-4457.2011.00412.x

59. Sebki W. Education and economic growth in developing countries: empirical evidence from GMM estimators for dynamic panel data. *Econ Bus*. (2021) 35:14–29. doi: 10.2478/eb-2021-0002

60. Li X, Ullah S. Caring for the environment: how CO2 emissions respond to human capital in BRICS economies? *Environ Sci Pollut R*. (2022) 29:18036–46. doi: 10.1007/s11356-021-17025-0

61. Jain-Chandra MS, Khor N, Mano R, Schauer J, Wingender MP, Zhuang J. Inequality in China–trends, drivers and policy remedies. *Int Monet Fund*. (2018) 18:1. doi: 10.5089/9781484357538.001

62. Wu JL, Qiao XC. Regional analysis of gender differences in healthy life expectancy of the elderly in China. *J Shandong Women's Univ*. (2023) 4:9–20.

63. Cooney TM, Curl AL. Transitioning from successful aging: a life course approach. *J Aging Health*. (2019) 31:528–51. doi: 10.1177/0898264317737892

64. Smith JP, Strauss J, Zhao Y. Healthy aging in China. *J Econ Ageing*. (2014) 4:37–43. doi: 10.1016/j.jeoa.2014.08.006

65. Zhang L, Sun L. Life expectancy inequalities between regions of China 2004–2020: contribution of age-and cause-specific mortality. *Front Public Health*. (2023) 11:1271469. doi: 10.3389/fpubh.2023.1271469

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Optimization of urban green space in Wuhan based on machine learning algorithm from the perspective of healthy city

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Introduction: Urban green spaces play a critical role in addressing health issues, ecological challenges, and uneven resource distribution in cities. This study focuses on Wuhan, where low green coverage rates and imbalanced green space allocation pose significant challenges. Adopting a healthy city development perspective, the research aims to assess the impact of green space optimization on urban health, economic performance, and social structure.

Methods: A multivariable model was constructed using random forest and Support Vector Machine (SVM) algorithms to evaluate the influence of key indicators on urban green space. Core indicators were integrated from three dimensions: residents' health, environmental quality, and community interaction. Multiple linear regression analysis was employed to quantify the potential benefits of green space optimization on economic and social outcomes.

Results: The findings reveal that optimizing health and environmental quality indices significantly enhances green space development. Green space improvements drive a 73% increase in economic efficiency by improving residents' health and extending life expectancy. Additionally, enhancements in social structure are achieved at rates of 61% and 52% through strengthened community cohesion and improved environmental quality, respectively. The model demonstrates high stability and adaptability after multiple iterations, providing a robust quantitative foundation for green space optimization.

Discussion: This study highlights the multidimensional value of green space optimization in promoting urban health, economic growth, and social stability. The results offer a solid theoretical basis and practical guidance for green space planning and management in healthy cities, contributing to scientific decision-making and sustainable urban development.

KEYWORDS

machine learning, random Forest algorithm, Support Vector Machine algorithm, optimization of urban green space, healthy city

1 Introduction

Amid rapid technological advancements, the accelerated urbanization process has led to a sharp increase in population density and resource allocation pressures, making urban green space planning and management an urgent issue (1, 2). As an important central city in China, Wuhan faces uneven distribution of green space resources in its urban areas, with an overall insufficient green area and a need for further improvement in green coverage. This situation poses significant challenges to both residents' quality of life and the sustainability of the urban ecosystem (3–5). The lack of urban green space may not only lead to a continuous decline in environmental quality but also significantly exacerbate residents' psychological stress and physical health issues.

Therefore, a comprehensive investigation into the intricate relationship between the optimization of green space layout and residents' health is crucial for understanding the mechanisms through which urban green spaces influence living environments. Such research can provide essential theoretical and practical support for enhancing urban planning and improving residents' quality of life (6).

In recent years, research exploring the relationship between urban green space and residents' health has advanced significantly. Studies have increasingly employed machine learning (ML) and spatial modeling techniques to examine the role of green space in optimizing living environments. For instance, Wu (7) developed a livability prediction model for Dutch cities using ML algorithms. By integrating features through decision jungles and decision forests, the model achieved over 90% prediction accuracy. This study highlighted that air pollution was a key factor affecting urban livability and demonstrated that green space, acting as an ecological buffer, could mitigate the effects of air pollution. ML techniques have proven to be highly effective in processing dynamic data and updating knowledge, offering valuable insights for analyzing complex urban ecosystems. Furthermore, Tella et al. (8) demonstrated the efficacy of the Random Forest (RF) algorithm in air pollution modeling, accurately predicting PM10 hotspots in Selangor, Malaysia. They revealed that the spatiotemporal distribution of air pollution could reflect deficiencies in green space in urbanized areas, which could exacerbate the negative health impacts of pollution exposure. While these studies have emphasized the environmental buffering role of green space, they have given less attention to its direct health benefits for urban populations.

From the perspective of urban expansion and land use, Elhamdouni et al. (9) analyzed the dynamic expansion of Khenifra city in Morocco from 1991 to 2017 using SVM techniques. Their findings revealed that the urban spatial occupancy rate surged from 12% to 36%, accompanied by a notable imbalance in the expansion pattern. This highlighted the potential adverse effects of rapid urbanization on the equity and spatial balance of green space distribution, which in turn exacerbates the reduction of residents' activity spaces and weakens community cohesion. In a similar vein, Chowdhury (10) compared the classification performance of ML algorithms and identified the high efficiency of SVM, RF, and Artificial Neural Networks (ANNs) in land use and cover classification, providing a scientific approach to modeling urban spatial dynamics. While these studies offer valuable technical insights into land use and urban expansion, they have not fully explored how the lack of green spaces indirectly affects overall quality of life by impacting residents' mental health and social interactions. As such, further systematic research is required to explore the specific roles of green spaces in enhancing both urban ecological and social functions.

The key findings of existing research can be summarized in two main points: first, the optimization of urban ecosystem stability and environmental quality through green space; and second, the positive impact of green space on residents' mental health and community interactions. However, from a critical perspective, there are still some issues in the current research. Most studies remain at the level of single-factor analysis and lack comprehensive research that considers urban environments, social factors, and other dimensions. Building upon these considerations, this study, based on machine learning algorithms, integrates both the RF and Support Vector Machine (SVM) algorithms to construct a new multivariable model. This model aims to systematically reveal the complex relationship between the layout of green space and residents' health in Wuhan's urban areas. Through nonlinear fitting and feature weight analysis, the model precisely captures the interactions between green space and various health indicators. Additionally, by optimizing kernel parameters and selecting decision tree features, it enhances the explanatory power of the relationship between health city indicators and green space, enabling data-driven prediction and optimization. Ultimately, the model provides a scientific basis for achieving health and sustainable urban development.

2 Relevant ideas of urban green space optimization based on ML from the perspective of healthy city

2.1 Healthy city

According to the World Health Organization (WHO) definition in 1994, a healthy city is one that places human health at its core, ensuring a healthy living and working environment for its citizens through systematic efforts in urban planning, construction, and management. The goal is to achieve the organic integration of healthy populations, environments, and societies (11). In recent years, this concept has been widely adopted, with its core focus on promoting comprehensive urban health development through improvements in environmental quality, the health of residents, and community cohesion (12, 13). The development of a healthy city requires the coordination of multiple sectors, including environmental protection, public health services, the implementation of social and economic policies, as well as community development and resident participation (14). For example, increasing urban green spaces and public open areas not only enhances residents' physical and mental health but also promotes community cohesion and social interaction (15). Studies have shown that the development of healthy cities can improve residents' quality of life, foster social harmony, and promote sustainable economic growth (16).

This study extracts key indicators from extensive research and practice, categorizing them into three main domains: residents' physical health, urban environmental quality, and community cohesion and interaction. First, urban green spaces are closely linked to residents' physical and mental health. Contact with natural environments has been shown to reduce psychological stress, improve mental health, and increase the frequency of physical activities (17). Second, optimizing urban environmental quality has a direct impact on improving residents' health. Properly planned green spaces can reduce air and noise pollution, thereby enhancing the overall environmental quality (18). Finally, community cohesion plays a vital role in healthy cities. The provision of green spaces and public areas not only strengthens community interaction and a sense of belonging but also promotes the integration and shared development of diverse cultures (19). These factors are interwoven, collectively forming a comprehensive system for healthy city development.

2.2 Optimization of urban green space

The optimization of urban green space involves enhancing both the quantity and quality of green areas through scientifically informed planning and management. This process aims to improve the urban ecological environment and, consequently, the quality of life for residents. Urban green spaces not only offer aesthetic value and recreational opportunities but also play a crucial role in climate regulation, air and soil purification, and water conservation (20). For example, urban green spaces can significantly mitigate the urban heat island effect by providing shade and evaporative cooling, thus lowering local temperatures. Additionally, these spaces contribute to improving air quality by absorbing carbon dioxide and other pollutants (21). Optimizing the layout of urban green spaces can bolster the stability and sustainability of urban ecosystems, while also enhancing residents' wellbeing and overall health (22, 23). Research has demonstrated that green spaces can substantially reduce the urban heat island effect, adjust local temperatures, and promote evaporative cooling (24, 25). Furthermore, green spaces improve air quality by capturing carbon dioxide and other pollutants, which in turn reduces the incidence of respiratory illnesses (26, 27). Properly optimizing the distribution of urban green spaces contributes to ecosystem stability and sustainability while simultaneously improving residents' health and happiness. Studies have shown that residents living in proximity to green spaces report better mental health and more frequent social interactions compared to those in areas without access to green space (28, 29). Additionally, the rational allocation of green spaces, along with efforts to increase their accessibility and diversity, enables better fulfillment of the needs of various age groups and social sectors. This promotes social equity and enhances public health and wellbeing (30). Modern urban planning should embrace a multi-center approach, creating self-sustaining urban communities that reduce residents' dependency on automobile transport while improving overall health and safety (21). This model has been successfully implemented in various global cities, such as the "15-min city" concept in Paris, where residents can meet all their daily needs within a 15-min walk or bike ride (31). Through these strategies, optimizing urban green spaces not only enhances environmental quality but also provides residents with improved health and social opportunities, thereby fostering the sustainable development of the city as a whole.

2.3 The ML algorithm

Machine learning (ML), as a critical branch of artificial intelligence, enables computers to learn from data and continuously optimize their performance by analyzing data, recognizing patterns, and building predictive models (32). Based on statistical and mathematical principles, ML constructs mathematical models to identify patterns in data, thereby automatically improving the performance of computational systems (33). RF and SVM are two classic machine learning algorithms that are widely applied due to their excellent performance in classification and regression tasks. The differences between these two algorithms are not only reflected in their specific implementation mechanisms but also in the types of scenarios they are best suited for. RF is particularly suitable for datasets with large amounts of redundant features and noise, as it can efficiently extract key features and perform classification tasks. On the other hand, SVM excels in solving nonlinear problems due to its ability to accurately describe complex decision boundaries and optimize classification margins. The two algorithms demonstrate highly complementary characteristics when addressing multidimensional and complex issues. RF offers stability and generalization ability, while SVM focuses on optimizing classification performance for nonlinear data. This complementary advantage provides a scientifically sound and efficient solution for handling complex datasets.

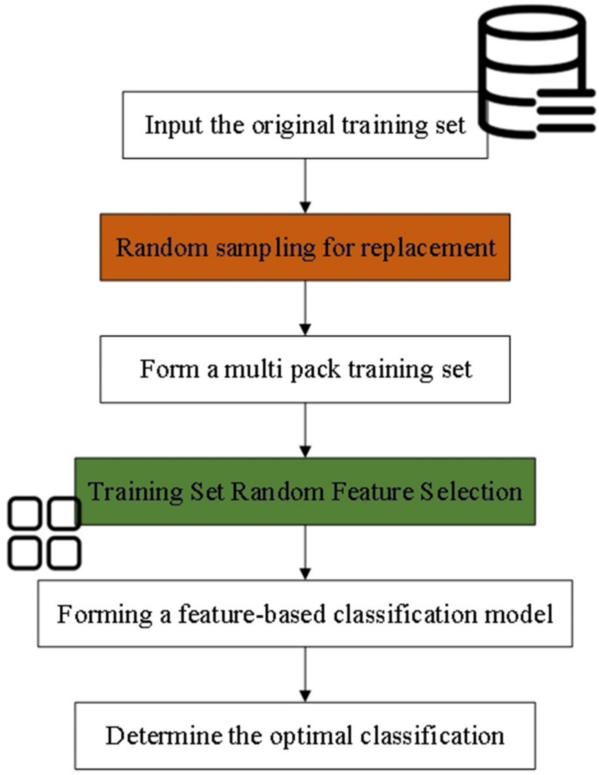

FIGURE 1
The implementation process of RF.

RF is an ensemble learning method that performs classification and regression tasks by constructing multiple decision trees. The core concept of RF lies in ensemble learning, where the fundamental unit is the decision tree. In essence, multiple weak classifiers (decision trees) are combined to create a strong classifier, thereby enhancing the overall performance of the model (34, 35). The implementation process of RF is illustrated in Figure 1.

In RF, each decision tree is constructed using randomly selected features and samples. This randomness reduces the model's variance and enhances its generalization ability (36). When constructing each decision tree, RF ensures diversity by employing bootstrap sampling and random feature selection, which helps differentiate each tree within the ensemble (37, 38). The operational principle of RF is illustrated in Figure 2

SVM is a powerful supervised learning method designed for classification and regression tasks (39, 40). The core idea of SVM is to maximize the margin between distinct sample points by

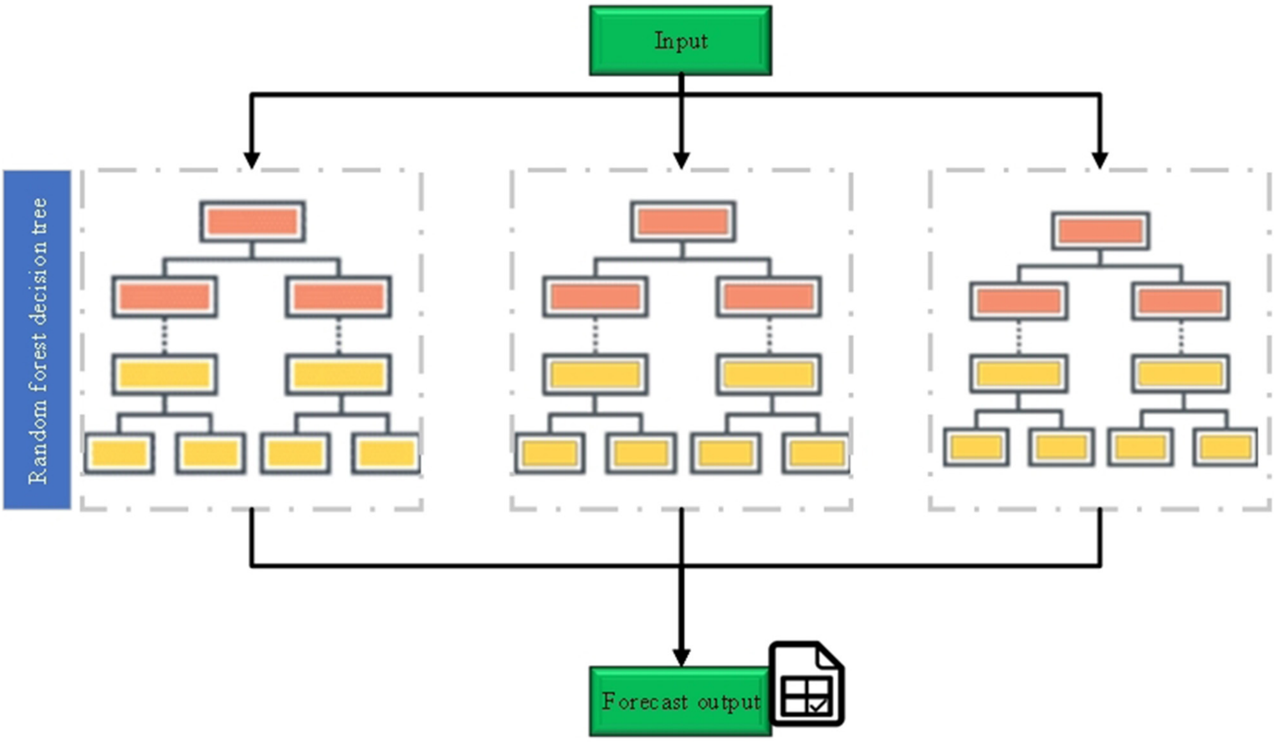

FIGURE 2
Schematic diagram of RF implementation.

identifying an optimal hyperplane (41). In classification tasks, SVM maximizes the distance between the nearest support vector and the decision boundary (42). When the data is not linearly separable, SVM employs a kernel function to map the data to a higher-dimensional space, where an optimal hyperplane can be identified in the nonlinear space (43).

The advantage of SVM lies in its strong generalization ability and its adaptability to high-dimensional data. It is particularly effective when dealing with small sample sets and nonlinear data. The core principle of SVM is to identify the optimal classification boundary by maximizing the margin between classes, thereby improving the model's robustness and classification accuracy (44). The flowchart depicting the implementation process of SVM is shown in Figure 3.

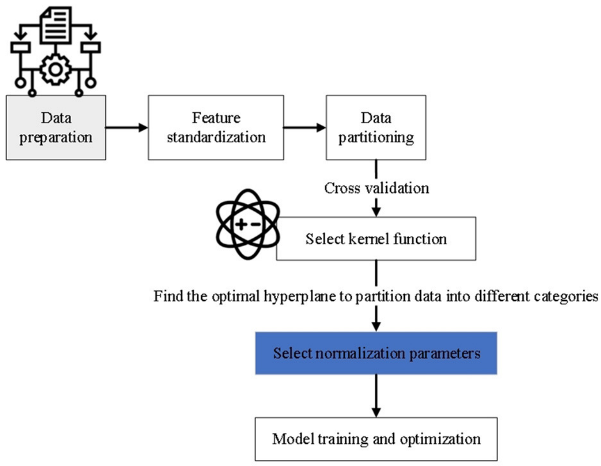

FIGURE 3
Flow chart of SVM implementation.

3 Multivariable model design of Wuhan urban green space based on the ML algorithm

Urban green spaces play a vital role in addressing climate change. They serve as natural infrastructure for regulating microclimates and mitigating the urban heat island effect. Additionally, they help reduce carbon emissions and enhance urban ecological resilience. Extreme climate events triggered by climate change—such as heatwaves, droughts, and heavy rainfall—have profoundly affected the stability and functionality of green space systems. Specifically, rising temperatures intensify evaporation and reduce soil moisture content, significantly impacting the growth cycles and biodiversity of vegetation within green spaces. Changes in precipitation patterns cause uneven spatial and temporal distribution of rainfall. This increases the complexity of water resource management in green spaces. As a result, their ecological functions and residents' quality of life are affected. Moreover, extreme weather events such as heavy storms and heatwaves are becoming more frequent. These events raise management costs and pose challenges to green space infrastructure, plant growth, and ecosystem service functions.

From an ecosystem services perspective, the relationship between urban green spaces and climate change is characterized by multiple interactions. Urban green spaces can effectively mitigate the negative impacts of climate change by expanding vegetation coverage, enhancing soil water retention, improving air quality, and regulating temperature and humidity. As the "carbon sinks" of cities, green spaces absorb and store carbon dioxide, thereby playing a crucial role in slowing climate change. However, climate change itself imposes new challenges on green space systems. High temperatures and drought put stress on plants in green spaces. Some may experience growth stagnation, reduced adaptability, or even death. This weakens their ability to sequester carbon and provide ecological protection. Additionally, extreme climate events such as heavy rainfall and flooding are becoming more frequent. These events cause soil erosion and waste water resources in green spaces. They may also lead to the collapse of ecological structures, further increasing urban vulnerability to climate change.

This study employs a multivariable modeling approach to explore the relationship between urban green spaces and healthy cities. It integrates diverse data on climate, the environment, and public health to reveal these complex interactions. The analysis of green spaces in urban Wuhan incorporates multiple indicators, including residents' health, environmental quality, and community interactions, to construct a comprehensive research framework. To capture the nonlinear relationships among these multidimensional data, this study utilizes two powerful machine learning algorithms: RF and SVM. These algorithms were selected due to their superior performance in handling complex datasets, uncovering latent patterns, and optimizing predictive accuracy.

In terms of theoretical methodology, the RF algorithm offers high tolerance and adaptability, while SVM excels in solving nonlinear problems in high-dimensional spaces. Specifically, RF learns from data by constructing multiple decision trees, employing bootstrap sampling and random feature selection during tree generation. This enhances the model's adaptability to complex relationships while reducing the risk of overfitting due to data noise. Furthermore, RF's ensemble nature allows it to process diverse input features, making it well-suited for heterogeneous urban health and environmental data, ensuring more accurate and stable predictions. Meanwhile, SVM achieves data classification by identifying the optimal decision boundary that maximizes the margin between support vectors and the hyperplane. When handling nonlinear relationships, SVM employs kernel functions to map data from lower-dimensional to higher-dimensional spaces, enabling the construction of more precise classification models. Notably, by optimizing kernel function parameters through grid search and cross-validation, the model's classification capability in complex data environments can be further enhanced. This advantage makes SVM particularly effective in analyzing the multifaceted impacts of urban green spaces on healthy city indicators, as it can identify subtle and latent associations.

The index data used in this study are sourced from publicly available official datasets, including annual statistical reports, environmental quality monitoring reports, and health survey data published by the Wuhan Municipal Bureau of Statistics and the Environmental Protection Bureau. As these datasets are publicly accessible, ethical concerns are not involved. However, potential sample selection biases may arise. For example, some indices may not fully represent the spatial distribution of Wuhan due to sampling being concentrated in specific urban districts. Additionally, certain environmental quality data may be limited by fixed monitoring schedules, which may hinder the capture of dynamic trends. To mitigate the impact of these biases, all raw data undergo a preprocessing stage, during which data cleaning is performed to address missing values and outliers. For missing data imputation, the k-nearest neighbors (k-NN) method based on similar samples is employed. This approach fills in missing values by calculating the mean of the nearest neighbors in the feature space, effectively preserving the overall relationships within the data. Specifically, for each missing value, the Euclidean distance between the target sample and other samples is first computed. The sample values of the k-nearest neighbors are then selected as references and imputed according to a weighted similarity, thereby retaining the intrinsic structural information of the dataset. For outlier detection, the 3σ rule is applied. The mean and standard deviation of each variable are calculated, and any values outside the range defined by the mean $\pm$ three times the standard deviation are identified as outliers and removed. This step prevents extreme values from distorting the model analysis. Subsequently, the Min-Max normalization method is used to standardize the data across different dimensions, scaling all values to the [0, 1] range to ensure consistency and comparability. To further optimize the dataset, Principal Component Analysis (PCA) is employed to reduce dimensionality, minimizing redundant information and enhancing the efficiency and accuracy of the model. During the PCA process, the number of principal components is selected based on a cumulative variance contribution rate of 95%. This dimensionality reduction not only improves data quality and consistency but also provides a solid foundation for the subsequent machine learning models. After preprocessing, the dataset is transformed such that each sample contains a set of standardized features, effectively reflecting the relationship between urban green space and healthy city indices in Wuhan.

This study adopts a multi-dimensional and multi-level approach to ensure a comprehensive and scientifically rigorous analysis. The selection of indices is designed to accurately reflect the real-world conditions and functional characteristics of urban green space. In line with established research literature and guidelines on urban greening and the development of healthy cities, the chosen indices are both scientifically sound and practically applicable. Specifically, fundamental indices such as green area, vegetation coverage rate, and green coverage density directly measure the extent and distribution of urban green space. These indices are commonly employed in urban ecology and environmental science research. Additional indices, such as the length of green corridors and the number of parks, offer further insights into the function and structure of green space, emphasizing its connectivity and accessibility for residents. These factors are significant in urban planning and design. Moreover, the garden quantity index captures the actual use and perception of green space by residents, making it a critical indicator for evaluating the social benefits and community interactions facilitated by these

TABLE 1 Indices of Wuhan.

Type	Index	Content
Indices of urban green space in Wuhan	Green area	The total area covered by green space in Wuhan includes parks, green belts, greenways, and other green spaces.
	Vegetation coverage	The proportion of vegetation coverage in the urban area of Wuhan reflects the degree of vegetation greening in the city.
	Green coverage density	It measures the distribution density of green space such as green space and green belt in Wuhan, that is, the number of green coverage per unit area.
	Green corridor length	The total length of all kinds of green corridors in the urban area of Wuhan, including tree-lined roads and riverside green belts, is an important channel connecting urban green spaces.
	Number of parks	The total number of parks in the urban area of Wuhan reflects the distribution of leisure and entertainment space in the city.
	Green coverage rate	The proportion of green space (including green space, green belt, etc.) in the urban area of Wuhan is an important index to evaluate the degree of urban greening.
	Number of gardens	The number of gardens within courtyards, communities, and public areas in Wuhan, such as community and school gardens, provides greenery and venues for resident activities.
Health indices of Wuhan residents	Health condition	The overall health status of Wuhan residents, including physical and mental health.
	Chronic disease incidence	The chronic disease incidence among Wuhan residents, including hypertension, diabetes, cardiovascular and cerebrovascular diseases, etc.
	Average life span	The average life expectancy of Wuhan residents reflects the overall health level and quality of life.
	Health consciousness	Wuhan residents' awareness and concern about health problems, including the mastery of health knowledge and health care awareness.
Urban environmental quality index of Wuhan	Air quality index	It reflects the concentration levels of various pollutants in the air of Wuhan, including PM2.5, PM10, sulfur dioxide, nitrogen dioxide, etc. It has an important impact on residents' health and environmental quality.
	Noise level	It measures the intensity and frequency of environmental noise in Wuhan, encompassing traffic, industrial, and community noise. It impacts residents' quality of life and physical and mental health.
	Water quality index	It is critical to reflect the concentration and water quality of various pollutants in Wuhan water. It includes heavy metals, organic pollutants, microorganisms, and so on, for residents' domestic water use and ecological environment protection.
	Soil pollution index	It measures the concentration and distribution of various pollutants in the soil of Wuhan, including heavy metals, organic pollutants, and pesticide residues. It has an important impact on the safety of agricultural products and the protection of the ecological environment.
	Light pollution index	It reflects the night light intensity and light pollution degree in Wuhan, covering the number and intensity of urban night lighting facilities. It has an impact on the quality of life of residents and the biological ecological environment at night.
Community interaction index of Wuhan	Frequency of community activities	It reflects the frequency and participation of various community activities in the Wuhan community, encompassing cultural and sports activities, voluntary services, social gatherings, etc.
	Community organization density	It measures the number and distribution density of various community organizations in the Wuhan community, including community neighborhood committees, industry committees, and volunteer organizations.
	Community interaction participation index	It reflects the communication and interaction among community residents in Wuhan, involving neighborhood relations, participation in community activities, community information transmission, etc.
	Utilization of community public facilities	It shows the utilization degree of various public facilities in the Wuhan community, encompassing fitness facilities, libraries, cultural activity centers, etc. It reflects the activity degree of the community and the utilization efficiency of public resources.

spaces. The indices used in this study for Wuhan are summarized in Table 1.

The selection of these indices aligns closely with the study objectives. First, indices such as green area and vegetation coverage directly reflect the scale and quality of urban green space. These factors are crucial for improving residents' health, enhancing air quality, and regulating urban microclimates. Second, indices such as green coverage density and green corridor length provide insights into the distribution and connectivity of green space, facilitating the creation of a cohesive green grid and enhancing the overall functionality of the urban ecosystem. The number of parks and gardens serves as a measure of green space accessibility and utilization, which directly influences residents' outdoor activity levels and the extent of community interaction. By examining these indices, the impact of green space on residents' health, urban environmental quality, and community vitality can be thoroughly evaluated, providing a solid scientific foundation for optimizing green space layout. Ultimately,

TABLE 2 Optimization process of ML algorithms.

Algorithm	Parameter	Initial value	Optimization process	Optimal parameter value
RF	n_estimators	100	Start from 100, gradually increase, and select the number that maximizes the model effect.	300
	max_features	Automatic	Trying different feature numbers [including sqrt(n_features) and log2(n_features)], and selecting the best feature number.	sqrt
	max_depth	None	Start with None and increase gradually until the model effect is no longer improved.	20
	min_samples_split	5	Step by step, select the number of segmentation samples that can maximize the model effect.	2
SVM	kernel	Radial Basis Function (RBF)	Trying different kernel functions (including RBF, linear kernel and polynomial kernel) and choosing the kernel function that is most suitable for the data.	RBF
	regularization parameter(C)	1	Through grid search or cross-validation, the optimal C value is selected from a certain range.	1
	gamma	scale	According to the different kernel functions, the optimal gamma value is selected.	scale
	epsilon	0.01	Choosing the optimal epsilon value from a certain range makes the tolerance of the model to errors more reasonable in different situations.	0.1

this approach supports the goal of building a healthy and livable city.

In this study, the parameters of the ML algorithms are optimized to ensure the model's high accuracy and robustness. The objective of parameter optimization is to enhance the model's adaptability and predictive performance by adjusting key parameters in the algorithm, thereby achieving the study goal of optimizing green space in Wuhan. The parameter optimization process is informed by both the characteristics of the algorithms and the specific nature of the data. Specifically, the two primary ML methods used—RF and SVM—each require the optimization of unique parameters. For RF, the focus is on parameters such as n_estimators, max_features, max_depth, and min_samples_split, which directly influence the model's complexity and predictive accuracy. The optimal combination of these parameters is identified through a systematic adjustment process. For SVM, key parameters including the kernel function, regularization parameter (C), gamma, and epsilon value play a critical role in determining the SVM's ability to map and classify data in high-dimensional space. The parameter optimization process for SVM involves grid search and cross-validation, allowing for the selection of the most suitable combination of parameters. The parameter optimization details for both RF and SVM are summarized in Table 2.

In the design of the multivariate model, RF performs random sampling and combines numerous features through feature selection and predictive model construction. This approach effectively identifies key features that significantly influence the dependent variables, thereby enhancing the prediction accuracy and stability of the model (45, 46). The primary mathematical process involved is as follows:

- Decision Tree Segmentation Calculation

To implement RF, it is necessary to determine the influence of each feature on the target variable through decision tree segmentation. This is achieved by calculating the Information Gain (IG), which quantifies the improvement in information provided by a feature when dividing the data. The feature with the highest IG is selected to split the data, thereby constructing the decision tree nodes. The specific calculation is represented in Equation 1:

$$Gain(X, Y) = Entropy(X) - \sum_{i=1}^{n} \frac{|X_i|}{|X|} \times Entropy(X_i) \tag{1}$$

X refers to a feature set. Y represents the target variable. $|X_i|$ stands for the size of the *i-th* subset in feature X. $|X|$ denotes the total size of feature set X. $Entropy(X)$ indicates the entropy of feature set X. In this way, the optimal features can be selected for segmentation to maximize the IG of the data.

- Information entropy calculation of decision tree nodes

The information entropy calculation at decision tree nodes measures the uncertainty inherent in the data. Higher information entropy indicates greater uncertainty, while a lower entropy suggests less uncertainty. During the construction of a decision tree, features that most effectively reduce information entropy are selected, thereby minimizing data uncertainty and enhancing the predictive power of the tree. The calculation of information entropy is given by:

$$Entropy(X) = -\sum_{i=1}^{m} p_i \times \log_2(p_i) \tag{2}$$

p_i represents the proportion of class i on the node. By calculating the information entropy, the effect of data segmentation with different features can be evaluated, and the features that can minimize the uncertainty can be selected for segmentation.

- Output of decision tree leaf nodes

Once the decision tree is constructed, each leaf node generates a predicted value, which is obtained by averaging the target variable values of all samples within the node. This approach effectively utilizes all available information in the leaf node to produce stable prediction outcomes. The output of the decision tree leaf node is calculated as follows:

$$\hat{y}_{tree} = \frac{1}{N}\sum_{i=1}^{N} y_i \tag{3}$$

N represents the sample number of leaf nodes. y_i represents the target variable value of sample i. Through this averaging method, the final predicted value of each leaf node can be obtained.

- Output of RF

Building on this, the final prediction output of the RF is derived by aggregating the predicted values from multiple decision trees. Specifically, the RF output is the average of the predictions from all trees, which serves to reduce the prediction error inherent in individual decision trees and enhances the stability and accuracy of the overall model. The RF output is represented by the following equation:

$$\hat{y}_{forest} = \frac{1}{T}\sum_{t=1}^{T} \hat{y}_{tree_t} \tag{4}$$

T represents the number of trees in the *RF*. $\hat{y}_{tree_t}$ refers to the predicted output of the t tree. Through this calculation, RF can synthesize the prediction results of multiple decision trees and provide a more stable and accurate prediction.

- Calculation of feature importance

In this study, RF determines the features that most influence the model's prediction outcomes by assessing the importance of each feature. This process is carried out by aggregating the IG across all decision trees. Calculating feature importance provides insights into which variables contribute most to the model's predictive power. The calculation is expressed as follows:

$$Importance(X_i) = \sum_{t=1}^{T} Gain(X_i, Y_t) \tag{5}$$

X_i represents the i-th feature. Y_t refers to the target variable of the t-th tree. The features that have a significant impact on the prediction results can be identified by calculating the importance of features, thus optimizing the model's performance.

- Error calculation

Finally, the model's prediction accuracy and goodness of fit are evaluated through error analysis. Typically, the performance of the RF model is measured by computing the mean squared error (MSE) between the predicted and actual values. The error calculation is given by the following equation:

$$Error_{forest} = \frac{1}{T}\sum_{t=1}^{T} (\hat{y}_{tree_t} - y)^2 \tag{6}$$

y represents the true value of the target variable. Error calculation is used to assess the model's prediction accuracy and goodness of fit. Based on the aforementioned algorithm and calculation process, RF is capable of capturing complex nonlinear relationships in large-scale, multidimensional data, thereby enhancing the model's robustness and generalization ability. As a result, RF provides a solid scientific foundation for optimizing urban green space in Wuhan.

SVM operates by mapping the data into a high-dimensional feature space to identify a hyperplane that maximizes the margin between different categories, thereby facilitating effective classification and prediction. In the design of a multivariable model, SVM is particularly useful for uncovering nonlinear relationships in the data, enabling effective classification and regression. This improves the model's ability to express and fit complex data relationships. The core mathematical process is outlined as follows:

4 Calculation of the decision function in a linear SVM classifier

SVM begins by determining the classification boundary through the calculation of the linear decision function. This decision function maps the input samples into a high-dimensional space, where classification is based on the distance between the samples and the decision hyperplane. The equation for the decision function of a linear SVM is as follows:

$$\hat{y}(x) = w^T \cdot x + b \tag{7}$$

$\hat{y}(x)$ represents the prediction category of the input sample x; w and b refer to model parameters. Through calculation, SVM can classify the input data into different categories.

- Calculation of objective function of linear SVM classifier

In linear SVM, the objective function is used to optimize the classification hyperplane by maximizing the margin between support vectors while minimizing classification errors. This objective function incorporates both the classification margin and an error term, which together enhance the model's classification performance. The equation is expressed as:

$$\min_{w,b} \frac{1}{2}||w||^2 + C\sum_{i=1}^{n} \max\left(0, 1 - y_i(w^T \cdot x_i + b)\right) \tag{8}$$

x_i and y_i respectively represent training samples and their corresponding categories. C stands for regularization parameter. Thus, SVM can find an optimal hyperplane that balances the classification interval and classification error.

- Calculation of decision function (kernel skill) of nonlinear SVM classifier

For data that is not linearly separable, SVM utilizes a kernel function to map the data into a higher-dimensional space, where it identifies the optimal hyperplane that maximizes the margin. The use of kernel methods enables the handling of complex data structures, thereby achieving more accurate classifications. The decision function equation for nonlinear SVM is:

$$\hat{y}(x) = \sum_{i=1}^{n_{sv}} \alpha_i y_i K(x, x_i) + b \tag{9}$$

n_{sv} represents the number of support vectors. α_i represents the Lagrange multiplier of support vector. $K(x, x_i)$ represents the kernel function. Through kernel function, SVM can classify in high-dimensional space and deal with nonlinear problems.

- The objective function calculation of SVM under kernel technique

In the kernel method, the objective function of SVM is employed to optimize the margin between support vectors, thereby enhancing classification performance by maximizing this margin. The equation integrates the Lagrange multiplier of the support vectors and the kernel function, enabling effective classification of nonlinear data. The calculation is expressed as:

$$\min_{\alpha} \frac{1}{2} \sum_{i=1}^{n_{sv}} \sum_{j=1}^{n_{sv}} \alpha_i \alpha_j y_i y_j K(x_i, x_j) - \sum_{i=1}^{n_{sv}} \alpha_i \tag{10}$$

The objective function calculation of SVM based on the kernel technique can find the optimal hyperplane in high-dimensional space and realize the accurate classification of complex data.

- The Karush-Kuhn-Tucker (KKT) condition of the dual problem is as follows:

During the SVM optimization process, the KKT conditions are applied to ensure the optimality of the solution. The KKT conditions are crucial for solving optimization problems, as they guarantee that the solution is globally optimal. The equation representing the KKT conditions is as follows:

$$\begin{cases} \alpha_i \geq 0 \\ y_i(w^T \cdot x_i + b) - 1 \geq 0 \\ \alpha_i[y_i(w^T \cdot x_i + b) - 1] = 0 \end{cases} \tag{11}$$

By satisfying the aforementioned conditions, SVM effectively captures nonlinear relationships in complex, multidimensional data, ensuring the optimal solution to the optimization problem and enabling accurate classification and prediction.

In this study, the Analytic Hierarchy Process (AHP) is employed to determine the weight of each index within the composite index. First, a hierarchical structure model is constructed, categorizing the indices into target, criterion, and index layers. The target layer aims at optimizing urban green space, while the criterion layer includes indices related to health, environmental quality, and community interaction. The index layer further refines these into specific quantitative metrics. This hierarchical approach ensures a systematic and structured determination of weights. In the operational process, professional judgment and evaluation are used to conduct pairwise comparisons of the indices at each level, determining their relative importance. A pairwise comparison matrix is then constructed, where each matrix element represents the relative importance ratio between two indices. The weights are calculated using the feature vector method, and the comparison matrix is normalized. The initial weight for each index is derived by calculating the maximum eigenvalue of the matrix and its corresponding eigenvector. To ensure consistency within the comparison matrix, the Consistency Ratio (CR) is calculated. The CR is determined by the ratio of the consistency index to the random consistency index, as outlined in Equation 12:

$$CR = \frac{CI}{RI} = \frac{\lambda_{\max} - n}{(n-1) \times RI} \tag{12}$$

$\lambda_{\max}$ is the largest eigenvalue of the comparison matrix. n means the order of the matrix. RI refers to the random consistency index, and CI denotes the consistency index. If the CR value is less than 0.1, it is considered that the matrix has good consistency. Otherwise, it is necessary to re-evaluate and adjust the element values in the comparison matrix.

In this study, three feedback optimization iterations were conducted. After the first optimization, the CR value was 0.15, exceeding the acceptable threshold of 0.1. Consequently, the results were returned to the expert group, with specific areas for improvement identified, prompting a re-evaluation and re-scoring. Following the second optimization, the CR value was reduced to 0.11. Although there was some improvement, the value still failed to meet the consistency requirements, necessitating further feedback, evaluation, and adjustment. After the third optimization, the CR value was successfully reduced to 0.08, meeting the consistency standard of <0.1. This ensured the consistency of the comparison matrix. Through these three optimization iterations, the final weights for each index were determined, accurately reflecting their relative importance in the comprehensive evaluation. The weights of each dependent variable index, categorized by type, are presented in Table 3.

To comprehensively assess the optimization of urban green space in Wuhan, this study introduces the calculation of a comprehensive index, which encapsulates the collective impact of several key factors on green space. This index reflects the interrelationships and significance of environmental quality, health, and community interaction indices. After determining the weight of each index through the AHP, these weights are applied to the actual data, enabling the quantification and holistic evaluation of each factor's contribution to urban green space. The calculation of the comprehensive index is expressed in Equation 13:

$$SI = \frac{\sum_{i=1}^{n} w_i * (p_i + \frac{1}{q_i})}{\sum_{j=1}^{m} \sum_{k=1}^{l} \left(\frac{x_{jk}}{\sum_{k=1}^{l} x_{jk}} \right) * (1 + \frac{y_{jk}}{\sum_{k=1}^{l} y_{jk}})} \tag{13}$$

Equation 13 integrates the scores and quantized values of the independent variables and urban green space indices. It computes

TABLE 3 Weight of each dependent variable index under each type.

Index	Health indices of Wuhan residents	Urban environmental quality index of Wuhan	Wuhan community interaction index
Green area	0.25	0.15	0.12
Vegetation coverage	0.20	0.18	0.10
Green coverage density	0.15	0.12	0.08
Green corridor length	0.10	0.20	0.05
Number of parks	0.08	0.14	0.20
Green coverage rate	0.07	0.10	0.22
Number of gardens	0.05	0.11	0.23

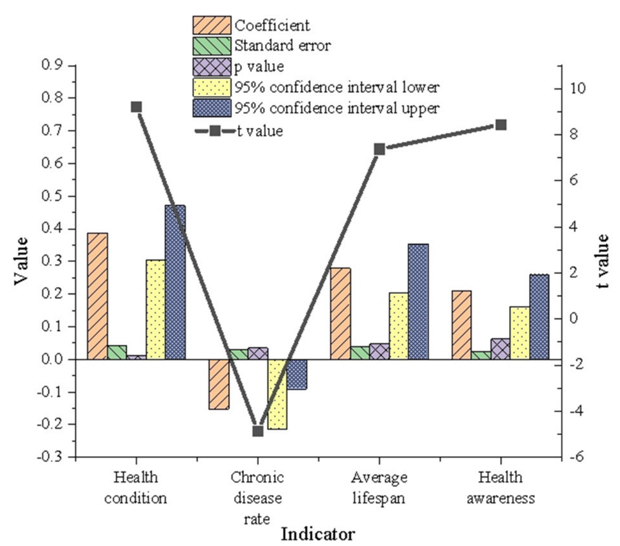

FIGURE 4
Verification results of multivariate model on residents' health in Wuhan.

the comprehensive index by taking the weighted average of the respective variables, alongside the normalized weighted sum of the urban green space indices. The equation's complexity arises from the combination of polynomial and fractional operations, reflecting the intricate relationships among multiple factors in the comprehensive evaluation. Here, w_i represents the weight of each variable index, p_i and q_i denote the score and quantized value of the independent variable, respectively. y_{jk} indicates the quantitative value of the urban green space index, while n and l correspond to the number and classification of the independent variable indices. x_{jk} and m refer to the score and count of urban green space indices.

5 Verification and analysis of multivariable models using ML algorithms

5.1 Regression analysis and verification of Wuhan residents' health

The multivariate model's verification and analysis results for Wuhan residents' health are revealed in Figure 4.

Figure 4 illustrates the regression results for the health condition index, with a coefficient of 0.387, a t-value of 9.214, and a p-value of 0.012. These values indicate that the health condition index significantly and positively influences urban green space. Similarly, the regression coefficient for average life expectancy is 0.279, with a p-value of 0.047 ($p < 0.05$), further demonstrating its significant positive effect on urban green space development. Conversely, while chronic disease incidence is statistically significant, its regression coefficient is -0.152, with a p-value of 0.035 ($p < 0.05$). This suggests a negative relationship between chronic disease incidence and urban green space. The impact of health awareness, although characterized by a regression coefficient of 0.211, appears less substantial, as its p-value exceeds the threshold for statistical significance. These findings underscore that enhancing residents' health levels and increasing average life expectancy contribute positively to the development and optimization of urban green spaces. Consequently, improvements in urban green infrastructure have the potential to elevate overall environmental quality and the quality of life for residents.

The regression analysis also highlights the critical role of urban green spaces in health promotion, particularly in enhancing life expectancy and overall health levels. However, the negative association observed with chronic disease incidence reveals potential regional disparities in the health benefits of green spaces, which may be attributed to underlying socioeconomic factors. Areas with high chronic disease prevalence are often characterized by limited green space availability and inadequate infrastructure. Residents in such areas, exposed to prolonged environmental stressors, may exhibit diminished health benefits from green spaces and an increased dependency on medical resources. Additionally, individuals with chronic diseases may use green spaces less frequently, further limiting the health-promoting effects of these areas. The findings highlight the need for strategic optimization of green space layouts to address disparities in accessibility and equity, particularly for vulnerable populations. Efforts to increase green coverage in densely populated areas, enhance infrastructure, and incorporate health-oriented design principles can significantly amplify the positive health impacts of green spaces. Such measures are essential for fostering the holistic development of healthy and sustainable urban environments.

5.2 Regression analysis and verification of urban environmental quality in Wuhan

The multivariate model's verification and analysis results for urban environmental quality in Wuhan are illustrated in Figure 5.

Figure 5 illustrates the degree and direction of the impact of Wuhan's urban environmental quality indices on urban green

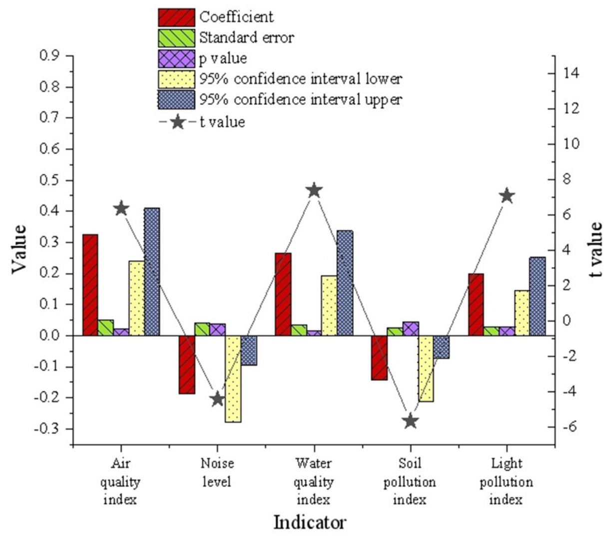

FIGURE 5
Verification results of multivariate model on urban environmental quality in Wuhan.

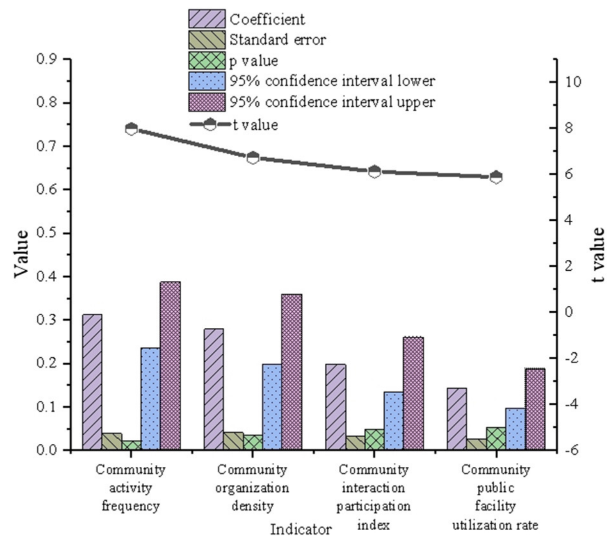

FIGURE 6
Verification results of multivariate model on community interaction in Wuhan.

space. The regression analysis reveals positive coefficients for air quality (0.324), water quality (0.265), and light pollution (0.198), indicating a positive correlation between these indices and urban green space. This suggests that improved environmental quality is associated with an increase in urban green space. Conversely, the regression coefficients for noise levels (−0.187) and soil pollution (−0.143) demonstrate a negative relationship with urban green space, signifying that deteriorating environmental conditions adversely affect green space availability. The *t*-values for noise levels (−4.429) and soil pollution (−5.684) further emphasize the significant influence of these factors on urban green space. The reliability of these results is supported by the 95% confidence interval's upper and lower bounds. These findings highlight the importance of enhancing air quality, water quality, and minimizing light pollution to support urban green space development. Simultaneously, addressing noise pollution and mitigating soil contamination are critical for improving overall environmental quality and fostering the expansion and optimization of urban green spaces.

A further analysis of these findings underscores not only the value of green spaces in improving environmental quality but also highlights their role in mitigating the urban heat island effect from a climate change perspective. Specifically, vegetation transpiration can reduce local urban temperatures, alleviating the adverse health impacts of extreme heat events on residents. Additionally, the soil and water retention functions of green spaces help alleviate the pressure on urban water systems during extreme rainfall events, demonstrating their critical regulatory role in the context of climate-induced extreme weather. Moreover, increasing ecological corridors and vegetation coverage in high-pollution areas can effectively reduce noise diffusion and the risks of soil contamination while enhancing the capacity for ecosystem services. From the intersectional perspective of climate change and healthy urban development, these measures provide actionable pathways for improving environmental quality and practical evidence for enhancing urban resilience.

Therefore, optimizing green space layouts should prioritize reducing noise and soil pollution while improving air and water quality indices. Through the planning of green buffer zones and the implementation of soil remediation projects, green spaces can simultaneously enhance environmental quality and ecosystem services, contributing greater value to the sustainable development of cities in the context of climate change.

5.3 Regression analysis and verification of community interaction in Wuhan

The verification and analysis results of multivariate model on Wuhan community interaction are indicated in Figure 6.

In Figure 6, the regression coefficients of community activity frequency and community organization density are relatively high, at 0.312 and 0.279, respectively, indicating that these factors have a substantial influence on urban green space. Conversely, the community interaction participation index and the utilization of community public facilities exhibit lower coefficients of 0.198 and 0.143, respectively, suggesting a more limited impact. Additionally, analysis of the standard error and *t*-values reveals that community activity frequency and community organization density have low standard errors and high *t*-values, underscoring the reliability and statistical significance of their estimates. In contrast, the higher standard errors and lower *t*-values associated with the community interaction participation index and the utilization of public facilities indicate that their estimates are less reliable and statistically significant. Overall, the frequency of community activities and the density of community organizations emerge as key drivers of urban green space optimization, whereas the influence of community

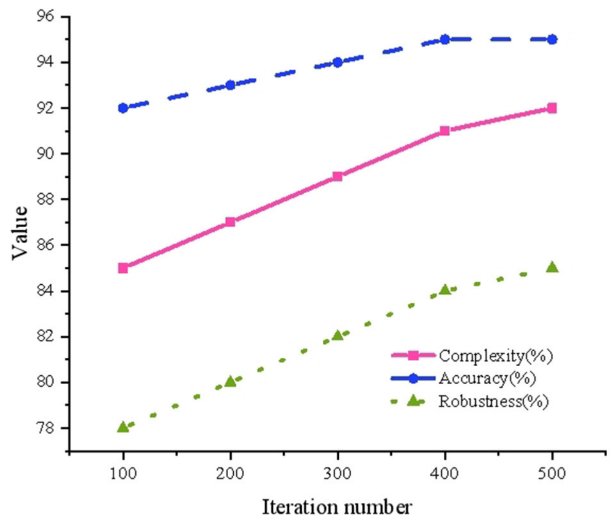

FIGURE 7
Performance verification analysis results of multivariate models.

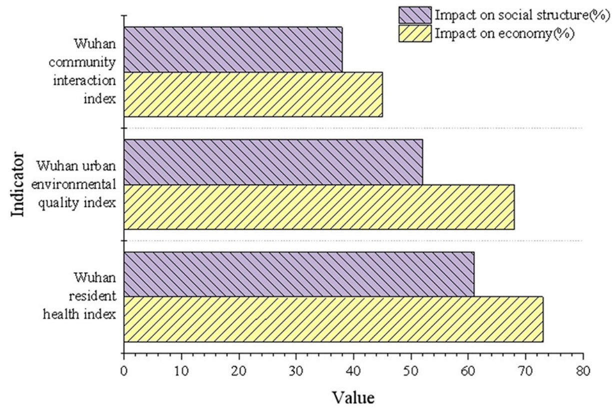

FIGURE 8
Analysis results of economic benefits and social structure impact.

interaction participation and public facility utilization remains comparatively modest.

The findings further emphasize the significant positive impact of community activity frequency and community organization density, highlighting the pivotal role of green spaces within the community ecosystem. These spaces not only facilitate resident interactions and enhance social cohesion but also strengthen the social value of urban green spaces. A deeper analysis reveals that increased community activity frequency correlates with more effective utilization of green spaces. Regular cultural and sports events, as well as everyday neighborhood interactions, contribute to fostering a strong sense of community belonging and active engagement. In contrast, lower indices of community interaction and public facility utilization suggest limited social participation among residents in certain areas, potentially reflecting inequities in the distribution of public resources. This shortfall may diminish the role of green spaces in fostering community vitality and improving residents' quality of life. These findings highlight deficiencies in the multifunctionality and equity of green space planning, particularly concerning the alignment of resident needs with spatial design. To address these issues, strategies such as the equitable allocation of community public facilities, increased investment in activity-oriented green spaces, and the promotion of diverse community governance participation can enhance the multifunctional potential of green spaces. These measures would allow green spaces to contribute more effectively to community ecosystems, achieving synergistic development across social, ecological, and environmental dimensions.

5.4 Performance verification analysis of multivariable models

The performance verification analysis results of multivariable models are suggested in Figure 7.

In Figure 7, an increase in the number of iterations corresponds to a gradual rise in model complexity, from 0.85 to 0.92, accompanied by a steady improvement in accuracy, which increases from 0.92 to 0.95. These trends indicate a progressive enhancement in the model's fitting capability and predictive performance. Simultaneously, the robustness index demonstrates an improvement from 0.78 to 0.85, suggesting increased model stability when applied to diverse datasets. These findings underscore that, even after multiple iterations, the multivariate model maintains high levels of accuracy and stability. Moreover, the model exhibits adaptability to complex data structures and variable environmental conditions, reinforcing its utility for dynamic prediction scenarios.

5.5 Analysis of the influence of the multivariate model on the economic benefit and social structure of Wuhan

The multivariate model's analysis results of the economic benefits and social structure of Wuhan are depicted in Figure 8.

In Figure 8, the optimization of health indices resulted in a 73% and 61% increase in the economic benefits and social structure impacts, respectively, within Wuhan's urban areas. Similarly, the environmental quality indices improved by 68% and 52%. These findings indicate that the optimization of green spaces significantly drives urban economic development and enhances social structures. Although the improvement rate of community interaction indices is relatively lower, its positive impact on economic and social structures reinforces the integral role of green spaces in the comprehensive enhancement of urban functions.

A deeper analysis reveals that green spaces mitigate urban heat island effects, directly reducing the adverse impacts of high temperatures on residents' productivity and daily lives. This contributes to a reduction in economic costs associated with energy consumption and medical expenses. Moreover, green spaces play a pivotal role in carbon sequestration by absorbing carbon dioxide, thereby providing crucial support for Wuhan's transition to a low-carbon economy. Additionally, rational green space layout and optimized distribution improve community interaction and social cohesion, making urban environments more adaptable to the dynamic demands of a climate-change context.

At the intersection of climate change adaptation and healthy city construction, the study demonstrates that integrating multidimensional dynamic optimization models can better align Wuhan's green space planning with ecological, economic, and social objectives. For high-density urban areas, priority should be given to the development of climate-adaptive ecological buffer zones. Enhancing vegetation diversity and improving green space accessibility can further maximize the synergistic effects of green spaces in improving resident wellbeing and promoting social stability. This optimization pathway not only strengthens the theoretical framework of the study but also provides robust support for future policy implementation.

6 Discussion

6.1 Research contributions

The findings of this study not only demonstrate the high applicability of the proposed model but also provide empirical data to better understand the multidimensional impacts of green spaces on urban health and environmental quality. These results hold significant reference value for similar urban contexts. Domestically, the study offers practical guidance for optimizing green space layouts in rapidly urbanizing, densely populated mid-to-large cities with limited green resources, such as Chongqing and Nanjing. These cities face considerable ecological pressures and an increasing demand for public health resources. By rationally allocating green spaces, improvements in quality of life and ecosystem service functions can be achieved to some extent. Internationally, for rapidly developing cities in Southeast Asia, such as Bangkok and Ho Chi Minh City, the study provides data-driven optimization pathways to address challenges such as uneven green space distribution, environmental pollution, and public health pressures. Additionally, for mid-sized cities with high population density, such as Budapest and São Paulo, as well as resource-constrained smaller cities, the machine learning techniques proposed in this study can precisely capture critical indicators to support scientific decision-making. This study deepens the understanding of healthy city metrics and offers universal solutions for green space management and planning across diverse global urban contexts. By doing so, it contributes to advancing sustainable urban development and improving urban resilience on a global scale.

The findings of this study are contextualized within the framework of existing research. The observed positive effects of health conditions and life expectancy closely align with the conclusions of Wu (7), who demonstrated that green spaces significantly enhance residents' quality of life by improving environmental quality and mental health. Similarly, the negative correlation between green space availability and chronic disease incidence supports the perspective that insufficient green spaces exacerbate exposure to pollution, thereby contributing to adverse health outcomes. Notably, the weaker influence of health awareness, a phenomenon seldom explored in depth in the literature, may be attributed to the underappreciation or limited utilization of green spaces by the public. This finding offers a promising avenue for future research to explore strategies for fostering greater awareness and engagement with green spaces. In terms of environmental quality, the results corroborate Tella and Balogun's (8) findings that noise pollution reduces the attractiveness and functionality of green spaces. Additionally, the significant negative impact of soil pollution on green space expansion, as identified in this study, underscores the critical need for ecological restoration strategies tailored to urban contexts. These findings provide a robust foundation for implementing targeted interventions, such as establishing ecological barriers to mitigate noise pollution and employing phytoremediation technologies to address soil contamination, thereby enhancing the sustainability and functionality of green spaces in Wuhan.

Considering these insights, and in light of Wuhan's specific urban dynamics, urban planners are encouraged to prioritize key indices identified in this study. For instance, leveraging the significant positive effects of health conditions and life expectancy aligns with the principles of the "healthy city" concept and can inform green space optimization strategies. In districts with limited green resources, the development of community parks and health trails can directly address residents' health needs and promote equitable access to green spaces. Furthermore, the strong correlations between air and water quality indices and environmental quality underscore the potential of green spaces to mitigate pollution. Urban planners can integrate these findings into the design of ecological barriers or vegetative buffers in areas with high pollution levels to enhance the regulatory functions of green spaces. Simultaneously, coordinated efforts in pollution control and green space restoration initiatives should be promoted to achieve synergistic benefits for the environment and public health.

When analyzed through the lens of academic advancements, this study significantly contributes to the exploration of the multifaceted functions of green spaces in the context of climate change. For instance, Pinto et al. (47) highlighted the link between urban heat island effects and extreme heat events, emphasizing the necessity of nature-based solutions to mitigate these phenomena. This study aligned closely with their perspective by demonstrating how optimized green space layouts effectively reduced urban heat island effects, providing region-specific insights for climate-adaptive urban planning. Similarly, Cherif et al. (48), through meta-analyses, revealed the temperature-regulating roles of green spaces under varying climatic conditions. Building on this, the findings of this study validated the substantial positive impact of green spaces in mitigating environmental stressors such as high pollution and noise levels, underscoring the regional specificity of these benefits. Furthermore, Han et al. (49), employing spatial econometric analyses, established that green spaces alleviated pollutants such as PM2.5. This study expands on their work by emphasizing the synergistic role of green ecosystems in simultaneously improving environmental quality and enhancing residents' wellbeing, thereby enriching the theoretical framework of green space ecosystem services. In summary, this study not only addresses a critical gap in the intersection of urban health and climate change research but also provides multidimensional data-driven insights to support policy formulation. It exemplifies the integration of academic and practical value, advancing the application of green spaces in building urban climate resilience and offering actionable strategies for green space management in diverse global urban contexts.

6.2 Limitations and future directions

Nevertheless, it is important to acknowledge certain limitations in this study that may affect the generalizability of the results. Firstly, the reliance on publicly available datasets introduces potential biases in data completeness and quality. For instance, the uneven spatial distribution of data points may lead to the underrepresentation or omission of certain areas, thereby weakening the model's performance in ensuring regional balance. Furthermore, the selection of health indicators was limited to quantifiable data, and non-quantifiable dimensions such as subjective wellbeing and mental health were not incorporated, which may constrain the comprehensive understanding of the social benefits of green spaces. Secondly, the assumption of linear relationships between variables oversimplifies the complexity of real-world interactions. The effects of green spaces on multidimensional indicators often exhibit non-linear characteristics; for example, health indicators may show non-linear jumps under certain threshold conditions, which linear analytical methods may fail to capture comprehensively. Lastly, the study's temporal and spatial scope was somewhat fixed, failing to account for the dynamic trends of green space usage across different seasons or over long-term urban planning periods. This raises the need for further research to evaluate the long-term effects of green spaces more comprehensively.

To overcome these limitations, future research should explore deeper advancements in data sources, methodological innovations, and the expansion of analytical scope. First, real-time data monitoring technologies should be integrated to enhance the dynamic nature and precision of the data, alongside community-based participatory approaches for data collection. This would ensure the inclusion of residents' subjective perceptions and cultural aspects, capturing the social benefits of green spaces and their adaptability to diverse population needs. Second, in terms of methodological innovation, future studies should integrate deep learning models or hybrid methods, applying non-linear analysis techniques to explore the relationships between multidimensional variables, thus providing a more comprehensive reflection of complex dynamic interactions. Such techniques can identify potential non-linear associations and multi-level mechanisms between variables, offering stronger support for the accuracy and interpretability of predictive outcomes. Furthermore, expanding the temporal and spatial scope of analysis is a critical direction for future development. For example, long-term data analysis could capture the dynamic trends of green space across different seasons and development stages, further revealing its potential contribution to addressing climate change and optimizing urban wellbeing (50). In summary, future research should drive the integration of data, methods, and scope optimization, fostering a deeper convergence between theory and practice in green space studies, and providing a more comprehensive scientific foundation for sustainable urban development.

7 Conclusion

This study explores the complex relationship between the optimization of urban green spaces in Wuhan and the multidimensional indices of a healthy city through the application of a multivariate model. By integrating RF with SVM algorithms, this study makes significant strides in quantifying the role of key indices and uncovering their interaction mechanisms. The findings demonstrate that green spaces are essential in improving residents' health and extending life expectancy. Additionally, these spaces play a crucial role in enhancing urban environmental quality and fostering community interaction. This study not only enriches the theoretical understanding of the interactive mechanisms between green spaces and healthy city development, but also provides critical empirical evidence to guide green space and urban planning efforts in Wuhan. Through a systematic analysis of indices such as environmental quality, community interaction, and health conditions, the study emphasizes the irreplaceable role of green spaces as a central element of urban resilience and social wellbeing.

From a practical perspective, the findings offer valuable decision-making support for urban planning in Wuhan within the framework of a healthy city. Positive indices, such as health conditions and life expectancy, highlight the potential of green spaces to optimize the living environment and underscore their importance in promoting ecosystem sustainability and improving residents' wellbeing. Furthermore, this study outlines specific strategies for addressing negative impacts such as noise and soil pollution, recommending the construction of ecological barriers and the promotion of phytoremediation technologies. These strategies provide practical pathways for balancing green space development with urban growth objectives. Additionally, the model architecture and empirical methods utilized in this study demonstrate strong generalizability, offering a reference framework and practical guidance for other cities facing similar challenges in green space optimization. Moving forward, the development and optimization of green spaces should not only focus on enhancing ecological and health benefits, but also on integrating them more deeply into social and cultural dimensions. This approach aims to fully harness the multifaceted contributions of green spaces to urban health, ecological balance, and social development.

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

XZh: Conceptualization, Formal analysis, Validation, Visualization, Writing – original draft. XZo: Data curation, Software, Supervision, Writing – original draft. WX: Investigation, Methodology, Project administration, Resources, Writing – review & 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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References

1. Javadi R, Nasrollahi N. Urban green space and health: the role of thermal comfort on the health benefits from the urban green space; a review study. *Build Environ.* (2021) 202:108039. doi: 10.1016/j.buildenv.2021.108039

2. Wu L, Kim SK. Health outcomes of urban green space in China: evidence from Beijing. *Sustain Cities Soc.* (2021) 65:102604. doi: 10.1016/j.scs.2020.102604

3. Li C, Liang F, Liang Y, Wang Z. Low-carbon strategy, entrepreneurial activity, and industrial structure change: evidence from a quasi-natural experiment. *J Clean Prod.* (2023) 427:139183. doi: 10.1016/j.jclepro.2023.139183

4. Li DD, Guan X, Tang TT, Zhao LY, Tong WR, Wang ZY. The clean energy development path and sustainable development of the ecological environment driven by big data for mining projects. *J Environ Manage.* (2023) 348:119426. doi: 10.1016/j.jenvman.2023.119426

5. Li C, Tang W, Liang F, Wang Z. The impact of climate change on corporate ESG performance: the role of resource misallocation in enterprises. *J Clean Prod.* (2024) 445:141263. doi: 10.1016/j.jclepro.2024.141263

6. Agyeman PC, Kebonye NM, John K, Boruvka L, Vasat R, Fajemisim O. Prediction of nickel concentration in peri-urban and urban soils using hybridized empirical Bayesian Kriging and support vector machine regression. *Sci Rep.* (2022) 12:3004. doi: 10.1038/s41598-022-06843-y

7. Wu J. The fourth paradigm: a research for the predictive model of livability based on machine learning for smart city in The Netherlands. *Landscape Architecture.* (2020) 27:11–29. doi: 10.14085/j.fjyl.2020.05.0011.19

8. Tella A, Balogun A-L, Adebisi N, Abdullah S. Spatial assessment of PM10 hotspots using Random Forest, K-Nearest Neighbour and Naïve Bayes. *Atmos Pollut Res.* (2021) 12:101202. doi: 10.1016/j.apr.2021.101202

9. Elhamdouni D, Arioua A, Karaoui I. Monitoring urban expansion using SVM classification approach in Khenifra city (Morocco). *Modeling Earth Syst Environ.* (2021) 8:293–8. doi: 10.1007/s40808-021-01092-w

10. Chowdhury MS. Comparison of accuracy and reliability of random forest, support vector machine, artificial neural network and maximum likelihood method in land use/cover classification of urban setting. *Environm Challen.* (2024) 14:100800. doi: 10.1016/j.envc.2023.100800

11. Chuchkova M. The healthy cities project of the World Health Organization and the approach to its realization. *Probl Khig.* (1994) 19:3–9. doi: 10.1934/S0042-96862003000300013

12. Vosheva NA, Kamynina NN, Korotkova EO, Voshev DV. Walkability as the key element of urban planning within the Healthy Cities concept (systematic review). *Health Care Russian Federat.* (2020) 64:294–300. doi: 10.46563/0044-197X-2020-64-5-294-300

13. Shah SA, Seker DZ, Rathore MM, Hameed S, Yahia SB, Draheim D. Towards disaster resilient smart cities: can internet of things and big data analytics be the game changers? *IEEE Access.* (2019) 7:91885–903. doi: 10.1109/ACCESS.2019.2928233

14. Vital Strategies. 10.L. Workshop: city-level action to promote public health. *Eur J Public Health.* (2021) 31:103321. doi: 10.1093/eurpub/ckab164.767

15. Wilkes-Allemann J, Kopp M, van der Velde R, Bernasconi A, Karaca E, Cepić S, et al. Envisioning the future—Creating sustainable, healthy and resilient BioCities. *Urban Forest Urban Green.* (2023) 84:127935. doi: 10.1016/j.ufug.2023.127935

16. De Leeuw E. Researching a diverse epistemic social movement: the challenges and rewards of european healthy cities healthy cities realist synthesis. In: Potvin L, Jourdan D, editors. *Global Handbook of Health Promotion Research, Vol.* 1: Mapping Health Promotion Research. Cham: Springer International Publishing (2022). p. 739–57.

17. Jevtic M, Zoric M, Orlovic S, Bouland C. Looking for a healthy breath - the importance and potential of urban green spaces in the city: Case study of Novi Sad, Vojvodina Province, Serbia. *Eur J Public Health.* (2021) 31:36–77. doi: 10.1093/eurpub/ckab164.493

18. Grazuleviciene R, Andrusaityte S, Dedele A, Grazulevicius T, Valius L, Rapalavicius A, et al. Urban environment and health: a cross-sectional study of the influence of environmental quality and physical activity on blood pressure. *Int J Environm Res Public Health.* (2021) 18:6126. doi: 10.3390/ijerph18116126

19. Zhang H, Feng Z, Chen P, Chen X. Development of a tree growth difference equation and its application in forecasting the biomass carbon stocks of Chinese Forests in 2050. *Forests.* (2019) 10:582. doi: 10.3390/f10070582

20. Vijayalaxmi RS, Dnyanesh MM. Assessment of carbon sequestration potential of urban green spaces (PMC gardens) in Pune City, India. *Modern Adv Geograp Environm Earth Sci.* (2021) 7:37–55. doi: 10.9734/bpi/magees/v7/2691E

21. Liu Q, Tian Y, Yin K, Zhang F, Huang H, Chen F. Landscape pattern theoretical optimization of urban green space based on ecosystem service supply and demand. *ISPRS Int J Geo-Inform.* (2021) 10:263. doi: 10.3390/ijgi10040263

22. Guan Y, Li X, Li S, Sun H, Liu H. Effect of Urban fringes green space fragmentation on ecosystem service value. *PLoS ONE.* (2022) 17:e0263452. doi: 10.1371/journal.pone.0263452

23. Wang L. Energy conservation optimization and numerical simulation of urban green space landscape pattern. *Int Trans Elect Energy Syst.* (2022) 2022:5324854. doi: 10.1155/2022/5324854

24. Wolch JR, Byrne J, Newell JP. Urban green space, public health, and environmental justice: The challenge of making cities 'just green enough'. *Landsc Urban Plan.* (2014) 125:234–44. doi: 10.1016/j.landurbplan.2014.01.017

25. Zhao C-X, Liu J-N, Li B-Q, Ren D, Chen X, Yu J, et al. Multiscale Construction of Bifunctional Electrocatalysts for Long-Lifespan Rechargeable Zinc–Air Batteries. *Adv Funct Mater.* (2020) 30:2003619. doi: 10.1002/adfm.202003619

26. Wijaya MIH, Ariyani NM, Priambudi BN, Gumelar A, Ichsanudin H. Urban heat island: identification of spatial patterns of green open space for mitigation in Kendal Industrial Park, Indonesia. *IOP Conf Series: Earth Environm Sci.* (2021) 887:012010. doi: 10.1088/1755-1315/887/1/012010

27. Thapa P, Torralba M, Buerkert A, Dittrich C, Plieninger T. Ecological and social outcomes of urbanization on regional farming systems: a global synthesis. *Ecol Soc.* (2021) 26:24. doi: 10.5751/es-12579-260324

28. Dzhambov AM, Dimitrova DD. Urban green spaces' effectiveness as a psychological buffer for the negative health impact of noise pollution: a systematic review. *Noise Health.* (2014) 16:157–65. doi: 10.4103/1463-1741.134916

29. Bloemsma LD, Wijga AH, Klompmaker JO, Hoek G, Janssen NAH, Oldenwening M, et al. Green space, air pollution, traffic noise and saliva cortisol in children: the PIAMA study. *Environm Epidemiol.* (2021) 5:e141. doi: 10.1097/ee9.0000000000000141

30. Derkzen ML, van Teeffelen AJA, Verburg PH. Green infrastructure for urban climate adaptation: How do residents' views on climate impacts and green infrastructure shape adaptation preferences? *Landsc Urban Plan.* (2017) 157:106–30. doi: 10.1016/j.landurbplan.2016.05.027

31. Allam Z, Bibri SE, Chabaud D, Moreno C. The '15-Minute City' concept can shape a net-zero urban future. *Humanities and Social Sciences Communications.* (2022) 9:126. doi: 10.1057/s41599-022-01145-0

32. Browning MHEM, Rigolon A, McAnirlin O, Yoon H. Where greenspace matters most: A systematic review of urbanicity, greenspace, and physical health. *Landsc Urban Plan.* (2022) 217:104233. doi: 10.1016/j.landurbplan.2021.104233

33. Rigolon A, Browning M, McAnirlin O, Yoon HV. Green space and health equity: a systematic review on the potential of green space to reduce health disparities. *Int J Environ Res Public Health.* (2021) 18:2563. doi: 10.3390/ijerph18052563

34. Nguyen PY, Astell-Burt T, Rahimi-Ardabili H, Feng X. Green space quality and health: a systematic review. *Int J Environ Res Public Health.* (2021) 18:11028. doi: 10.3390/ijerph182111028

35. Ali MJ, Rahaman M, Hossain SI. Urban green spaces for elderly human health: a planning model for healthy city living. *Land Use Policy.* (2022) 114:105970. doi: 10.1016/j.landusepol.2021.105970

36. Du H, Zhou F, Cai Y, Li C, Xu Y. Research on public health and well-being associated to the vegetation configuration of urban green space, a case study of Shanghai, China. *Urban Forest Urban Green.* (2021) 59:126990. doi: 10.1016/j.ufug.2021.126990

37. Knobel P, Dadvand P, Alonso L, Costa L, Español M, Maneja R. Development of the urban green space quality assessment tool (RECITAL). *Urban Forest Urban Green.* (2021) 57:126895. doi: 10.1016/j.ufug.2020.126895

38. Georganos S, Grippa T, Niang Gadiaga A, Linard C, Lennert M, Vanhuysse S, et al. Geographical random forests: a spatial extension of the random forest algorithm to address spatial heterogeneity in remote sensing and population modelling. *Geocarto Int.* (2019) 36:121–36. doi: 10.1080/10106049.2019.1595177

39. Guo Q, Zhang J, Guo S, Ye Z, Deng H, Hou X, et al. Urban tree classification based on object-oriented approach and random forest algorithm using unmanned aerial vehicle (UAV) multispectral imagery. *Remote Sens.* (2022) 14:3885. doi: 10.3390/rs14163885

40. Shafizadeh-Moghadam H, Minaei M, Pontius Jr RG, Asghari A, Dadashpoor H. Integrating a forward feature selection algorithm, random forest, and cellular automata to extrapolate urban growth in the tehran-karaj region of Iran. *Comput Environ Urban Syst.* (2021) 87:101595. doi: 10.1016/j.compenvurbsys.2021.101595

41. Casali Y, Aydin NY, Comes T. Machine learning for spatial analyses in urban areas: a scoping review. *Sustain Cities Soc.* (2022) 85:104050. doi: 10.1016/j.scs.2022.104050

42. Oukawa GY, Krecl P, Targino AC. Fine-scale modeling of the urban heat island: a comparison of multiple linear regression and random forest approaches. *Sci Total Environm.* (2022) 815:152836. doi: 10.1016/j.scitotenv.2021.152836

43. Tariq A, Yan J, Gagnon AS, Riaz Khan M, Mumtaz F. Mapping of cropland, cropping patterns and crop types by combining optical remote sensing images with decision tree classifier and random forest. *Geo-Spatial Inform Sci.* (2022) 26:302–20. doi: 10.1080/10095020.2022.2100287

44. Darabi H, Torabi Haghighi A, Rahmati O, Jalali Shahrood A, Rouzbeh S, Pradhan B, et al. A hybridized model based on neural network and swarm intelligence-grey wolf algorithm for spatial prediction of urban flood-inundation. *J Hydrol.* (2021) 603:126854. doi: 10.1016/j.jhydrol.2021.126854

45. Lučin I, Lučin B, Carija Z, Sikirica A. Data-driven leak localization in urban water distribution networks using big data for random forest classifier. *Mathematics.* (2021) 9:672. doi: 10.3390/math9060672

46. Khajavi H, Rastgoo A. Predicting the carbon dioxide emission caused by road transport using a Random Forest (RF) model combined by Meta-Heuristic Algorithms. *Sustain Cities Soc.* (2023) 93:104503. doi: 10.1016/j.scs.2023.104503

47. Pinto BG, Magalhães J, Silva Lopes H. Urban heat island and extreme heat in Portuguese cities of Tâmega and sousa: a comprehensive study on climate change impacts. In: Filho WL, Vidal DG, Dinis MAP, editors. *Planetary Health and Climate Change: Understanding the Impacts of Climate Change to the Well-Being of Our Planet.* Cham: Springer Nature Switzerland (2024). p. 283–308.

48. Cherif A, Lasram A, Lopes H, Silva L. The extent of the impact of green spaces on urban heat Islands: a meta-analysis of research using remote sensing between 2010 and 2023. *Preprint* (2024). doi: 10.21203/rs.3.rs-4534390/v1

49. Han L, Zhang R, Wang J, Cao S-J. Spatial synergistic effect of urban green space ecosystem on air pollution and heat island effect. *Urban Climate.* (2024) 55:101940. doi: 10.1016/j.uclim.2024.101940

50. Atmojo ME, Darumurti A, Hanif NA. A dynamics of urban transport arrangement policies to support the achievement of sustainable transportation. *J Contemp Govern Public Policy.* (2024) 5:1–18. doi: 10.46507/jcgpp.v5i1.185

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From Urban village housing to tenant mental health: the crucial role of community attachment in Chinese megacities

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Housing has been a longstanding social issue in China's megacities, profoundly affecting the residents' quality of life. Urban villages in megacities, despite their substandard living conditions, provide affordable housing for many residents. The study of living conditions and their social implications in urban villages has been a central theme in Chinese urban research. However, previous research on Chinese urban villages has paid less attention to the relationship between tenants' mental health, housing quality and community attachment. This study selects seven typical urban villages in Shenzhen as the study cases, collecting first-hand anonymous questionnaire data to study tenants' mental health status and explore the mediating role of community attachment in the relationship between housing quality and residents' mental health. The finds show that the housing quality (β = 0.228, p = <0.05) and housing affordability (β = 0.196, p = <0.05) have a significant effect on tenants' mental health. Specifically, better the housing quality and lower the housing affordability are associated with improved mental well-being among urban village tenants. Additionally, community attachment (β = 0.416, p = <0.05) has a significant positive impact on tenants' mental health, and serves as an important mediating factor in the relationship between housing quality and tenants' mental health. This study proposes that improving living quality in megacity urban villages and creating a favorable living environment can increase tenants' attachment to urban villages, and significantly improve their mental health. These factors should be emphasized in the current urban renewal policy for Chinese megacities.

KEYWORDS

Urban villages, housing quality, community attachment, tenant mental health, megacities, Shenzhen

1 Background

China's rapid economic development over the past few decades has driven an substantial migration from rural areas and small towns to large, economically prosperous cities in pursuit of employment opportunities and a better quality of life. According to China's seventh population census (2020), the urbanization rate has exceeded 60%. The migrant population is an important force driving the rapid development of cities, but due to the concentrated flow of migration in China, the housing supply in megacities has long been insufficient. As a result, housing shortages remain one of the most significant barriers to the integration of China's so-called "migrant population" into megacities (1). Faced with unaffordable housing prices in megacities, many urban dwellers opt for rental accommodation. Urban villages are a special type of settlement in the structure of China's megacity housing market. Unlike commercial residential property, urban villages generally offer substandard living conditions and lack essential public services, leading to a high concentration of cheap rental housing (2). As urban villages accommodate a large number of low-and middle-income earners and "urban outsiders," they have become a long-standing social issue in China (3).

Urban villages are a unique spatial phenomenon emerging from China's urbanization process (4). Due to the dualistic structure of the land system (division between collective and state-owned land), some villages that have not been expropriated and demolished by the government have gradually been surrounded by urbanized areas. As a result, urban villages are often surrounded by a large number of high-rise buildings, and many are located next to the urban central district (5). Their close proximity to major employment centers, coupled with affordable rental costs, renders them particularly appealing to low-income groups (6). However, living conditions in urban villages are often substandard, with common issues including overcrowding, environmental pollution, high building density and inadequate infrastructure.

While numerous studies have focused on the living conditions of urban village residents (2), few scholars have paid attention to the community attachment and mental health of residents. Despite poor living conditions, urban villages often function as long-term residences for many migrants, effectively becoming an alternative home. As a result, the extent of tenants' community attachment to urban villages has remained a subject of debate in the academic literature (7, 8). Therefore, it is necessary to consider the role of community attachment in shaping the relationship between housing quality and mental health of tenants, to gain a deeper understanding of the real living conditions of urban village tenants in megacities.

This study investigates the relationship between housing quality in urban villages and tenants' mental health, with a particular focus on the mediating role of community attachment. A survey was conducted in seven typical urban villages in Shenzhen, one of China's most densely populated megacities. Despite its economic prosperity, Shenzhen faces urban challenges, such as high property prices, housing affordability issues. Against this background, Shenzhen's urban villages have played an important role in housing supply providing shelter to a large migrant population (9, 10). According to the *Shenzhen Urban Village Building Dictionary 2022*, issued by the China Development Institute (Shenzhen), Shenzhen's urban villages accounts for 36.3% of the city's total housing floor area, and may be able to accommodate approximately 10 million residents. Recognizing their role in relieving housing pressures, the Shenzhen government has implemented various renewal policies to promote the housing quality. In recent years, Shenzhen has promoted 'the unified renovation and unified leasing' model for urban villages, allowing private enterprises to participate in housing improvement. While this policy has enhanced housing conditions, it has also led to rental costs. Given the large number of long-term residents in urban villages, Shenzhen provides an ideal case for studying the impact of the living environment on tenants' mental health. The findings of this study can also provide urban renewal policies for urban villages in China.

2 Literature review and research hypotheses

2.1 The relationship between housing quality and residents' mental health

China's rapid urbanization over the past few decades has driven large-scale migration from the countryside to the cities, creating a unique landscape of urban villages under the dualistic land system (11). In particular, the growing population size of China's megacities have resulted in migration into these economically prosperous cities, exacerbating the tension between population expansion and housing supply. Due to limited affordable housing resources in megacities, urban villages with substandard living conditions provide a large amount of cheap housing for the migrant population (3).

However, these cheap housing units in urban villages are often widely criticized for their cramped living space, poor community living environment, lack of public services, low-quality construction, safety concerns etc. (12, 13). Many scholars have conducted extensive research on the housing quality in urban villages. For example, Li et al.'s study in Xiamen showed that the poor indoor environment of low-cost housing in urban villages had significant negative health effects on tenants (14). However, some researchers have suggested that many migrant workers are more concerned about the distance from their place of employment and the cost of living than the housing quality (15). Without urban villages, many low-income migrant workers would be unable to sustain their livelihoods in the city (*Ibid*).

Therefore, the first question is whether the housing quality in urban villages has an impact on the mental health of the residents, a topic that remains controversial in the literature. While poorer housing quality can affect the mental health of residents in some urban villages to a certain extent (32), housing conditions vary significantly across different cities, and their effects on tenants may differ. In particular, in Chinese mega-cities such as Shenzhen, urban villages have long served as key settlement for migrants, playing a crucial role in facilitating the integration of low-income groups into the urban fabric. Therefore, we first test the relationship between objective living conditions and tenant mental health in megacity urban villages.

Based on established research, this study proposes hypothesis 1: *Better housing quality in urban villages can significantly and positively affect tenants' mental health (H1).*

While the literature on housing quality provides valuable insights into how the physical characteristics of living environments directly influence mental health outcomes, it is important to recognize that residents' well-being is also shaped by the economic burden of housing. In the context of urban villages—where many tenants face financial constraints—the affordability of housing emerges as a critical factor that may compound or mitigate the effects of substandard living conditions. The next section, therefore, shifts the focus from the physical attributes of housing to examine how housing affordability influences residents' mental health.

2.2 The relationship between Housing affordability and residents' mental health

The large number of jobs in megacities serves as a major driver of sustained population inflows. However, a number of studies have shown that urban residents have a higher risk of mental illness than rural residents (16). Several scholars have conducted extensive research on the relationship between community living environments and residents' mental health. For example, Ma et al. (2018) examined the association between various types of noise pollution and mental health symptoms in Beijing residents, finding that higher perceived exposure to noise pollution was significantly correlated with poorer mental health (33).

In addition, housing conditions, which are related to the costs and quality of life of urban residents, have also been cited by many scholars as an influencing factor on the mental health of residents. As Seo and Park (17), in their study of the Survey of Living Conditions and Welfare Needs of Korean Adolescents ($n = 1{,}308$), found that material hardship caused by housing cost burdens was negatively associated with mental health in single-person households (17). Xiao et al. (2018) used a structural equation modeling approach to explore the impact of housing conditions on mental health among Shanghai's migrant population, demonstrating that housing conditions have a direct impact on mental health. Their findings indicated that housing conditions have an indirect impact on mental health through neighborhood satisfaction (34).

While many migrants in China's megacities reside in urban villages—whose substandard housing conditions have been widely criticized—their affordability remains a crucial yet often overlooked factor. Therefore, it is necessary to consider housing affordability as an influencing factor, while many migrants in China's megacities reside in urban villages—whose substandard housing conditions have been widely criticized—their affordability remains a crucial yet often overlooked factor.

Accordingly, this paper proposes hypothesis 2: *Housing affordability is negatively correlated with tenant mental health in megacity urban villages (H2).*

Although housing affordability is a key determinant of mental health—reflecting the financial pressures faced by residents—it does not capture the full spectrum of psychosocial factors inherent in urban living. In urban villages, the emotional bonds and sense of belonging that tenants develop with their communities can also have a profound impact on their mental well-being. Consequently, the subsequent section explores the role of community attachment, aiming to elucidate how these emotional ties may mediate and moderate the relationship between housing conditions and mental health outcomes.

2.3 The role of community attachment in urban villages

Community attachment is an important dimension in evaluating the relationship between residents and their community. As the predecessor of the urban village was a traditional rural community with a clan-based society, indigenous residents maintain strong emotional bonds and economic ties to their communities. However, for the large number of non-local tenants renting in urban villages, their emotional connections to urban villages are complicated (18).

On the one hand, for many low-income earners, urban villages serve as long-term places of residence, where their living conditions are closely related to the surrounding environment. On the other hand, within a specific institutional context, they are often regarded as "outsiders" or "strangers to the city" and may leave the urban villages at any time, either voluntarily or involuntarily (19, 20). In this scenario, the nature of tenants' community attachment to urban villages remains a subject worthy of further exploration.

Du and Li's (21) study on migrants in Guangzhou's urban villages found that these settlements provide a transitional refuge for migrants' integration into urban life. Their findings further indicate that community qualities and community relations influence migrants' sense of attachment to urban villages. Similarly, Chang et al. (22) demonstrated that housing conditions, neighborhood environments, and social relationships are positively related to community attachment, with variations in social relationships and physical environments leading to differing level of community attachment. Liu et al. (23) concluded that residential uncertainty and poor neighborhood environments reduce migrants' sense of urban belonging.

Given that community attachment has a positive impact on residents' life status, it is also shaped by external living conditions and, in turn, may affect residents' mental health. Accordingly, we used community attachment as a mediating and moderating variable to analyze its role in the relationship between housing quality and tenants' mental health in urban villages.

Thus, the third hypothesis proposed in this study is: *Community attachment mediates and moderates the relationship between housing quality and tenant mental health (H3).*

In summary, this study analyses the relationship between community attachment, housing quality, housing affordability and tenants' mental health, thereby constructing a theoretical analysis framework (Figure 1). The proposed model conceptualizes housing quality and housing affordability as independent variables, while tenant mental health serves as the dependent variable. It further

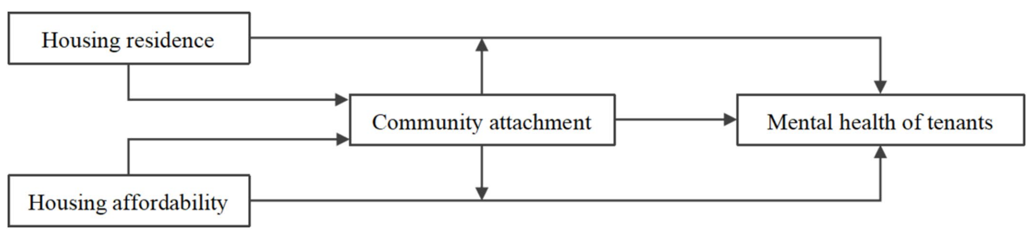

FIGURE 1
Theoretical framework of this study.

validates the role and mechanisms of community attachment within these relationships.

3 Data and methodology

3.1 Data collection

Through stratified sampling approach, one community was randomly selected from the villages that had been transformed into urban villages in each district of Shenzhen. After fully considering the feasibility of the survey, 7 communities of the research object were finally obtained.

The study used anonymous collection to distribute questionnaires from December 2023 to January 2024 to tenants within the following seven communities: the Nanling Village and Longxi Community in Longgang District, Shenzhen; the Buchong Village and Xinqiao Community in Bao'an District; the Zhangge Village in Longhua District; the Shuiwei Village in Futian District; and the Baimang Community in Nanshan District (Figure 2). Researchers coordinated with local community staff to facilitate questionnaires in the community during both working and non-working hours. A systematic sampling method was adopted to distribute questionnaires. Questionnaires were distributed every 10 households according to the house numbers of residents' addresses until the target sample size was reached.

In this survey, a total of 750 questionnaires were distributed, of which 703 were deemed valid, yielding a valid response rate of 93.7. The questionnaire categorized the observed variables into five sections: housing quality in housing and community, housing affordability, community attachment, tenant mental health and individual economic and social attributes. The first four of these were obtained through subjective evaluations by the respondents, using a Likert scale with values ranging from 1 to 5 according to the degree of agreement or satisfaction.

3.2 Descriptive statistical analyses

This paper uses SPSS 26.0 software to statistically analyze the main characteristics of the individual economic and social attributes of the research samples, such as gender, age, marital status, and childbearing status (Table 1).

The results showed that the gender distribution of the study samples was balanced with 53.8% male and 46.2% female. The average age of the respondents was 39 years. Regarding marital status, nearly two-thirds of the respondents were married.

Regarding fertility status 40.0% of respondents had two children—the most common category—while 22.6% had no children, 29.9% had one child, and 7.5% had three or more children. In terms of educational attainment, the proportions of respondents graduated from primary or secondary school, junior high school, senior high school, junior college or bachelor's degree, and master's degree or above were 10.2, 35.3, 24.5, 29.3, and 0.7%, respectively.

In terms of monthly income level, 32.3% of the respondents had a monthly income of "less than CNY 3,000," 33.3% had a monthly income of "CNY 3,000-6,000," 20.9% had a monthly income of "CNY 6,000-9,000," and a smaller proportion had a monthly income of more than CNY 9,000.CNY.

Table 2 shows the descriptive statistics for each variable. The means of the respondents' scores for housing quality, cost of residence, and community attachment all ranged from 3.182 to 3.707. The average rating score of respondents on the housing quality in urban villages was 3.71, reflecting that in general respondents rated urban villages relatively favorably. Respondents'

FIGURE 2
Map of the surveyed communities' distribution.

TABLE 1 Description of the samples' socioeconomic characteristics.

Basic information	Classification	Count	Sample proportion	Average value
Gender	Male	378	53.8%	—
	Female	325	46.2%	—
Age		—	—	39
Marital status	Unmarried	140	19.9%	—
	Married	562	79.9%	—
	Else	1	0.1%	—
Fertility status	Zero child	159	22.6%	—
	One Child	210	29.9%	—
	Two children	281	40.0%	—
	Three children and above	53	7.5%	—
Academic qualification	Primary school	72	10.2%	—
	Junior high school	248	35.3%	—
	Senior high school	172	24.5%	—
	Junior college or undergraduate degree	206	29.3%	—
	Master's degree or above	5	0.7%	—
Monthly income level	Less than 3,000 CNY	227	32.3%	—
	3,000–6,000 CNY	234	33.3%	—
	6,000–9,000 CNY	147	20.9%	—
	9,000–12,000CNY	47	6.7%	—
	12,000–15,000CNY	27	3.8%	—
	15,000 CNY or more	21	3.0%	—

TABLE 2 Descriptive statistics of the means of the variables.

Variable name	N	Minimum value	Maximum values	Average value	Standard deviation
Housing quality	703	1.00	5.00	3.7073	0.69620
Community attachment	703	1.00	5.00	3.5602	0.72360
Housing affordability	703	1.00	5.00	3.1821	0.66097

TABLE 3 Scoring results of tenants' mental health in the surveyed urban villages in Shenzhen.

Variable	Score ($\bar{x} \pm s$)	*t*-value	*p*-value
Mental health	74.6401±12.6318	0.4909	0.001

community attachment to the urban village was 3.56, also indicating that the surveyed tenants in general showed a potentially strong attachment to the urban village in which they live.

Compared to the former two variables, surveyed tenants rated the cost of housing relatively low, with an average score of 3.18, reflecting the fact that housing affordability of living in a megacity urban village was perceived as relatively affordable.

In this study, the variable of mental health of tenants was calculated using the SF scale scoring method proposed about mental health (MH), with higher MH scores indicating better mental health. The results in Table 3 show the mental health scores of tenants in this survey and compared with the results of the quality-of-life research conducted by Wang et al. in five Chinese cities, the mental health scores of tenants in urban villages in Shenzhen were below the mean value of 77.61 (24).

3.3 Variable measurement

Housing quality: This study uses two dimensions (housing internal conditions and housing external conditions) of housing quality for evaluation (Table A-1). Among them, the evaluation of housing internal conditions includes indicators such as housing location, housing quality, housing spatial layout, and housing facilities. The evaluation of housing external conditions includes community public service facilities, community road, community environment and sanitation, community management and security.

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Housing affordability: In the measurement of housing affordability (Table A-1), this study combines three aspects: living expenses, rental costs, and commuting costs.

Community attachment: The measurement of community attachment used in this study (Table A-1) is proposed by Williams et al.'s research, which measures six dimensions, including community meaning, community identity, community nostalgia, community pride, community significance and community belonging (25–27).

Mental health: Tenant mental health was the dependent variable in this study. This study used the medical outcomes study 36-item short form health survey (SF-36), which evaluates the dimensions of nervousness, dumps, calmness, mood, and happiness.

3.4 Tests of reliability and validity of the variables

In this study, the internal consistency of the variables was tested through the Cronbach's a coefficient to ensure the data quality of the measurements and to ensure that the next analyses could be carried out. The results of the Cronbach's a coefficient test for each dimension of the variables shows that the Cronbach coefficient values corresponding to the dimensions included in the variables of this study are all greater than 0.80, and the total correlations of the correction terms are all greater than 0.6, which indicates that the dimensions of the variables of the present study have high reliabilities, and all of them have good internal consistency.

To test the multicollinearity between the factors and to exclude the factors with small effects, for the validity test this study conduct exploratory factor analysis on the variables (Table 4). The principal component extraction method was used to extract the common factors and the extracted common factors were rotated using the variance maximization orthogonal rotation method, and the factor loading values of the measured indicators after orthogonal rotation ranged from 0.76–0.93, which indicates that the observed variables are affected by the latent variables with a high intensity, and all of them can be explained by the latent variables in a better way, and therefore the validity of the observed variables is reliable.

TABLE 4 Results of the exploratory factors analysis.

Dimension	Variable name	Factor load	Cronbach's Alpha	Eigenvalue	Cumulative variance contribution(%)
Housing quality	Housing location	0.877	0.823	44.850	27.852
	Housing quality	0.866	—	—	—
	Housing spatial layout	0.841	—	—	—
	Housing Facilities	0.808	—	—	—
	Community public service facilities	0.821	—	—	—
	Community road	0.819	—	—	—
	Community environment and sanitation	0.844	—	—	—
	Community management and security	0.820	—	—	—
Housing affordability	Daily living expense	0.899	0.918	8.792	42.195
	Rental costs	0.900	—	—	—
	Commuting cost	0.902	—	—	—
Community attachment	Community meaning	0.894	0.902	15.662	65.255
	Community identity	0.898	—	—	—
	Community nostalgia	0.888	—	—	—
	Community pride	0.905	—	—	—
	Community significance	0.901	—	—	—
	Community belonging	0.902	—	—	—
Mental health of tenants	Nervousness	0.888	0.906	10.622	85.069
	Dumps	0.915	—	—	—
	Calmness	0.889	—	—	—
	Mood	0.904	—	—	—
	Happiness	0.921	—	—	—

3.5 Methods

This study used multiple linear regression models to examine the effects of housing quality and cost of residence on tenants' mental health. Additionally, it analyzed the mediating and moderating roles of community attachment in the relationship between housing quality and tenants' mental health.

The methodology used for the mediation effects test was mainly proposed by Baron and Kenny (28, 29). In addition, MacKinnon (30) proposed that the mediation effect can be tested by directly examining the "path coefficient of independent variable X to mediator variable M" and the "path coefficient of mediator variable M to dependent variable Y." Therefore, this study uses the above method to validate the mediating effect in the proposed theoretical model.

Analysis of variance (ANOVA) was conducted when both the moderator and independent variables were categorical. If the interaction effect between the two is significant, the moderating variable has a moderating effect.

For the continuous moderator variable, hierarchical regression technique can be used to test the independent variables (31). Specifically, the size of the main effect of the independent variable and the moderator variable on the dependent variable is examined separately. Subsequently, the interaction term (independent variable × moderator variable) is included in the regression equation. A statistically significant coefficient for this item confirms the presence of a moderating effect.

4 Results

4.1 Impact of housing quality on tenants' mental health

Multiple linear regression analyses were conducted with housing quality and housing affordability in urban villages as independent variables and tenants' mental health as the dependent variable. It was found (Table 5) that the standardized coefficients of Models 2a and 2b improved in comparison to Model 1, indicating that both the housing quality and housing affordability have a significant positive effect on tenants' mental health. Model 2c further compares the results of the models for the different independent variables, suggesting that housing quality has a slightly higher positive effect on tenants' mental health than housing affordability.

4.2 Tests of the mediating effect of community attachment

The article combines two analytical methods, stepwise regression analysis and bootstrap, to test the mediating effect of community attachment (Tables 6, 7). With community attachment as the dependent variable in Model 3, the results show that housing quality and housing affordability all have significant positive effects on community attachment. In Model 4, we add the dependent variable of tenant's mental health to Model 3, and the results show that community attachment has a significant positive effect in both housing quality-tenant's mental health, and housing affordability-tenant's mental health, and is an important factor influencing the relationship between the two.

Bootstrap analyses show that in the Path 1 model with housing quality as the independent variable, tenants' mental health as the dependent variable, and community attachment as the mediator variable, the model indirect effect value was 0.195, with bootstrap confidence intervals ranging from 0.138 to 0.257, suggesting that the mediating effect of community attachment in the housing quality-tenants' mental health relationship is relatively significant. In the path 2 model with housing affordability as the independent variable, tenants' mental health as the dependent variable, and community attachment as the mediator variable, the model indirect effect value is 0.182, and the bootstrap confidence interval is 0.128–0.240, which suggests that community attachment has a significant mediating effect in the relationship between housing affordability and tenants' mental health. Community attachment plays a more important mediating effect in these models.

4.3 Test of moderating effects of community attachment

In this study, two moderated effects tests were done using regression models with housing quality and housing affordability as independent variables, tenants' mental health as dependent variable and community attachment as moderating variable, and the results of the tests are shown below (Tables 8, 9).

Model 5a shows that housing quality exhibits significance at the 95% level ($p < 0.05$) on tenants' mental health without considering the interference of community attachment as a moderating variable, suggesting that the housing quality have a significant effect on tenants' mental health. Model 5b adds the moderating variable of community attachment, and Model 5c adds the variables of housing quality and community attachment to Model 5b. The results show that the interaction term of housing quality and community attachment exhibits significance at the 95% level ($p < 0.05$), indicating that there is a significant moderating effect of community attachment between housing quality and tenants' mental health.

A slope plot based on the results of the moderating effects test (Figure 3) shows that different levels of community attachment moderate the relationship between housing quality and tenants' mental health to varying degrees. At low levels of community attachment, housing quality plays a lesser role in positively influencing tenants' mental health. The positive effect of housing quality on tenants' mental health is greater at high levels of community attachment. Overall, it shows that community attachment has a positive moderating effect on the relationship between housing quality and tenants' mental health.

In the moderating effects test with housing affordability as the independent variable, Model 6a shows that without considering community attachment as a moderating variable, Housing affordability exhibits significance at the 95% level on tenants' mental health ($p < 0.05$), suggesting that housing affordability has a significant effect on tenants' mental health. Model 2 adds the moderating variable of community attachment, and Model 6c adds the variables of housing affordability and

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TABLE 5 Results of multiple linear regression model analysis.

Variables	Model 1 (DV: mental health of tenants)			Model 2a (DV: mental health of tenants)			Model 2b (DV: mental health of tenants)			Model 2c (DV: mental health of tenants)		
	Coefficient	standard error	*p*	Coefficient	standard error	*p*	Coefficient	standard error	*p*	Coefficient	standard error	*p*
Housing quality	—	—	—	0.301***	0.045	0.000	—	—	—	0.228***	0.049	0.000
Housing affordability	—	—	—	—	—	—	0.295***	0.050	0.000	0.196***	0.054	0.000
Gender (reference group: male)	—	—	—	—	—	—	—	—	—	—	—	—
Female	−0.138*	0.076	0.069	−0.143*	0.073	0.051	−0.120*	0.074	0.104	−0.130*	0.073	0.074
Age	−0.009**	0.004	0.013	−0.010**	0.003	0.016	−0.008**	0.003	0.021	−0.009**	0.003	0.011
Academic qualifications (reference group: primary school)	—	—	—	—	—	—	—	—	—	—	—	—
Junior high school	−0.034	0.122	0.783	−0.055	0.118	0.643	−0.065	0.119	0.583	−0.071	0.117	0.547
Senior high school	−0.222	0.136	0.102	−0.223*	0.132	0.091	−0.232*	0.133	0.080	−0.230*	0.131	0.079
Junior college or undergraduate degree	−0.028	0.144	0.845	−0.051	0.139	0.714	−0.083	0.141	0.557	−0.082	0.139	0.555
Master's degree or above	−0.220	0.404	0.585	−0.333	0.392	0.396	−0.521	0.397	0.190	−0.505	0.391	0.197
Marital status (reference group: unmarried)	—	—	—	—	—	—	—	—	—	—	—	—
Married	−0.127	0.215	0.555	−0.028	0.209	0.892	−0.137	0.210	0.513	−0.059	0.207	0.776
Else	0.639	0.495	0.124	0.655	0.475	0.145	0.620	0.480	0.151	0.612	0.468	0.164
Fertility status (reference group: zero child)	—	—	—	—	—	—	—	—	—	—	—	—
One child	−0.131	0.205	0.522	−0.162	0.199	0.415	−0.091	0.200	0.649	−0.128	0.197	0.516
Two children	−0.095	0.205	0.644	−0.120	0.199	0.547	−0.032	0.201	0.872	−0.073	0.198	0.713
Three children and above	0.288	0.235	0.222	0.243	0.228	0.287	0.328	0.230	0.153	0.281	0.227	0.216
Monthly income level	−0.032	0.032	0.323	−0.040	0.031	0.206	−0.049	0.032	0.127	−0.049	0.031	0.119
Constant	4.000***	0.210	0.000	2.890***	0.264	0.000	3.055***	0.259	0.000	2.531***	0.279	0.000
R^2	0.061			0.117			0.107			0.134		

*, **, and *** indicate $p < 0.10$, $p < 0.05$, and $p < 0.01$, respectively.

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TABLE 6 Results of the mediating effect of community attachment (1).

Variables	Model 3a (DV: Community attachment)			Model 3b (DV: Community attachment)			Model 4a (DV: Mental health of tenants)			Model 4b (DV: Mental health of tenants)		
	Coefficient	standard error	*p*	Coefficient	standard error	*p*	Coefficient	standard error	*p*	Coefficient	standard error	*p*
Housing quality	0.457***	0.036	0.000	—	—	—	0.115**	0.048	0.017	—	—	—
Housing affordability	—	—	—	0.445***	0.040	0.000	—	—	—	0.110**	0.051	0.031
Community attachment	—	—	—	—	—	—	0.406***	0.046	0.000	0.416***	0.045	0.000
Gender (reference group: male)	—	—	—	—	—	—	—	—	—	—	—	—
Female	0.026	0.057	0.657	0.060	0.059	0.307	−0.153**	0.070	0.028	−0.145**	0.070	0.038
Age	0.001	0.003	0.730	0.003	0.003	0.246	−0.010***	0.003	0.003	−0.009***	0.003	0.005
Academic qualifications (reference group: primary school)	—	—	—	—	—	—	—	—	—	—	—	—
Junior high school	0.032	0.092	0.731	0.016	0.095	0.863	−0.068	0.112	0.546	−0.072	0.112	0.521
Senior high school	−0.051	0.103	0.620	−0.065	0.106	0.537	−0.202	0.125	0.106	−0.205	0.125	0.102
Junior college or undergraduate degree	−0.078	0.109	0.474	−0.125	0.112	0.264	−0.019	0.132	0.883	−0.031	0.133	0.818
Master's degree or above	−0.093	0.307	0.762	−0.374	0.316	0.237	−0.295	0.372	0.427	−0.366	0.375	0.331
Marital status (reference group: unmarried)	—	—	—	—	—	—	—	—	—	—	—	—
Married	−0.124	0.164	0.449	−0.290	0.167	0.083	0.022	0.199	0.912	−0.017	0.199	0.932
Else	0.661	0.484	0.334	0.613	0.491	0.382	0.687	0.431	0.174	0.665	0.432	0.179
Fertility status (reference group: zero child)	—	—	—	—	—	—	—	—	—	—	—	—
One child	0.058	0.156	0.711	0.166	0.159	0.299	−0.186	0.189	0.325	−0.160	0.189	0.398
Two children	−0.054	0.156	0.729	0.079	0.160	0.622	−0.098	0.189	0.603	−0.065	0.190	0.732
Three children and above	0.075	0.179	0.674	0.204	0.183	0.265	0.213	0.217	0.327	0.244	0.217	0.262
Monthly income level	0.012	0.025	0.622	−0.001	0.025	0.771	−0.045	0.030	0.135	−0.048	0.030	0.109
Constant	1.911***	0.206	0.000	2.177***	0.206	0.000	2.115***	0.265	0.000	2.150***	0.264	0.000
R^2	0.206			0.177			0.215			0.205		

*, **, and *** indicate $p < 0.10$, $p < 0.05$, and $p < 0.01$, respectively.

TABLE 7 Results of mediating effect of community attachment (2).

Pathway	Effect type	Effect	LLCI	ULCI
Housing quality→Community attachment→Mental health of tenants	Total effect	0.3271***	0.2374	0.4169
	Direct effect	0.1317***	0.0364	0.2270
	Indirect effect	0.1954***	0.1379	0.2596
Housing affordability→Community attachment→Mental health of tenants	Total effect	0.3225***	0.2276	0.4175
	Direct effect	0.1397***	0.0423	0.2371
	Indirect effect	0.1828***	0.1286	0.2401

*, **, and *** indicate $p < 0.10$, $p < 0.05$, and $p < 0.01$, respectively.

TABLE 8 Results of the moderating effects test for community attachment.

Variables	Model 5a			Model 5b			Model 5c		
	Coefficient	standard error	*p*	Coefficient	standard error	*p*	Coefficient	standard error	*p*
Housing quality	0.301***	0.045	0.000	0.115**	0.048	0.017	0.103**	0.047	0.028
Community attachment	—	—	—	0.406***	0.046	0.000	0.390***	0.045	0.000
Housing quality×Community attachment	—	—	—	—	—	—	0.292***	0.050	0.000
Gender (reference group: male)	—	—	—	—	—	—	—	—	—
Female	−0.143*	0.073	0.051	−0.153**	0.070	0.028	−0.142	0.068	0.105
Age	−0.010***	0.003	0.006	−0.010***	0.003	0.003	−0.009***	0.003	0.005
Academic qualifications (reference group: primary school)	—	—	—	—	—	—	—	—	—
Junior high school	−0.055	0.118	0.643	−0.068	0.112	0.546	−0.066	0.109	0.547
Senior high school	−0.223	0.132	0.191	−0.202	0.125	0.106	−0.206	0.122	0.189
Junior college or undergraduate degree	−0.051	0.139	0.714	−0.019	0.132	0.883	−0.034	0.129	0.790
Master's degree or above	−0.333	0.392	0.396	−0.295	0.372	0.427	−0.518	0.365	0.157
Marital status (reference group: unmarried)	—	—	—	—	—	—	—	—	—
Married	−0.028	0.209	0.892	0.022	0.199	0.912	0.057	0.194	0.769
Else	0.755	0.475	0.145	0.587	0.431	0.174	0.475	0.414	0.187
Fertility status (reference group: zero child)	—	—	—	—	—	—	—	—	—
One child	−0.162	0.199	0.415	−0.186	0.189	0.325	−0.220	0.185	0.234
Two children	−0.120	0.199	0.547	−0.098	0.189	0.603	−0.139	0.185	0.452
Three children and above	0.243	0.228	0.287	0.213	0.217	0.327	0.110	0.212	0.605
Monthly income level	−0.040	0.031	0.206	−0.045	0.030	0.135	−0.047	0.029	0.105
R^2	0.117			0.206			0.244		
Adjustment R^2	0.101			0.190			0.228		
F-value	7.056			12.7733			14.788		
$\triangle R^2$	0.056			0.089			0.038		
$\triangle F$	43.739			76.976			34.336		

*, **, and *** indicate $p < 0.10$, $p < 0.05$, and $p < 0.01$, respectively.

TABLE 9 Results of the moderating effects test of community attachment.

Variables	Model 6a			Model 6b			Model 6c		
	Coefficient	Standard error	*p*	Coefficient	Standard error	*p*	Coefficient	Standard error	*p*
Housing affordability	0.295***	0.050	0.000	0.110**	0.051	0.031	0.234*	0.057	0.096
Community attachment	—	—	—	0.416***	0.045	0.000	0.314***	0.045	0.000
Housing affordability×Community attachment	—	—	—	—	—	—	0.176***	0.059	0.003
Gender (reference group: male)	—	—	—	—	—	—	—	—	—
Female	−0.120	0.074	0.104	−0.145**	0.070	0.038	−0.145**	0.069	0.037
Age	−0.008**	0.003	0.021	−0.009***	0.003	0.005	−0.009***	0.003	0.006
Academic qualifications (reference group: primary school)	—	—	—	—	—	—	—	—	—
Junior high school	−0.065	0.119	0.583	−0.072	0.112	0.521	−0.072	0.112	0.520
Senior high school	−0.232*	0.133	0.080	−0.205	0.125	0.102	−0.219*	0.125	0.079
Junior college or undergraduate degree	−0.083	0.141	0.557	−0.031	0.133	0.818	−0.042	0.132	0.752
Master's degree or above	−0.521	0.397	0.190	−0.366	0.375	0.331	−0.469	0.375	0.212
Marital status (reference group: unmarried)	—	—	—	—	—	—	—	—	—
Married	−0.137	0.210	0.513	−0.017	0.199	0.932	0.010	0.198	0.959
Else	0.720	0.480	0.051	0.465	0.432	0.079	0.309	0.429	0.115
Fertility status (reference group: zero child)	—	—	—	—	—	—	—	—	—
One child	−0.091	0.200	0.649	−0.160	0.189	0.398	−0.182	0.188	0.334
Two children	−0.032	0.201	0.872	−0.065	0.190	0.732	−0.096	0.189	0.610
Three children and above	0.328	0.230	0.153	0.244	0.217	0.262	0.194	0.217	0.371
Monthly income level	−0.049	0.032	0.127	−0.048	0.030	0.109	−0.044	0.030	0.142
R^2	0.107			0.205			0.215		
Adjustment R^2	0.090			0.189			0.198		
F-value	6.361			12.676			12.568		
$\triangle R^2$	0.046			0.098			0.010		
$\triangle F$	36.266			84.722			8.985		

*, **, and *** indicate $p < 0.10$, $p < 0.05$, and $p < 0.01$, respectively.

community attachment to Model 6b, which shows that the interaction term of housing affordability and community attachment exhibits significance at the 95% level ($p < 0.05$), suggesting that community attachment has a significant moderating effect.

Slope plots based on the results of the moderating effects test (Figure 4) indicates that different levels of community attachment moderate the relationship between housing affordability and tenants' mental health to varying degrees. At low levels of community attachment, housing affordability plays a lesser role in positively influencing tenants' mental health. At high levels of community attachment, housing affordability plays a larger role in positively influencing tenants' mental health. Overall, it shows that community attachment enhances the relationship between housing affordability and tenants' mental health.

5 Discussion and conclusion

This study analyses the relationship between housing quality, community attachment and mental health of urban village tenants, using seven urban villages in Shenzhen City as the research case. Housing quality and housing affordability are important factors affecting the mental health of tenants, and this

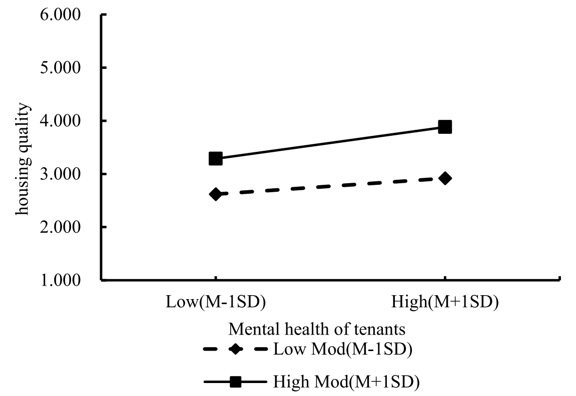

FIGURE 3
Slope plot of the moderating effect of community attachment on the relationship between housing quality and tenants' mental health.

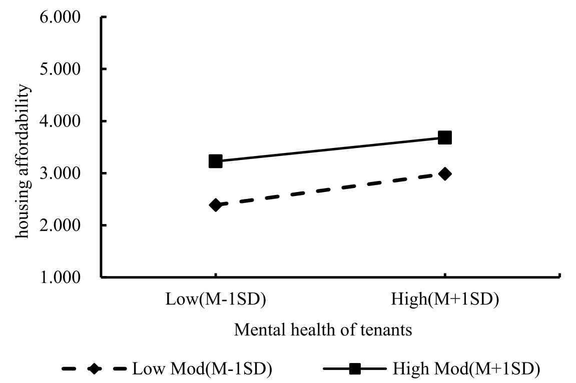

FIGURE 4
Slope plot of the moderating effect of community attachment on the relationship between housing affordability and tenants' mental health.

study verifies the direct impact of housing quality (β = 0.228, p = <0.05) and housing affordability (β = 0.228, p = <0.05) on the mental health of tenants in urban villages. Therefore, effectively improving the housing quality and reducing the cost of residence can promote the mental health among urban village tenants.

The improvement in housing quality can be divided into two main components: the quality of housing and the living environment of the neighborhood. The quality of housing in existing urban villages mainly suffers from several problems, i.e., incomplete public service facilities, safety hazards, dilapidated buildings, lack of space for public activities, all of which have a long-term implication for the mental health of tenants.

Reducing the living cost in urban villages can also benefit the mental health of tenants to a certain extent. Housing affordability in this study is assessed through three components: daily living expenses (meals, clothing, etc.), rental costs, and commuting costs. In this survey, it is found that the residents' evaluation of housing affordability was moderate, with a mean score of 3.18. However, some tenants perceived housing affordability as poor, likely due to the insufficient supply of affordable housing in the area of city center and the impact of recent urban village renewal policies in Shenzhen on rental prices. Thus, this suggests that the housing quality and housing affordability are interconnected factors in urban villages within China's megacities.

In addition, this research tests the community attachment as a mediating and moderating variable, respectively. The finding indicated that community attachment has a mediating and moderating role in the relationship between housing quality and tenants' mental health (β = 0.292, p = <0.05), as well as housing affordability and tenant mental health (β = 0.176, p = <0.05). Therefore, besides the direct effects of housing quality and housing affordability, fostering a stronger residents' sense of community attachment can further enhance tenants' mental health. Community attachment refers to the complex and comprehensive emotional bond that is formed between residents and their place, which has an imperceptible influence on the lives of residents. A positive sense of community attachment enables residents to experience greater happiness and fulfilment, thereby demonstrating more positive mental health.

Finally, this study proposes that the mental health of tenants should be an important consideration in the current urban village renewal in China's megacities. Furthermore, the relationship between housing quality, housing affordability and community attachment should be dealt with in the urban village renewal projects.

Based on the above research, we also can find the contradictions in the process of urban village renewal in Shenzhen. While improving substandard housing conditions is essential for residents' mental health, renewal efforts often lead to increasing housing prices, which may further affect affordability. Therefore, it is crucial to strike a balance between improving housing quality and maintaining affordable living costs. Shenzhen's current urban village renewal policy adopts an inclusive approach, preserving the original rental market while encouraging state-owned enterprises to intervene in rental prices in areas with tight housing supply through unified purchase, renewal, and re-leasing of urban village properties. This strategy aims to maintain relatively low rental levels for residents, thereby enhancing living standards and protecting affordable rents. While this policy has alleviated some pressure on residents, the acquisition process remains complex. Ensuring the interests of both property owners and original tenants during acquisitions is a topic that warrants further investigation. Moreover, this research confirms that community attachment significantly influences residents' mental health. Thus, promoting community cultural development and enhancing cohesion are essential topics in Shenzhen's urban village renewal policies.

Data availability statement

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

Author contributions

JH: Data curation, Resources, Writing – original draft. HC: Conceptualization, Writing – review & editing. YC: Data curation, Writing – original draft. ZL: Methodology, Writing – review & editing. JY: Supervision, Writing – review & editing.

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Conflict of interest

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References

1. Wang YP. Housing reform and its impacts on the Urban poor in China. *Hous Stud*. (2000) 15:845–64. doi: 10.1080/02673030020002573

2. Li Z, Wu F. Residential satisfaction in China's informal settlements: a case study of Beijing, Shanghai, and Guangzhou. *Urban Geogr*. (2013) 34:923–49. doi: 10.1080/02723638.2013.778694

3. Hao P, Sliuzas R, Geertman S. The development and redevelopment of urban villages in Shenzhen. *Habitat Int*. (2011) 35:214–24. doi: 10.1016/j.habitatint.2010.09.001

4. Zhan Y. The urbanisation of rural migrants and the making of urban villages in contemporary China. *Urban Stud*. (2018) 55:1525–40. doi: 10.1177/0042098017716856

5. Pan W, Du J. Towards sustainable urban transition: A critical review of strategies and policies of urban village renewal in Shenzhen, China. *Land Use Policy*. (2021) 111:105744. doi: 10.1016/j.landusepol.2021.105744

6. Zeng H, Yu X, Zhang J. Urban village demolition, migrant workers' rental costs and housing choices: evidence from Hangzhou, China. *Cities*. (2019) 94:70–9. doi: 10.1016/j.cities.2019.05.029

7. Lin S, Wu F, Li Z. Beyond neighbouring: Migrants' place attachment to their host cities in China. *Popul Space Place*. (2021) 27:e2374. doi: 10.1002/psp.2374

8. Wang YP, Wang Y, Wu J. Urbanization and informal development in China: Urban villages in Shenzhen. *Int J Urban Reg Res*. (2009) 33:957–73. doi: 10.1111/j.1468-2427.2009.00891.x

9. Yan S, Zenou Y, Ding C. Let's not throw the baby out with the bath water: the role of Urban villages in housing rural migrants in China. *Urban Stud*. (2008) 45:313–30. doi: 10.1177/0042098007085965

10. Zhu H, Gao X, Tian W, Wei M, Zhang X, Chen Y. Investigating the mechanisms of sustainable urban land renewal: a perspective of spatial development rights. *Sustain Cities Soc*. (2024) 109:105536. doi: 10.1016/j.scs.2024.105536

11. Kochan D. Placing the Urban village: a spatial perspective on the development process of Urban villages in contemporary china. *Int J Urban Reg Res*. (2015) 39:927–47. doi: 10.1111/1468-2427.12287

12. He S, Liu Y, Wu F, Webster C. Social groups and housing differentiation in China's Urban villages: an institutional interpretation. *Hous Stud*. (2010) 25:671–91. doi: 10.1080/02673037.2010.483585

13. Wu F. Housing in Chinese Urban villages: the dwellers, conditions and tenancy informality. *Hous Stud*. (2016) 31:852–70. doi: 10.1080/02673037.2016.1150429

14. Li J, Yuan J, Huang Y, Zhang Y. Revealing the widespread existence and serious adverse health consequences of low-price rental housing in urban villages in Xiamen, China. *Humanities Soc Sci Commun*. (2023) 10:1–11. doi: 10.1057/s41599-023-01907-4

15. Jin X, Ren T, Mao N, Chen L. To stay or to leave? Migrant workers' decisions during Urban village redevelopment in Hangzhou, China. *Front Public Health*. (2021) 9:782251. doi: 10.3389/fpubh.2021.782251

16. Peen J, Schoevers RA, Beekman AT, Dekker J. The current status of urban–rural differences in psychiatric disorders. *Acta Psychiatr Scand*. (2009) 121:84–93. doi: 10.1111/j.1600-0447.2009.01438.x

17. Seo BK, Park GR. Housing, living arrangements and mental health of young adults in independent living. *Int J Environ Res Public Health*. (2021) 18:5250. doi: 10.3390/ijerph18105250

18. Li J, Rose N. Urban social exclusion and mental health of China's rural-urban migrants–a review and call for research. *Health Place*. (2017) 48:20–30. doi: 10.1016/j.healthplace.2017.08.009

19. Chan KW, Zhang L. The Hukou system and rural-urban migration in china: processes and changes. *China Quarterly London*. (1999) 160:818–55. doi: 10.1017/S0305741000001351

20. Pan T. Strangers in the City: reconfigurations of space, power, and social networks within China's floating population (review). *Anthropol Q*. (2003) 76:359–60. doi: 10.1353/anq.2003.0029

21. Du H, Li SM. Migrants, urban villages, and community sentiments: a case of Guangzhou, China. *Asian Geogr*. (2010) 27:93–108. doi: 10.1080/10225706.2010.9684155

22. Chang J, Lin Z, Vojnovic I, Qi J, Wu R, Xie D. Social environments still matter: The role of physical and social environments in place attachment in a transitional city, Guangzhou, China. *Landsc Urban Plan*. (2023) 232:104680. doi: 10.1016/j.landurbplan.2022.104680

23. Liu S, Zhang F, Wu F. Contrasting migrants' sense of belonging to the city in selected Peri-urban neighbourhoods in Beijing. *Cities*. (2022) 120:103499. doi: 10.1016/j.cities.2021.103499

24. Wang R, Wu C, Ma XQ, et al. Health-related quality of life in Chinese people: a population-based survey of five cities in China. *Scandinavian J Public Health*. (2011) 39:410–8.

25. Brehm JM, Eisenhauer BW, Krannich RS. Dimensions of Community Attachment and Their Relationship to Well-Being in the Amenity-Rich Rural West*. *Rural Sociol*. (2004) 69:405–29. doi: 10.1526/0036011041730545

26. Mihaylov N., Perkins D. (2013). Community place attachment and its role in social capital development. Available online at: http://doc.paperpass.com/foreign/rgChap2013158165277.html

27. Williams DR, Patterson ME, Roggenbuck JW, Watson AE. Beyond the commodity metaphor: examining emotional and symbolic attachment to place. *Leis Sci*. (1992) 14:29–46. doi: 10.1080/01490409209513155

28. Baron RM, Kenny DA. The moderator-mediator variable distinction in social psychological research: Conceptual, strategic, and statistical considerations. *J Pers Soc Psychol*. (1999) 51:1173–82. doi: 10.1037/0022-3514.51.6.1173

29. James LR, Mulaik SA, Brett JM. A Tale of Two Methods. *Organ Res Methods*. (2006) 9:233–44. doi: 10.1177/1094428105285144

30. Mackinnon DP, Lockwood CM, Hoffman JM, West SG, Sheets V. A comparison of methods to test mediation and other intervening variable effects. *Psychol Methods*. (2002) 7:83–104. doi: 10.1037/1082-989X.7.1.83

31. Fairchild A, Mackinnon D. A general model for testing mediation and moderation effects. *Prev Sci*. (2008) 10:87–99. doi: 10.1007/s11121-008-0109-6

32. Adli M, Schndorf J. Does the city make us ill? The effect of urban stress on emotions, behavior, and mental health. *Bundesgesundheitsblatt-Gesundheitsforschung-Gesundheitsschutz*. (2020) 63:979–86. doi: 10.1007/S00103-020-03185-W

33. Jing M, Chunjiang L, Mei-Po K, Yanwei C. A multilevel analysis of perceived noise pollution, geographic contexts and mental health in Beijing. *Int J Environ Res Public Health*. (2018) 15:1479-. doi: 10.3390/ijerph15071479

34. Yang X, Siyu M, Chinmoy S, Huizhi G, Yi L. Exploring the impacts of housing condition on Migrants' mental health in Nanxiang, Shanghai: a structural equation modelling approach. *Int J Environ Res Public Health*. (2018) 15:225. doi: 10.3390/ijerph15020225

Appendix

TABLE A1 Description of the indicators measured.

Dimension	Variable name	Description	Standard for evaluation
Housing quality	Housing location	Location of housing	1 = very dissatisfied; 2 = dissatisfied; 3 = fair; 4 = satisfied; 5 = very satisfied
	Housing quality	Quality of construction and renovation of housing	1 = very dissatisfied; 2 = dissatisfied; 3 = fair; 4 = satisfied; 5 = very satisfied
	Housing layout	Spatial structure and layout within housing	1 = very dissatisfied; 2 = dissatisfied; 3 = fair; 4 = satisfied; 5 = very satisfied
	Housing Facilities	Housing facilities (lifts, utilities, gas, etc.)	1 = very dissatisfied; 2 = dissatisfied; 3 = fair; 4 = satisfied; 5 = very satisfied
	Community service facilities	Community public service facilities (hospitals, schools, activity areas for the older adult and children, etc.)	1 = very dissatisfied; 2 = dissatisfied; 3 = fair; 4 = satisfied; 5 = very satisfied
	Community road	Roads, traffic organization etc. within the community	1 = very dissatisfied; 2 = dissatisfied; 3 = fair; 4 = satisfied; 5 = vervy satisfied
	Community environmental sanitation	Green environment and hygiene of the community	1 = very dissatisfied; 2 = dissatisfied; 3 = fair; 4 = satisfied; 5 = very satisfied
	Community management and safety	Community management and community safety	1 = very dissatisfied; 2 = dissatisfied; 3 = fair; 4 = satisfied; 5 = very satisfied
Housing affordability	Daily living expense	I can afford daily living expenses (meals, clothing, etc.)	1 = very dissatisfied; 2 = dissatisfied; 3 = fair; 4 = satisfied; 5 = very satisfied
	Rental price	I can afford to rent a room	1 = very dissatisfied; 2 = dissatisfied; 3 = fair; 4 = satisfied; 5 = very satisfied
	Commuting cost	I can afford the commute	1 = very dissatisfied; 2 = dissatisfied; 3 = fair; 4 = satisfied; 5 = very satisfied
Community attachment	Community meaning	This community means a lot to me	1 = very dissatisfied; 2 = dissatisfied; 3 = fair; 4 = satisfied; 5 = very satisfied
	community identity	I think I belong in this community	1 = very dissatisfied; 2 = dissatisfied; 3 = fair; 4 = satisfied; 5 = very satisfied
	Community nostalgia	I would miss this neighbourhood if I moved away from it	1 = very dissatisfied; 2 = dissatisfied; 3 = fair; 4 = satisfied; 5 = very satisfied
	Community pride	I'm proud of the community I live in	1 = very dissatisfied; 2 = dissatisfied; 3 = fair; 4 = satisfied; 5 = very satisfied
	Importance of community	This community is very important to me	1 = very dissatisfied; 2 = dissatisfied; 3 = fair; 4 = satisfied; 5 = very satisfied
	Community belonging	This community gives me a sense of belonging	1 = very dissatisfied; 2 = dissatisfied; 3 = fair; 4 = satisfied; 5 = very satisfied
Mental health of tenants	Nervousness	Have you been a very nervous person?	1 = all of the time; 2 = most of the time; 3 = a good bit of the time; 4 = some of the time; 5 = a little of the time; 6 = none of the time
	Dumps	Have you felt so down in the dumps that nothing could cheer you up?	1 = all of the time; 2 = most of the time; 3 = a good bit of the time; 4 = some of the time; 5 = a little of the time; 6 = none of the time
	Calmness	Have you felt calm and peaceful?	1 = all of the time; 2 = most of the time; 3 = a good bit of the time; 4 = some of the time; 5 = a little of the time; 6 = none of the time
	Mood	Have you felt downhearted and blue?	1 = all of the time; 2 = most of the time; 3 = a good bit of the time; 4 = some of the time; 5 = a little of the time; 6 = none of the time
	Happiness	Have you been a happy person?	1 = all of the time; 2 = most of the time; 3 = a good bit of the time; 4 = some of the time; 5 = a little of the time; 6 = none of the time

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Evaluation of the cold island effect of the urban parks in the main urban area of Wuhan from the perspective of supply and demand

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Background: Rapid urbanization has led to a series of "urban diseases" that have garnered significant social attention. Among these, the urban heat island effect has emerged as one of the most pronounced environmental concerns, presenting formidable challenges for urban planning in terms of sustainable development and environmental livability. In this process, the construction of urban parks is particularly susceptible to discrepancies between supply and demand.

Methods: In this study, urban parks with an area of more than 3hm^2 in the main urban area of Wuhan were selected as research objects. Utilizing remote sensing data and urban vector data, this study applied kernel density analysis and Thiessen polygons development to assess the supply capacity of parks' cold islands from a supply perspective, and the residents' cold island demand level index from a demand perspective.

Results: The findings revealed that ① The spatial distribution of cold island supply and demand exhibited significant heterogeneity. High-supply units were strongly correlated with water body distribution, while high-demand units aligned closely with population density and POI density centers, displaying a "scattered overall, locally concentrated" pattern. ② A significant supply–demand mismatch in cold island effects was observed, with 19 units (accounting for approximately 40%) exhibiting insufficient supply relative to demand. These units were predominantly concentrated in areas with complex building environments, high population density, low vegetation coverage, and poor landscape connectivity.

Discussion and conclusions: Drawing on these results, the study established an interplay between supply and demand perspectives by applying the theory of locational entropy and proposed optimization strategy for urban parks in Wuhan, aiming to achieve "a match between supply and demand in cold islands" across varying equilibrium stages of the research units. Specific measures include: optimizing the scale and layout of existing parks, reserving green spaces for ecological restoration, strengthening the protection of blue-green ecological foundations, and establishing a blue-green cold island corridor network to enhance ecological connectivity. Our work extends the understanding of the cold island effect of urban parks, assisting urban planners in proposing more targeted and effective management strategy and measures to improve the urban thermal environment, thereby contributing to the creation of healthy, equitable, and sustainable cities.

KEYWORDS

supply and demand evaluation, cold island effect, urban parks, planning strategy, urban heat and cold islands

1 Introduction

In recent years, the global climate has exhibited significant fluctuations, leading to a rise in the frequency of extreme weather events, thereby posing formidable challenges to urban development and human survival. Of particular concern is the urban heat island problem, which has garnered widespread attention due to its strain on various aspects of the urban system, including urban construction space, urban ecology, and urban energy supply (1, 2). Meanwhile, the emergence of the urban heat island effect, characterized by elevated summer temperatures, has been found to be linked to increased greenhouse gas emissions, exacerbation of air pollution, and adverse effects on public health and living comfort (3, 4), which warn against sustainable urban development. As an essential part of the urban system, urban parks exhibit a noticeable cold island effect (5, 6). They play an essential role in maintaining ecosystems (7) and safeguarding residents' physical and mental health by providing quality landscapes and activity spaces (8).

Extensive studies on the urban parks' cold island effect home and abroad can be summarized as follows: ① Research on influencing factors from the perspective of cold island supply: Numerous studies have demonstrated that the cooling effects of parks are closely associated with their area and shape (9–11). Generally, larger parks with more compact shapes exhibit superior cooling effect. Additionally, the internal landscape composition of parks, including water bodies, green vegetation, etc., has been widely recognized as critical factors influencing cooling performance. Kong et al. highlighted that vegetation coverage is a primary factor affecting the intensity and distribution of cold islands, showing a significant positive correlation (12). However, Xie et al. found that water bodies contribute most significantly to the park cold island effect, while vegetation coverage shows no significant correlation with the average land surface temperature within parks (13). In cases where water body coverage is high, the cooling effect of vegetation may be attenuated due to the interactive influences of multiple variables on the cold island effect. Furthermore, the internal green space structure of parks also plays a role in mitigating the urban heat island effect, albeit with variations (14). Chen et al. suggested that tree-shrub-grass communities exhibit the most effective cooling performance (15), whereas Zhang et al. experimentally demonstrated that tree-grass-dominated green spaces achieve the greatest temperature reduction (16). These differences may stem from variations in vegetation types and their spatial configurations. However, the cooling effects of parks are not only influenced by their internal landscape features but also by surrounding environmental conditions such as impervious surfaces, building morphology, and composition (e.g., building density (BD) and building height (BH)) (17–19). Additionally, the cooling effects of urban parks are closely associated with the spatial aggregation of green spaces and resident visitation patterns. Research indicates that the intensity of the park cold island effect is significantly positively correlated with the average proximity of green spaces, i.e., the more concentrated the distribution of green spaces, the stronger the intensity of the cold islands (20). Simultaneously, the cooling effects are inversely proportional to the frequency and distance of park visits by residents (21). ② Research on residents' physical and mental health from the perspective of cold island demand: Living close to recreation-friendly urban parks is conducive to improving residents' physical fitness and self-rated health (22). Residents' frequent use of parks can effectively reduce their risk of cardiovascular disease (23). Additionally, the park's vegetation environment has a positive impact on people's emotional recovery (24). Above all, existing research only discusses the influencing factors of the cold island effect in urban parks or explores the positive benefits on people's physical and mental health. However, there are very few studies on alleviating the heat island effect from the perspective of urban cold and heat island supply–demand equilibrium. There is also a lack of research on park planning in spatial decision-making that considers human needs and insufficient comprehensive quantitative research on the integration of "demand subjects" (residents) and "supply subjects" (urban parks). This deficiency makes it challenging to formulate comprehensive solutions to address urban heat environment issues.

The relationship between supply and demand generally refers to the dynamic and relative relationship between production and consumption in the commodity market economy. Correspondingly, at the level of urban park systems, it denotes the equilibrium pursued between the cold island supply capacity of urban parks and the targeted needs of residents for living and production. In the context of high-quality development and the awakening of national health awareness, it is of significant theoretical and practical importance to quantitatively analyze the cool island effect of urban parks from the perspective of supply and demand in order to plan and utilize it reasonably to maximize its ecological service functions. This is crucial for mitigating the urban heat environment and promoting the construction of ecologically livable cities (25).

As a prototypical "furnace city," Wuhan has faced increasingly prominent thermal environment problem issues in recent years due to the city's rapid expansion and the sharp growth of its population. Therefore, this study focuses on the main urban area of Wuhan, where the urban heat island (UHI) effect is most pronounced. By integrating multi-source data and establishing a dual-perspective evaluation system from both supply and demand sides, the research aims to ① reveal the spatial distribution characteristics and patterns of the urban parks' cold island effect from both supply and demand perspectives; ② analyze the degree of supply–demand matching for the cold islands of the urban parks and their spatial differentiation patterns; ③ propose targeted park planning optimization strategies based on the supply–demand matching results, providing scientific and reasonable suggestions to the construction sequence and optimization emphasis of the urban parks in a point-to-point way.

2 Materials and methods

2.1 Description of the study area

Situated in the eastern part of the Jianghan Plain, Wuhan (29°58′ ~ 31°22′N, 113°41′ ~ 115°05′E) is at the confluence of the Yangtze River and Han River. It serves as the capital city of Hubei Province and the core city of the city cluster in the middle reaches of the Yangtze River. The city covers an area of 8,494 km^2 and includes 13 municipal districts, among which Jiang'an District, Jianghan District, Qiaokou District, Hanyang District, Wuchang District, Hongshan District, and Qingshan District are the main urban areas, with an area of 678km^2. Characterized by a subtropical monsoon climate, Wuhan experiences an annual average temperature ranging

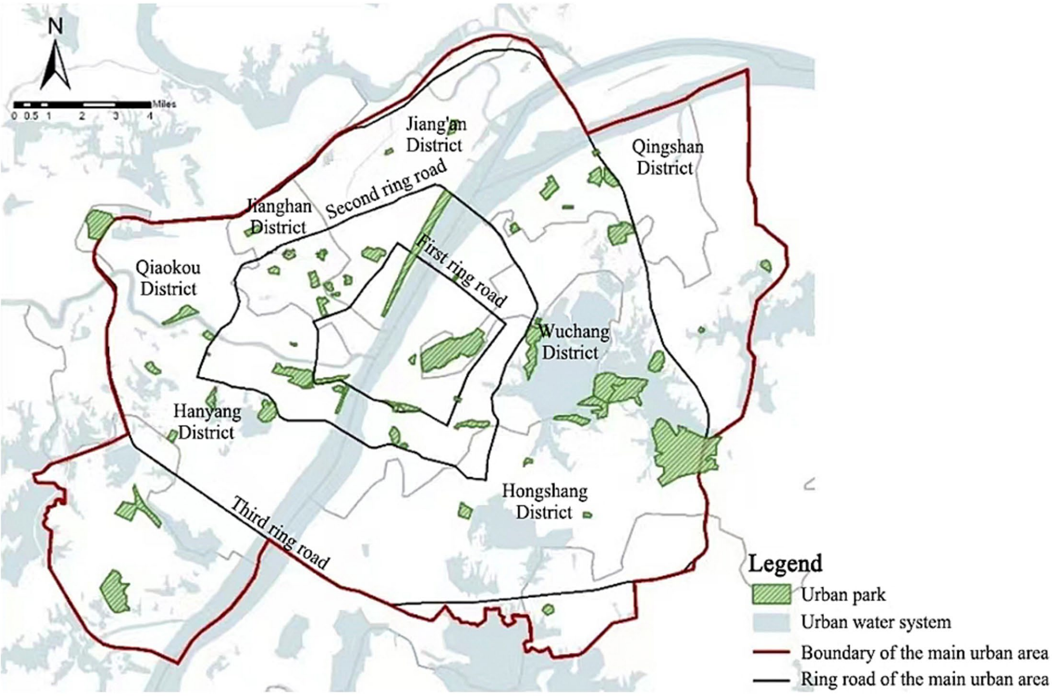

FIGURE 1
Distribution of the urban parks with an area of more than 3hm^2 in the main urban area of Wuhan.

from 15.8 to 17.5°C, with summer extreme temperatures reaching up to 41.3°C (26), creating significant thermal environment challenges. This paper selected 60 urban parks with an area of more than 3hm^2 in the above-mentioned seven main urban areas as the research objects to conduct the supply and demand evaluation of the urban parks' cold island effect in the main urban area of Wuhan (Figure 1).

2.2 Data sources and processing

The remote sensing data source in this paper is the Landsat 8 satellite image on 29 July 2018 with orbit number 123/39, obtained from the official website of the United States Geological Survey (USGS).[1] The reasons for choosing this image are as follows: ① On this day, the maximum temperature reached 37°C, significantly intensifying the urban heat island effect and increasing residents' demand for the cooling effects of urban parks. This provides a clearer reflection of the supply–demand relationship of urban parks' cold island effects, particularly in identifying areas with supply–demand imbalances. ② The Landsat image for this day was cloud-free and of high quality, ensuring reliable analysis of land surface temperature and other parameters. ③ Studies show that under breezy conditions with little prior precipitation, air and land surface temperatures correlate more closely. Wuhan had no rainfall for 10 consecutive days prior to July 29, 2018, with a wind speed of force 2 (breezy) recorded on that day, further validating the suitability of this date for reliable thermal analysis.

The image data were processed through the remote sensing image processing software platform ENVI and the GIS (Geographic Information System) software platform ArcGIS 10.3. The urban vector data included the road network data of the main urban area of Wuhan,[2] POI (Points of Interest) data,[3] Chinese population spatial distribution raster data,[4] and urban park data obtained from information released by Wuhan Municipal Landscape Gardens and Forestry Bureau, and 2018 Wuhan Statistical Yearbook and corresponding socio-economic statistics and so on.

2.3 Analytical workflow

Figure 2 illustrates the operational process of the model for evaluating the cold island effect of the urban parks from the perspective of supply and demand:① define the objectives and targets of the planning; ② conduct a comprehensive assessment of the current situation and problems by taking into account the resource base and regional status of the parks; ③ develop an index system from both the supply and demand perspectives; ④ formulate the evaluation process to presuppose the relationship between supply and demand; ⑤ determine optimization strategies for different supply–demand patterns; ⑥ plan for implementation and recycle this route for the next planning stage.

1 http://glovis.usgs.gov/

2 data source: https://www.openstreetmap.org/, acquired in 2018

3 data source: https://lbs.amap.com/, accessed in 2018

4 data source: https://www.worldpop.org/, accessed in 2018

2.4 Delineation of park service units

Traditional cold island effect measurements often rely on buffer analysis, but this method has two main limitations: first, it requires predefined buffer distances, leading to subjective results; second, it struggles to accurately reflect spatial competition between parks, particularly in complex urban environments with irregular park distributions. In contrast, Thiessen polygons automatically assign available space to the nearest point element based on spatial distance, without predefined parameters. It not only removes subjectivity but also more objectively reflects spatial competition between elements. Therefore, this study divided the city into several park cold island service areas centered on urban parks by constructing Thiessen polygons. Using these service areas as spatial units, the supply and demand of the urban parks' cold island effect were evaluated and identified. Since the city park is a polygon element, the procedure involves several steps (Figure 3). The first step is to use the "Feature Vertices to Points" tool to convert the vertices of the polygon elements into point elements. Subsequently, the "Create Thiessen Polygons" tool is utilized, followed by the "Dissolve" tool to merge the Thiessen polygons with common fields, thereby accomplishing the creation of Thiessen polygons for polygon elements.

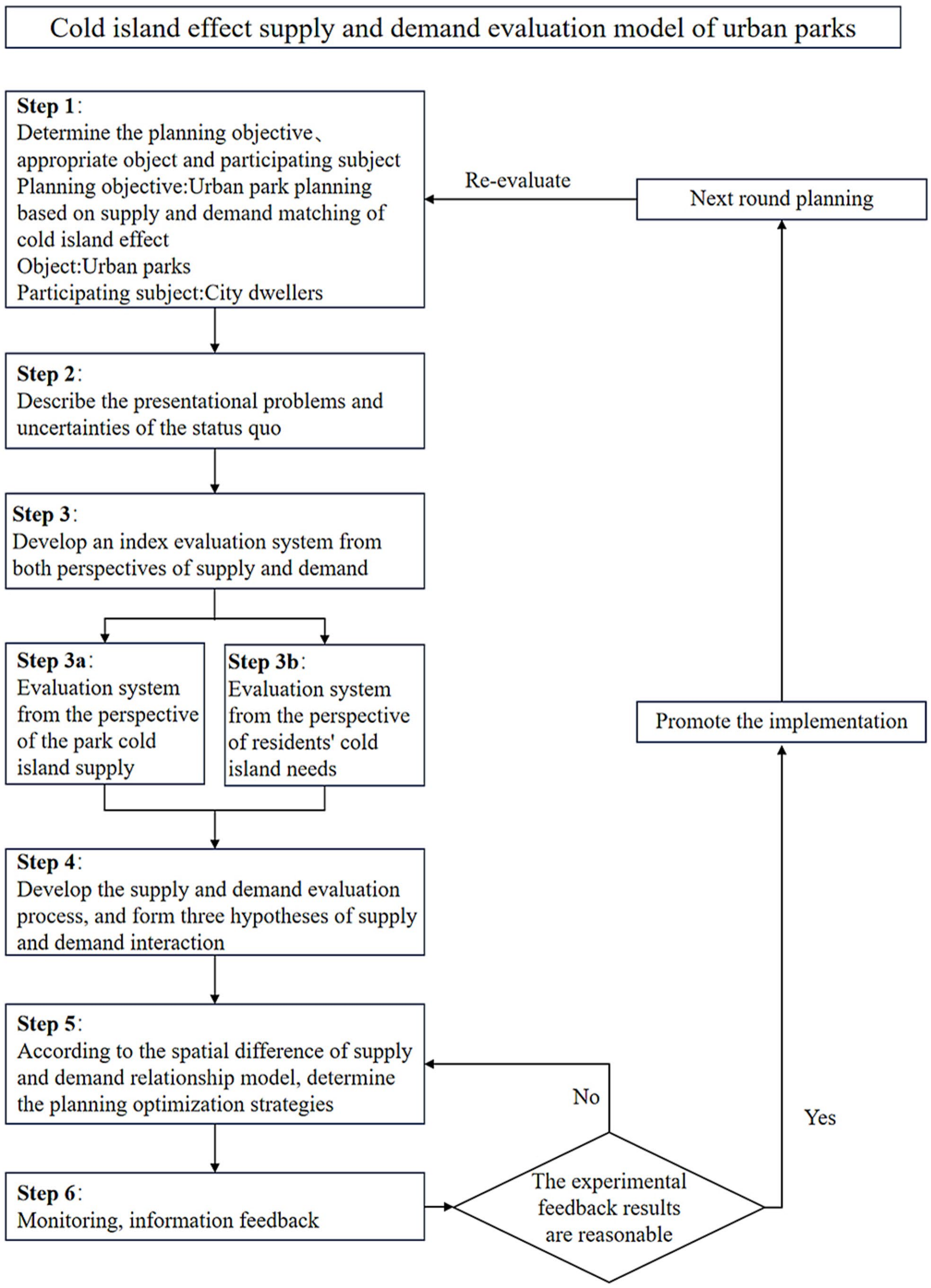

FIGURE 2
Logic diagram of the supply and demand evaluation model of the urban parks' cold island effect.

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However, the urban spatial texture is complicated, thus lacking correspondence with the urban space in actual urban research. Hence, when delineating the park service units, the Thiessen polygons of geometrical significance was combined with the regulatory planning units taking into account the spatial fabric of the city to enhance the accuracy of research.

2.5 Evaluation model for park cold island supply

2.5.1 Evaluation index system construction from the supply perspective

The park cold island evaluation index system from the supply perspective mainly focuses on: ecological supply and social supply (Table 1). Among them, the core carrier of ecological supply is blue-green spaces, which refer to a spatial system composed of various types of water bodies, wetlands, green spaces, and other open areas (27, 28). As an essential component of urban ecosystems, blue-green spaces not only provide critical ecological services to urban residents but also significantly reduce local temperatures and create cold island effects through mechanisms such as evapotranspiration, shading effects, and water body cooling (29–31). These mechanisms play a key role in regulating urban climate and mitigating thermal environments (28). Based on this, this study focuses on three types of blue-green spaces with significant cold island effects: the park itself, vegetation, and water bodies (32, 33). Their scale and quality are crucial indicators for measuring the supply capacity of park cold islands (34, 35). Social supply can be further subdivided into access methods and per capita availability. There are two ways in which the cold island effect of urban parks is transmitted to the users, one is directly through the air, and the other requires the users to arrive within the radiation range of the park's cold island. Given the limited spatial extent of urban parks, the per capita park area accessible to residents within its service range and the park's accessibility have become significant factors that cannot be ignored when evaluating the supply capacity of the cool island effect (36).

2.5.2 Calculation of evaluation indicators from the supply perspective

2.5.2.1 Fractional vegetation cover

The downloaded Landsat 8 series images were loaded into ENVI (The Environment for Visualizing Images) for initial processing, including radiometric calibration, FLAASH atmospheric correction, image fusion, stitching, and cropping. The fractional vegetation cover (FVC) of the study area was calculated using the pixel dichotomy model. This model assumes that each pixel's surface consists of two components: vegetated and non-vegetated areas. The FVC value for a pixel is defined as the proportion of its area covered by vegetation. The formula is as follows:

$$FVC = \frac{NDVI - NDVI_S}{NDVI_V - NDVI_S}, \tag{1}$$

In Equation 1, $NDVI_S$ represents the NDVI value of bare soil pixels, and $NDVI_V$ represents the NDVI value of pure vegetation pixels. The upper and lower thresholds of NDVI were selected at a 5% confidence level, and the NDVI values within the threshold range were averaged to obtain $NDVI_S$ and $NDVI_V$.

2.5.2.2 Accessibility

The two-step floating catchment area method (2SFCA) was applied to calculate the accessibility within the study area, with city parks as the supply side and residents of residential quarters as the demand side. The traditional 2SFCA ignores the importance of

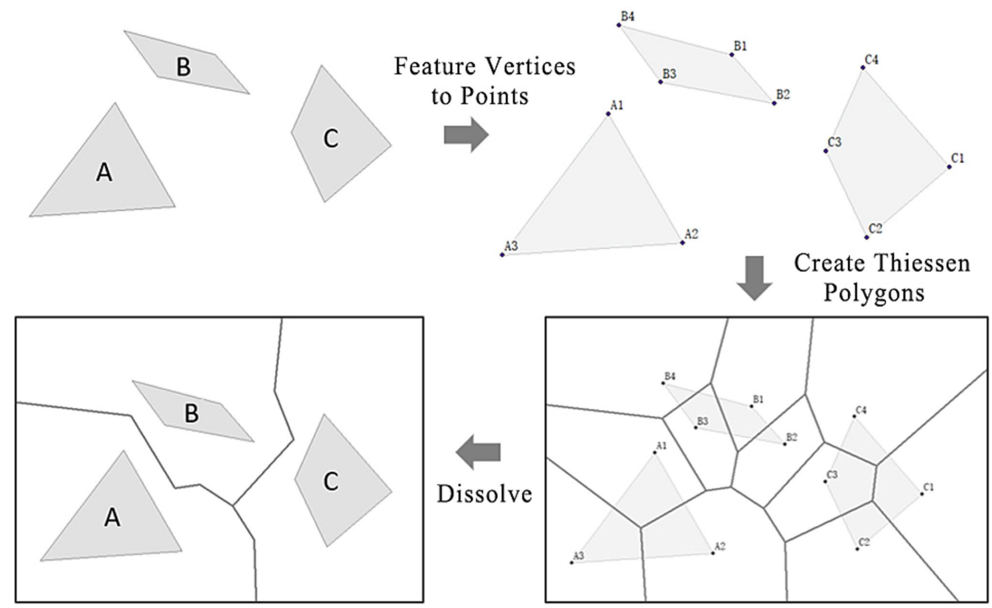

FIGURE 3
Process of generating Thiessen polygons from polygon elements.

TABLE 1 Evaluation index system of the park cold island effect from the supply perspective.

Supply categorization	Functional carrier	Evaluation index	Abbreviation/Unit	Definition
Ecological supply	The park itself	Park size	parkS/hm^2	Area of urban parks in cities that can effectively provide the cold island effect
	Water body	Water size in the park	wS/hm^2	Water area in city parks
	Vegetation cover	Fractional vegetation coverage	FVC/ -	Average of all FVC measurement points in city parks
Social supply	Mode of visit	Accessibility	A/(m^2/person)	Residents' accessibility to parks determined by the Gaussian two-step floating catchment area method
	Per capita access to parks	Per capita park size	perS/(m^2/person)	Ratio of urban park area to total population in the corresponding service area

distance --the urban parks' cold island supply capacity weakens as users move further away from them (37). Consequently, a Gaussian function is introduced as the distance attenuation function for 2SFCA. The Gaussian two-step floating catchment area approach (Ga2SFCA) incorporates distance as a factor in its reachability calculation, hence enhancing the realism of the results (38). The search radius d_0 calculated in this study based on the 15-min living circle definition of accessibility was 1 km. The formulas are as follows:

$$R_j = \frac{S_j}{\sum_i^m D_i \times G(d_{ij})}, \tag{2}$$

$$G(d_{ij}) = \frac{e^{-\frac{1}{2}\times\left(\frac{d_{ij}}{d_0}\right)^2} - e^{-\frac{1}{2}}}{1 - e^{-\frac{1}{2}}}, d_{ij} \le d_0, \tag{3}$$

$$A_i = \sum_j^n R_j \times G(d_{ij}), \tag{4}$$

In Equation 2, R_j is the per capita park size (m^2/person) for the potential demanders within the search range d_0 of the urban park; i is the residential quarters within the search radius d_0; j is the city park; m is the number of the residential quarters within the search distance d_0; D_i is the number of the inhabitants in the residential quarter i (person); d_{ij} is the distance between the centroid of the residential quarter i and the boundary of the city park j; S_j is the size of the park j (m^2).

Equation 3 is the distance decay function – the Gaussian function.

In Equation 4, A_i is the accessibility of the residential quarter i (m^2/person); n is the number of the urban parks j within the search radius d_0; R_j is the per capita park size of the demander within d_0 as required by Equation 2.

2.5.2.3 Per capita park size

The number of people in demand within the park service unit is filled, i.e., the number of people living within the park's service area is summed up and used as the basis for calculating the per capita area of the corresponding park, to measure the per capita provisioning capacity allocated to the park in the spatial layout planning process. The formula for this calculation is as follows:

$$perS_k = \frac{S_j}{\sum_t^e P_t}, \tag{5}$$

In Equation 5, k is the urban park service unit; $perS_k$ is the per capita park size within the park service unit k; j is the urban park within the service unit k; S_j is the size of the park j (m^2); t is the residential quarter within the park service unit k; e is the total number of the residential quarters within the park service unit k; and P_t is the number of the inhabitants in the residential quarter t (person).

2.5.3 Park cold island supply index calculation

The comprehensive cold island supply index was determined based on six key factors: the dominant park area within the service unit (parkS), vegetation cover within the park (FVC), water area (wS), per capita park size within the service unit (perS), accessibility (A) and each index's weight calculated using the subjective-objective composite weighting method. To enhance the accuracy of the weighting process, this study employed a combined weighting method that integrates the subjective Analytic Hierarchy Process (AHP) and the objective entropy weight method, thereby addressing the limitations of relying on a single weighting approach. Specifically, the AHP method was used to calculate subjective weights, while the entropy weight method was applied to determine objective weights. The final combined weights were derived based on the principle of minimum information entropy (39). Based on the weights and scores of the five indicators (Table 2), the park cold island supply index was obtained by weighted summation in Arcgis10.3 using the raster calculation tool. The calculation formulas are as follows:

$$SW_n = \frac{\sqrt{SW_{\alpha n} * SW_{\beta n}}}{\sum_{n-1}^5 \sqrt{SW_{\alpha n} * SW_{\beta n}}} \tag{6}$$

$$SI_k = \sum_{n=1}^m S_n \times SW_n, (\mathrm{n} = 1,2,......,5; \mathrm{k} = 1,2,......,48) \tag{7}$$

In Equations 6 and 7, SW_n is the comprehensive weight of the nth supply indicator, $SW_{\alpha n}$ denotes its subjective weight, and $SW_{\beta n}$

signifies its objective weight; SI_k is the park cold island supply index of the unit k, and there are 48 park service units, numbered from 1 to 48; S_n is the nth park cold island supply capacity index; n is a natural number from 1 to 5.

2.6 Evaluation model for residents' cold island demand

2.6.1 Construction of evaluation index system from the demand perspective

The construction of the park cold island evaluation index system (Table 3) from the demand perspective is based on the multi-level needs of urban residents, specifically including the following two aspects: ① At the physiological demand level, the focus lies on residents' physiological health conditions and their correlation with the thermal environment. With the frequent occurrence of global high-temperature weather, urban residents face an increased risk of heat-related illnesses, cardiovascular and cerebrovascular diseases, respiratory diseases, and other health hazards (40, 41). Research has demonstrated that land surface temperature (LST) directly influences human thermal comfort and serves as a critical indicator of the urban thermal environment (42), while the spatial extent of heat island patches identifies the scale of impacted areas and pinpoints regions requiring targeted mitigation efforts (43). Therefore, land surface temperature and heat island patch size have been selected as key indicators to intuitively reveal the presence and distribution of thermal environmental risks. The higher the thermal environmental risk, the more urgent residents' demand for park cold islands becomes. ② The psychological needs dimension focuses both on the potential impact of the hot environment on residents' mental health and on the environmental justice issues. Studies have shown that prolonged exposure to hot environments may lead to psychological stress (44) and negative emotions among residents, which in turn reduces their life satisfaction (45). At the same time, it is emphasized that every individual should enjoy equal access to high-quality park cold island services (46, 47). The essence of spatial equity in urban parks lies in the rational allocation of space, and although the total amount of park cold island services is determined by the supply side, the quality of cold island services available per capita is influenced by the number of demanders on the demand side. For this reason, population density and POI density are introduced as key indicators for assessing exposure. Among them, the density of resident population reflects the local static demand dominated by the residential function (48); while POI (Points of Interest), as an important characterization of the functional nodes of the city, the degree of aggregation directly reflects the intensity of human activities, i.e., the nonlocal dynamic demand (49, 50).

2.6.2 Calculation of evaluation indicators from the demand perspective

2.6.2.1 Population density

Regions with high population density suggest a more extensive and intensive number of users, implying a higher demand for cold islands. Through the population raster data obtained from WorldPop, the population density distribution of the computational units within the study area was acquired with the following formula.

$$PD_k = \frac{P_k}{S_k}, \tag{8}$$

In Equation 8, k is the urban park service unit k; PD_k is the per capita park size of the park service unit k; S_k is the size of the park service unit k (km^2); and P_k is the total number of people living in the service unit k (person).

2.6.2.2 POI kernel density

The kernel density of POI (Points of Interest) can characterize urban social activity levels. Regions with high POI kernel density suggest that residents engage in social activities more frequently and actively there, implying a higher demand index. Initially, the captured POI data underwent a cleaning and filtering process. Subsequently, the data coordinates were characterized as the GCS_WGS_1984 coordinate system and projected for the subsequent calculation and analysis. Then, the "Kernel Density" tool within the ArcGIS software was employed to calculate the kernel density of points of interest. The calculation of the kernel density of points in space is given in Equation 9:

$$\mathrm{f_n}(\mathrm{x}) = \frac{1}{\mathrm{nR}} \sum_{\mathrm{i}=1}^{\mathrm{n}} \mathrm{K}\left(\frac{\mathrm{x} - \mathrm{x_i}}{\mathrm{R}}\right), \tag{9}$$

In Equation 9, n is the number of point samples; R is the radius of the search window; $K\left(\frac{x - x_i}{R}\right)$ is the kernel function.

2.6.2.3 Land surface temperature

Evidently, LST (Land Surface Temperature) is an essential index in the study of urban heat island effect. Especially with the gradual application of remote sensing data, various algorithms, including split-window, single-channel, and single-window algorithms, have

TABLE 2 Combined subjective and objective weighs from the supply perspective.

Weight type	Park size (parkS)	Water size in the park (wS)	Fractional vegetation cover (FVC)	Per capita park size (perS)	Accessibility (A)
Subjective weighs	0.29	0.17	0.32	0.08	0.11
Objective weighs	0.10	0.14	0.27	0.12	0.15
Subject-objective combination	0.18	0.17	0.31	0.10	0.14

TABLE 3 Evaluation index system of the park cold island effect from the demand perspective.

Demand categorization	Evaluation index	Abbreviation/Unit	Definition
Physiological requirement	Heat island patch size	hiS/hm^2	Area of clustered heat island patches
Mental requirement	Land surface temperature	LST/°C	Land surface temperature from remote sensing image inversion
	Population density	PD/ (person/ km^2)	Residential population per square kilometer
	POI kernel density	PoiKD/–	The agglomeration of POI (Points of Interest) in urban spatial distribution

become the most commonly used LST retrieval algorithms (51). Compared with the traditional radiative transfer equation, the single-channel algorithm has several benefits including a straightforward model, enhanced computational efficiency, and fewer required parameters. Hence, this paper chose the single-channel algorithm to calculate the land surface temperature using the following equations, ultimately yielding the land surface temperature (LST) raster image:

$$\tau = \varepsilon \times \tau, \tag{10}$$

$$D = (1-\varepsilon)\left[1+(1-\varepsilon)\tau\right], \tag{11}$$

$$LST = \frac{a(1-C-D)+\left[b(1-C-D)+C+D\right]\times T_b + D\times Ta}{C}, \tag{12}$$

In Equations 10–12, ε is the land surface emissivity; τ is the atmospheric transmittance and can be queried on the NASA official website for the corresponding region; C and D can be calculated.

2.6.2.4 Heat island patch size

The mean-standard deviation method was applied to classify the surface temperature obtained from the inversion (Table 4). Then, the heat island patches were extracted and subsequently quantified in terms of their respective actual sizes with the following formula. Due to the difference in patch sizes and the discontinuous nature of these values, the assignment of values for the real size of heat island patches was conducted to ensure the validity of data calculations. The specific assignment criteria are shown in Table 5.

$$hiS_k = \sum_{h}^{a} I_h, \tag{13}$$

In Equation 13, hiS_k is the heat island patch score for the park service unit k; k is the urban park service unit k; h is the heat island patch within the service unit k; I_h is the size-assigned score for the heat island patch h; and a is the total number of the heat island patches within the service unit k.

2.6.3 Residential cold island demand index calculation

Following the same method as described in section 2.5.3, the park cool island demand index was calculated using the following formula, based on the weights and scores of the four demand indicators (Table 6).

$$DW_n = \frac{\sqrt{DW_{\alpha n} * DW_{\beta n}}}{\sum_{n-1}^{4}\sqrt{DW_{\alpha n} * DW_{\beta n}}} \tag{14}$$

$$DIk = \sum_{n=1}^{m} D_n \times DW_n, (\mathrm{n}=1,2,\ldots\ldots,4; \mathrm{k}=1,2,\ldots\ldots,48) \tag{15}$$

In Equations 14 and 15, DW_n is the comprehensive weight of the nth demand indicator, $DW_{\alpha n}$ denotes its subjective weight, and $DW_{\beta n}$ signifies its objective weight; DI_k is the residential cold island demand index of the unit k, and there are 48 park service units, numbered from 1 to 48; D_n is the nth residential cold island demand index; n is a natural number from 1 to 4.

2.7 Identification and evaluation of supply and demand balance relationship of cold islands in urban parks

The interaction between supply and demand perspectives means the superposition, differentiation, and comparison of supply capacity and demand targets in the regional space. To achieve this, this paper introduces the location entropy used to measure and evaluate the state of spatial distribution characteristics of factors within a given region, as a path to establish the relationship:

$$LQ_k = (SI_k / DI_k)/(SI / DI), \tag{16}$$

In Equation 16, SI_k is the park cold island supply index for the region k, DI_k is the residents' cold island demand index for the region k, SI is the average supply index for the cold island effect within the study area, and DI is the average demand index for the cold island effect within the study area.

The values of LQ_k are discussed in terms of mean-standard deviation (A is the mean value of LQ_k in the study area, while sd is the standard deviation of LQ_k), from which three kinds of relative relationships between supply and demand can be obtained:

If the value of LQ_k is less than A-0.5sd, it indicates an unsatisfied demand in the region, implying that the supply is insufficient compared to the demand. Conversely, if LQ_k exceeds A + 0.5sd, it suggests a relatively sufficient supply in the region, indicating that the supply exceeds the demand. In the case where LQ_k falls within the range of A-0.5sd to A + 0.5sd, it signifies the supply and demand

TABLE 4 Classification of the land surface temperature.

Rank	Cold Island Zone	Central Temperature Zone	Heat Island Zone
Land surface temperature range T (°C)	$23.5 < T \leq 31.2$	$31.2 < T \leq 35.5$	$35.5 < T \leq 56.1$

TABLE 5 Criteria for assigning heat island patch size.

Score I	0	2	4	6	8	10
Actual size of heat island patch h (hm^2)	S = 0	$0<S \leq 5$	$5<S \leq 10$	$10<S \leq 50$	$50<S \leq 100$	S>100

capacity ratio of the cold island effect in the region is within a specific range, meaning a state of "relative balance."

3 Results

3.1 Delineation of park service units

According to the method of 2.4, the 60 urban parks in the main urban area of Wuhan got 48 park service units. The spatial distribution map of these park service units (Figure 4) reveals that the size of service units gradually increases from the core of the study area (within the first ring road) to its outskirts (the third ring road). The urban parks in the central area along the riverbanks were mostly embedded in the urban space in the way of "small areas with multiple dots," resulting in smaller overall service units. In the suburbs, larger patches of parkland existed, yet there were also instances where the area of the service unit was large despite the dominant urban park within it being very small, such as in the Guanshan Unit, South Lake Unit, Yunhu Unit, and Houhu Unit. The information for park service units can be queried from Supplementary Table 1.

3.2 Evaluation of the park cold island supply capacity from the supply perspective

3.2.1 Visual analysis of park cold island supply

3.2.1.1 Fractional vegetation cover

The raster image of vegetation cover in the study area (Figure 5) shows that the region's global average vegetation coverage is 0.44, with a general gradual increase in the vegetation coverage from the center to the periphery, which is significantly higher on the eastern side of the study area than in the rest of the region. Several water bodies in the main urban area were with high vegetation coverage, and the "blue space" and "green space" could be effectively connected through vegetation. The East Lake Scenic Area was the area with the most extensive area of high vegetation coverage in the main urban area, while Hankou River Beach Park, Turtle Mountain Scenic Area, etc., all had a discernible concentration of clusters with high vegetation coverage.

3.2.1.2 Accessibility

The accessibility distribution map of each park service unit (Figure 6) shows that, in general, the accessibility in the eastern region of the Yangtze River is significantly better than the western region. According to the "Series of Standards for National Garden Cities" (after this referred to as "the Standards"), the basic indicator for per capita public green space in Wuhan is 7.5 m^2. The "Wuhan Main Urban Area Green Space System Plan (2011–2020)" (after this referred to as "the Plan") proposes that by 2020, the planned indicator for per capita park green space in the urban core of Wuhan should reach 16.8 m^2. In 2018, there were 10 park service units within the main urban area of Wuhan that met the standard requirements of "the Plan." These parks were mainly located in Wuchang and Hongshan Districts, with the Shahu Park and the East Lake Scenic Area assuming the leading roles. Seven service units met the requirements of the "the Standards" but were lower than those of "the Plan." These units were primarily situated in the northeastern tip of the study area. The distribution of a larger number of urban parks of a certain size and with fewer inhabitants are the main reasons for their exceptional accessibility.

3.2.1.3 Per capita park size

Figure 7 shows the distribution pattern of per capita park size in the study area. East Lake Scenic Area, Yangchun Lake, Qingshan Park, White Jade Park, and Bamboo Leaf Sea units had high per capita park areas, all of which reached 32.03 m^2 or more. There were 25 service units with per capita park area lower than 1.87 m^2, accounting for 52.08% of the total number of service units. The results indicate that some parts of the city experience an overwhelmed park supply capacity, resulting in a shortage in per capita park size. Hence, many residents in these underserved area still lack access to parks (52).

3.2.2 Overall characterization of the park cold island supply capacity

The calculated park cold island supply index SI was assigned to the corresponding spatial location. Then the spatial distribution map of the cold island supply capacity of urban parks in the main urban area of Wuhan was obtained (Figure 8A). By analyzing the map, the following characteristics were presented: ① The supply index of various units within the study area ranges from 0.05 to 0.69, demonstrating significant spatial heterogeneity. High-supply-capacity units are primarily concentrated around urban water systems, with the East Lake Scenic Area unit exhibiting the highest supply index, ranging from 0.53 to 0.69. In contrast, low-value areas are predominantly located in regions with lower vegetation coverage, such as the New District Park unit, South Lake unit, Houhu unit, and Zhuodaoquan Park unit within the second-third ring road of the study area, where the supply index is only 0.05–0.19. ② Furthermore, the average supply capacity of cold islands across different layers ranges from 0.32 to 0.36, indicating relatively minor overall variation (as shown in Figure 8B). The highest average cooling island supply capacity is observed within the first ring, followed by a gradual decrease and subsequent increase as the ring layers expand. Within

TABLE 6 Combined subjective and objective weighs from the demand perspective.

Weight type	Land surface temperature (LST)	Heat island patch size(hiS)	POI kernel density (PoiKD)	Population density (PD)
Subjective weights	0.48	0.29	0.08	0.15
Objective weights	0.24	0.26	0.24	0.26
Subject-objective combination	0.35	0.29	0.15	0.21

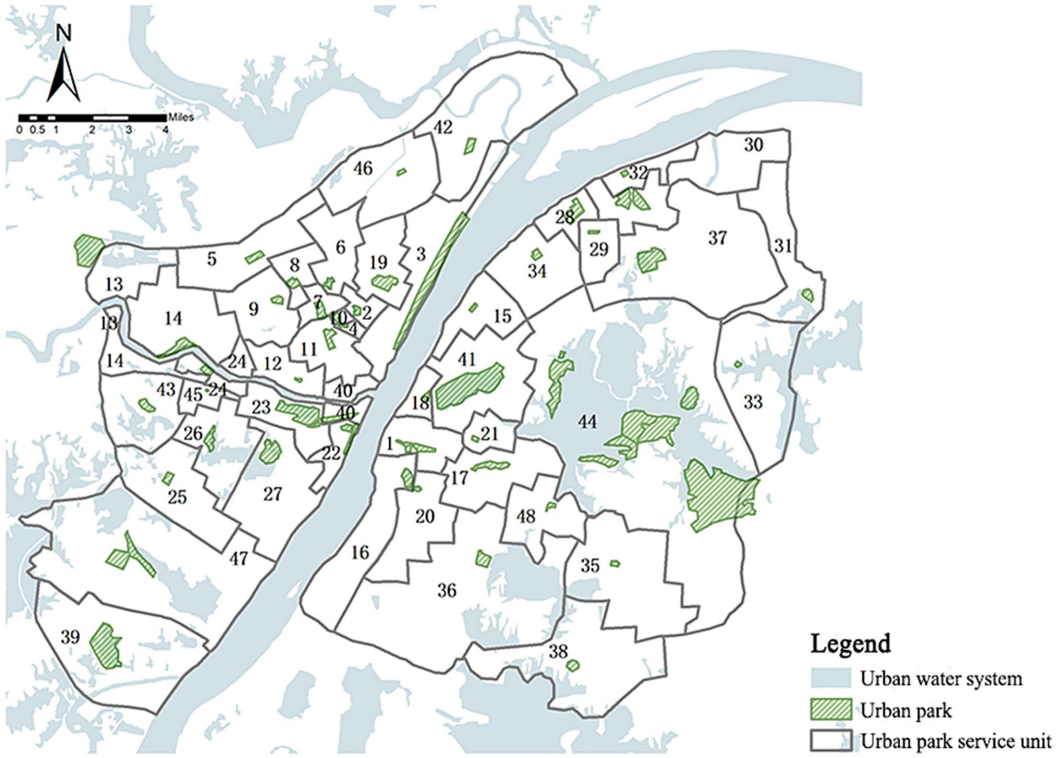

FIGURE 4
Spatial distribution of the urban park service units in the main urban area of Wuhan; The numbers 1–48 represent the park service unit number.

the first-second ring road, the development and construction intensity are high, resulting in limited available space for park construction. Consequently, the cold island supply capacity is lower than that of other rings. Inside the second-third ring road are large areal lakes and parks, such as East Lake Scenic Area, Moon Lake Scenic Area, Wuhan Zoo, Ink Lake, etc. Despite that the intensity of urban construction is similar to that of the second ring road, a relatively high cold island supply is still maintained. Outside the third ring road, because of its proximity to the city's outskirts, the intensity of development is diminishing. Consequently, there is more space to maintain its natural ecology in its original state, and the supply capacity of cold islands has been improved compared with that of the second ring road.

The findings of this study corroborate existing research on the critical role of water bodies in amplifying park cooling effects, as high-supply units typically feature a higher proportion of internal or adjacent water bodies. Notably, water bodies exhibit higher cooling intensity and magnitude compared to tree-dominated green spaces (53–55), particularly when exceeding 30% coverage within parks (28, 56). Furthermore, the synergistic interaction of blue-green spaces enhances cooling ranges and spatial impacts: water bodies improve thermal convection efficiency, while vegetation regulates radiative balance through shading and air circulation, collectively accelerating urban convection systems to establish localized cooling zones that surpass the performance of isolated landscape elements (57, 58). These mechanisms align precisely with the observed spatial distribution patterns, solidifying the robustness of our conclusions.

3.3 Evaluation of the residential cold island demand index from the demand perspective

3.3.1 Visual analysis of residential cold island demand

3.3.1.1 Population density

Figure 9 illustrates that the population density in the main urban area of Wuhan shows an overall trend of decreasing distribution with

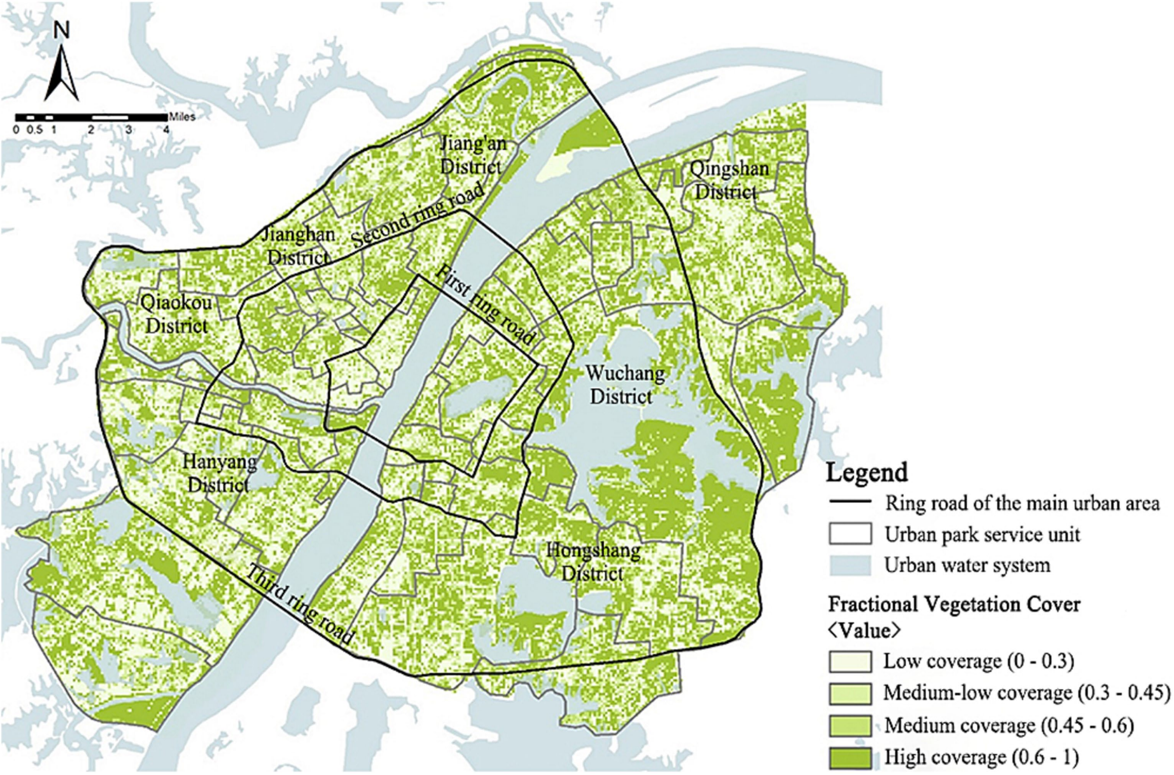

FIGURE 5
Spatial distribution of the vegetation coverage in the main urban area of Wuhan.

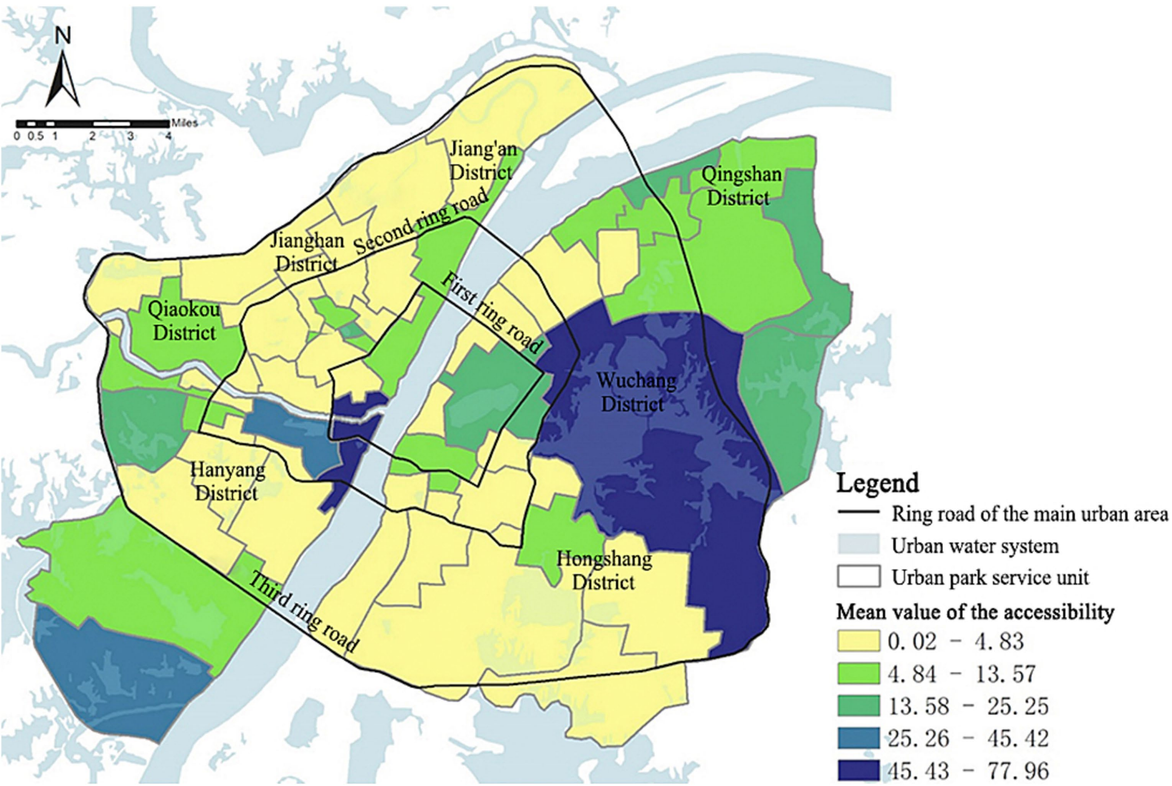

FIGURE 6
Spatial distribution of the park accessibility in the main urban area of Wuhan.

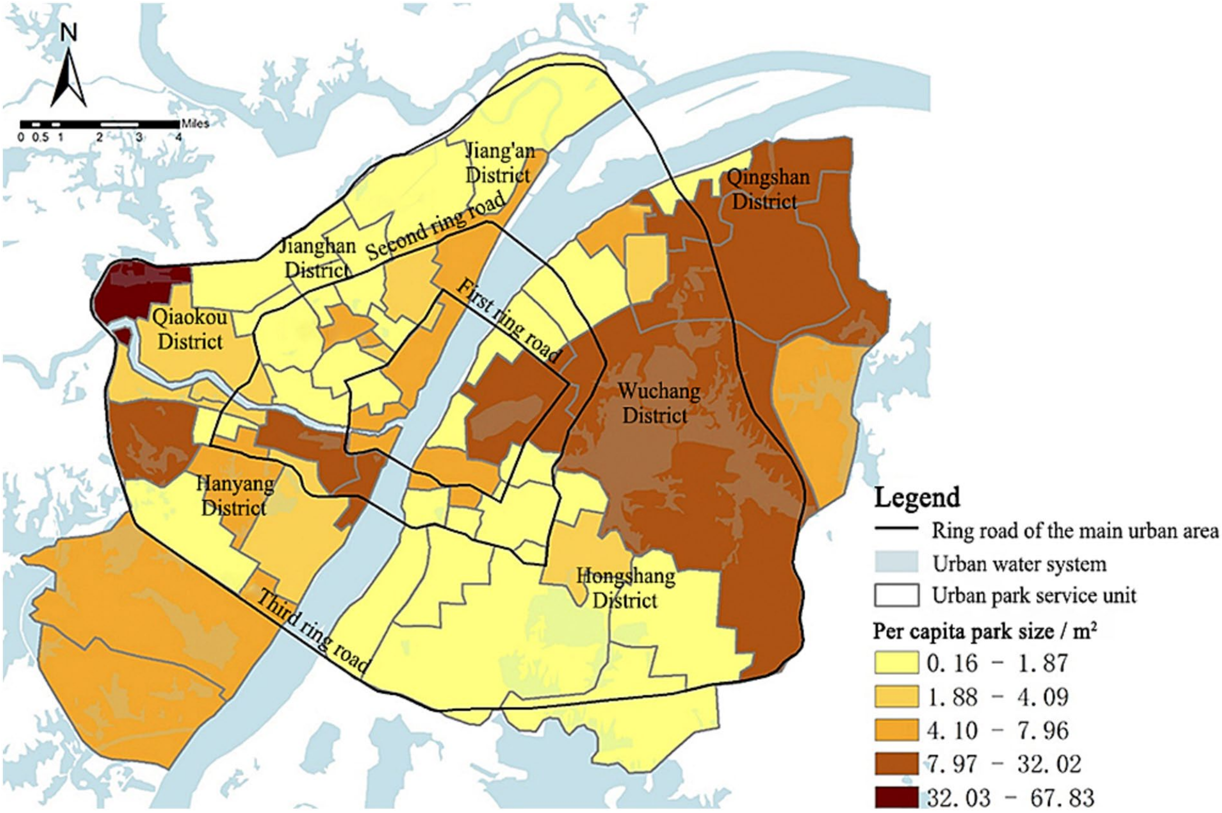

FIGURE 7
Per capita park size in each park service unit in the main urban area of Wuhan.

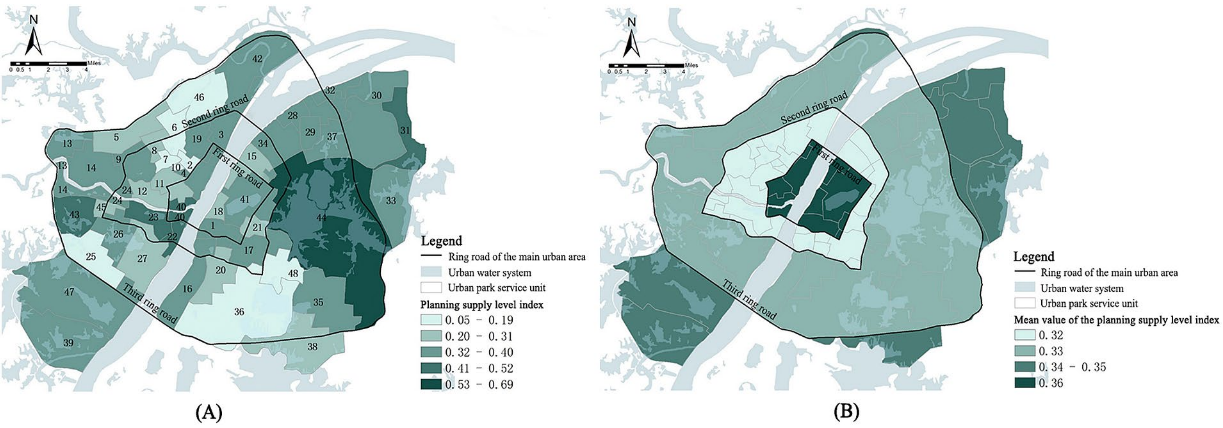

FIGURE 8
(A) Spatial distribution of the cold island supply capacity; **(B)** The cold island supply capacity within each ring road in the study area.

the Yangtze River serving as the central axis extending to the east and west wings. There were 8 high population density areas (PD > 8,000 people/km^2), accounting for 16.67% of the total number of service units. These areas were mainly distributed in service units such as Yellow Crane Tower, Neisha Lake, Turtle Mountain Scenic Area, Zhongshan Park, Qiaokou Park, and Treasure Island Park, located at the confluence of the Yangtze River and the Han River. There were 10 low-value zones (PD < 2,861 people/km^2), accounting for 20.83% of the total number of service units. These zones were concentrated in the northeastern, northwestern, and southwestern parts of the region, including Qingshan Park, White Jade Park, Yangchun Lake Park, Dijiao Park, Tang Lake Park, and other service units.

3.3.1.2 POI kernel density

The kernel density of social activity POIs exhibited a geographical distribution pattern that aligned with the kernel density of the population (Figure 10). Within the first ring road is the core area of urban activities, and the POI density gradually decreased from the first ring road to the outside. The high-value areas (PoiKD >880) were mainly located in service units such as Zhongshan Park, Minor South Lake Park, Yellow Crane Tower, and Simei Tang Park along the banks of the river in the central region, as well as in the service units such as Guanshan Park, Ziyang Park, and Hongshan Park in the eastern Hongshan District. While the low-value areas (PoiKD <98) were centrally located in the outer part of the study area in the service units of White Jade Park, Yangchun Lake Park, Tang Lake, and Dijiao Park.

3.3.1.3 Land surface temperature

The results of land surface temperature retrieval indicated that the land surface temperature in the main urban area of Wuhan ranged from 23.5°C to 56.1°, highlighting a significant temperature difference within the region (Table 4). The cold and heat islands in the study area exhibited a mosaic distribution pattern, with the cold island space mostly showing point and line distribution, while the heat island space shows a large and widely distributed pattern (Figure 11). Specifically, units adjacent to water bodies or containing large water areas have lower average temperatures, such as East Lake Scenic Area, the Yangtze River, Han River, South Prince Edward Lake, Longyang Lake, and Ink Lake, suggesting that large water bodies have a significant mitigating effect on high-temperature environments. The average temperatures within park service units at the northeastern and southeastern ends of the study area were higher, indicating a high risk of thermal environment and a high demand for cold islands among residents.

3.3.1.4 Heat island patch size

The score distribution map of heat island patches was obtained by counting the size of each heat island patch within each park service unit and assigning the corresponding value (Figure 12). The unit with the highest heat island patch score was No. 40 East Lake Scenic Area unit, with 24.6% of the range covered by heat islands. Among it, the largest heat island patch had a size of about 1,100 hm^2, located in the East Lake High-tech Development Zone (Optics Valley). It suggests that the cold island effect of the East Lake Scenic Area exerts a limited influence, while the active development of the high-tech zone also generates significant heat. The unit with the highest percentage of heat island coverage was the No. 20 Chuwangtai unit, at 83.8 percent. As the unit is located along Baishazhou Avenue, the development intensity is high. This unit faces a challenge in terms of the scarcity of expansive, environmentally sustainable parks and green spaces within its boundaries. Consequently, it encounters difficulties in mitigating the effects of the urban heat island phenomenon, particularly during the summer season.

3.3.2 Overall characterization of the residential cold island demand index

The calculated residents' cold island demand index DI was assigned to the corresponding spatial location. Then the spatial distribution map of the residents' cold island demand index in

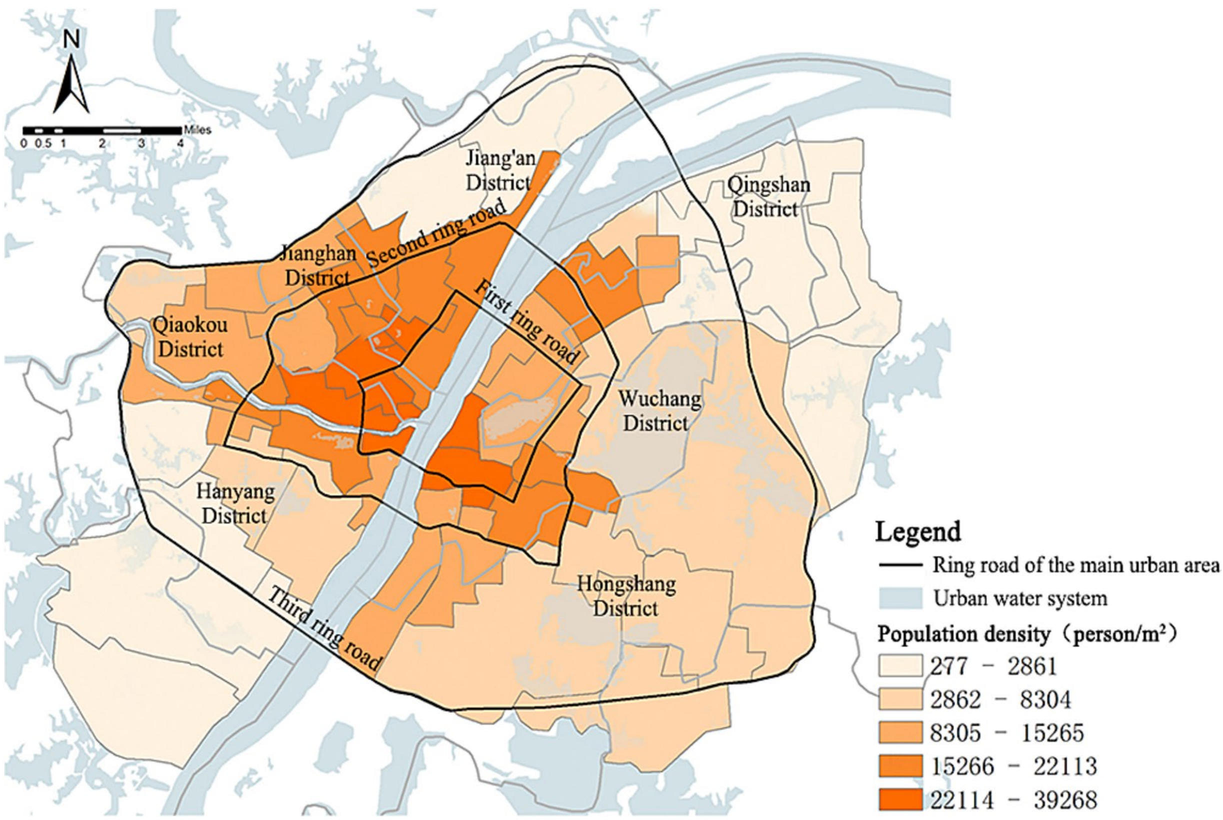

FIGURE 9
Population density distribution in the main urban area of Wuhan.

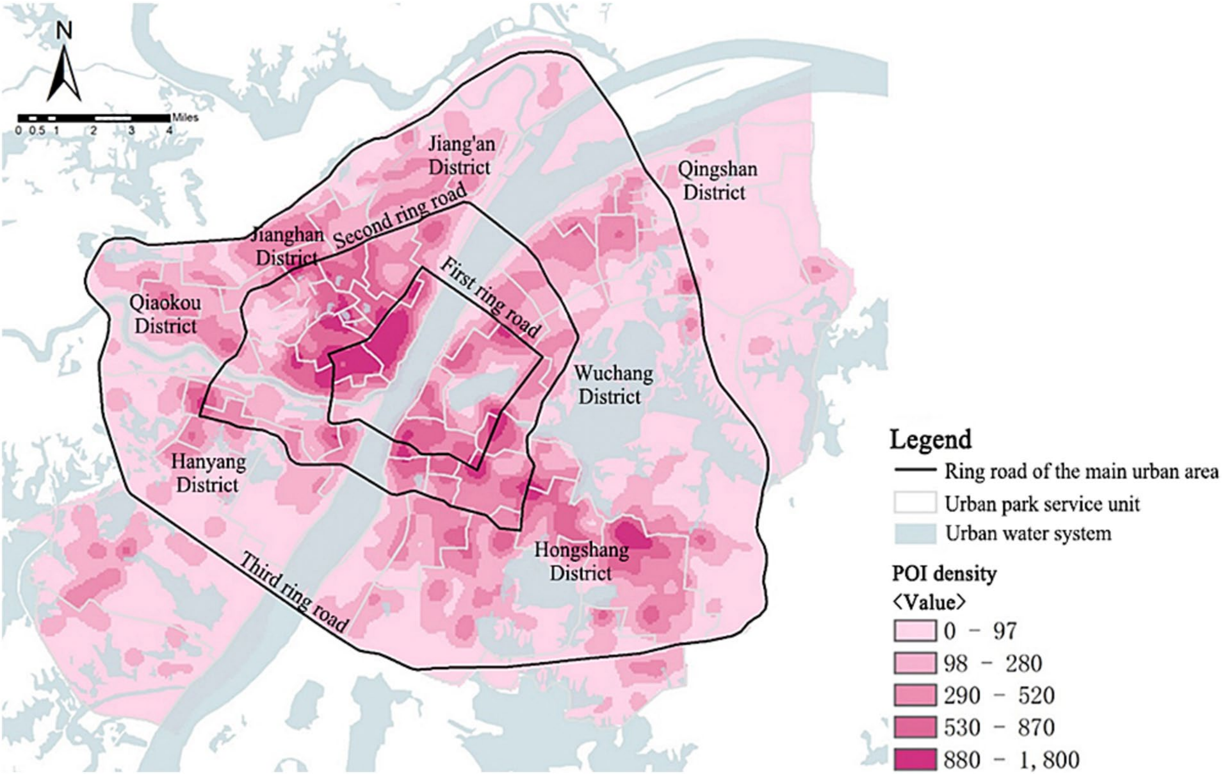

FIGURE 10
POI kernel density in the main urban area of Wuhan.

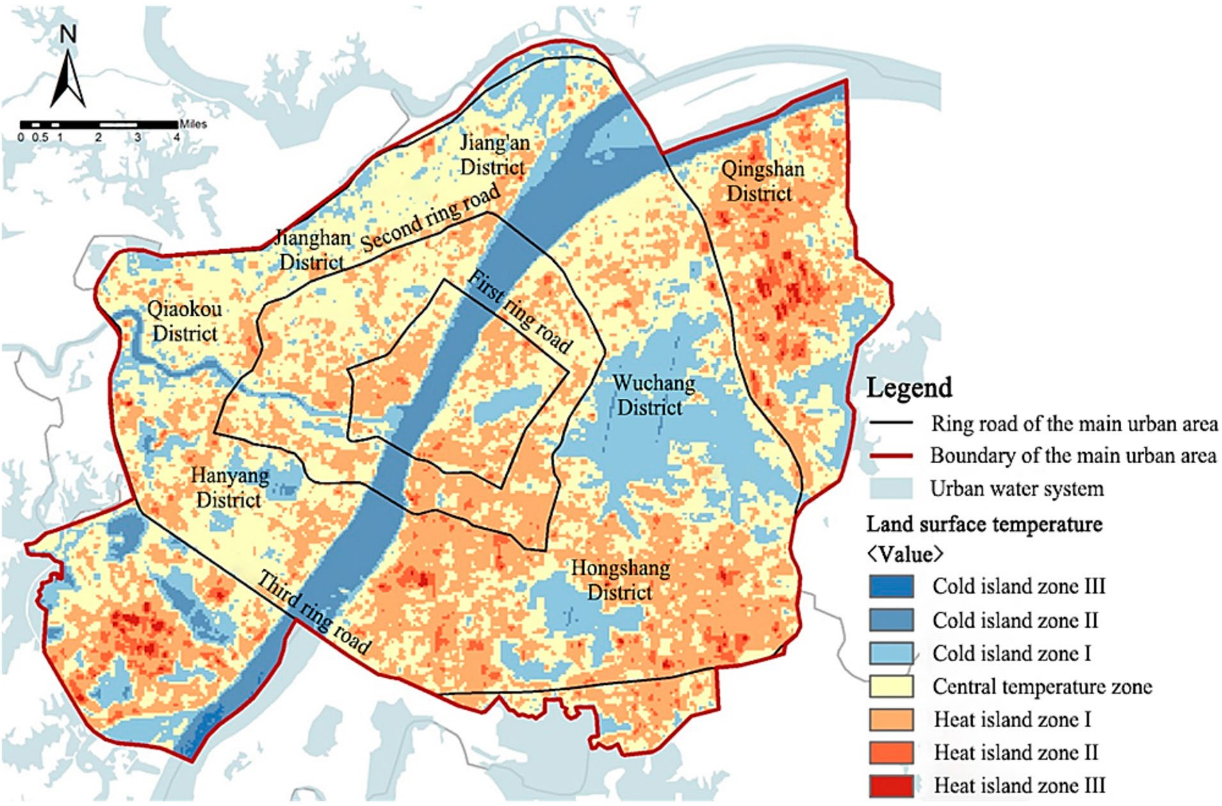

FIGURE 11
Inversion of land surface temperature in the main urban area of Wuhan.

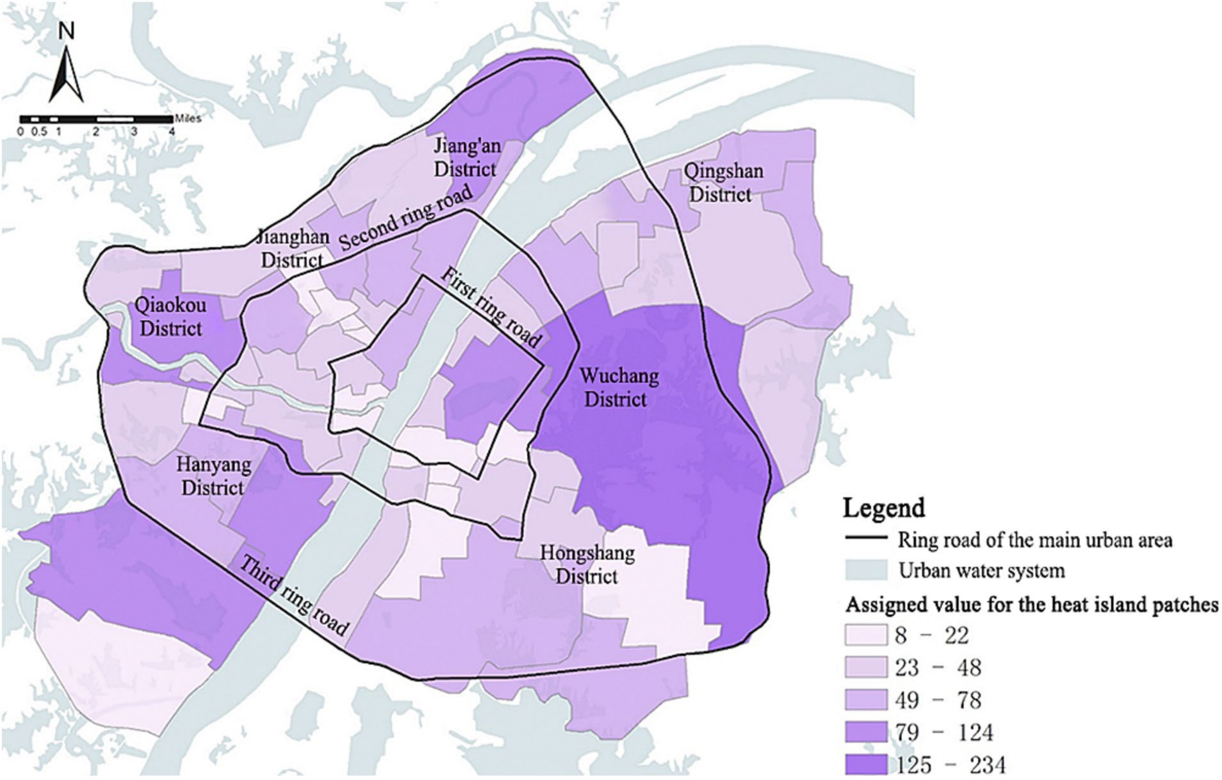

FIGURE 12
Spatial distribution of assigned values for heat island patches in the main urban area of Wuhan.

urban park units in the main urban area of Wuhan was obtained (Figure 13A). The darker the color of the unit color block, the stronger the demand for cold islands for residents. The following characteristics were presented: ① The demand level for cold islands in urban parks within the main urban area of Wuhan exhibits a spatial distribution characterized by "scattered across the entire region with localized concentrations." The high-demand units match with the center of distribution of population density and POI density. Seven units, including Ziyang Park Unit, Hongshan Park Unit, Chuwangtai Unit, Hongshan Square Unit, Rhyme Lake Unit, Wangjiadun Unit, and Zhongshan Park Unit, had residential demand indexes ranging from 0.44 to 0.54, indicating a higher level of urgency in terms of resident demand. ② The average demand index is spatially linked to the first, second, and third ring circles of the main urban area of Wuhan (Figure 13B). The demand values of each circle decreased from the core area outwards. This suggests that in general, the demand-side indicators have a certain correlation with the intensity of urban development and construction. Furthermore, the first ring of Wuhan's main urban area carries more functions of urban activities and attracts a large number of people to gather, resulting in elevated cooling island demand.

This finding aligns with Xin Ruhong et al.'s research on urban thermal regulation service demand, where communities with higher resident population density and POI density tend to face higher thermal environment risks, and thus have a higher level of cold island demand (59). The spatial distribution of population density and POI density, as an indirect characterization of the intensity of socio-economic activities, is closely related to the level of cold island demand. Studies have shown that anthropogenic heat generated by high-intensity socio-economic activities significantly raises surface and air temperatures in the region and surrounding (60). In areas with high urban development intensity, on the one hand, the rise in the proportion of impervious surfaces leads to a reduction in heat capacity, exacerbating the heat island effect and elevating the surface base temperature (61–63); on the other hand, dense high-rise buildings seriously impede air circulation and inhibit the spread of the cold island effect (64, 65). Therefore, the correlation mechanism between urban development intensity and the level of cold island demand is mainly reflected in the expansion of impervious surfaces and the deterioration of ventilation conditions, which provides scientific support for the regulation of urban thermal environment and the optimization of park planning.

3.4 Identification and evaluation of supply and demand balance relationship of cold islands in urban parks

From the park cold island supply indicator (SI) and resident cold island demand indicator (DI) of the 48 park service units in the study area, the location entropy theory was introduced to evaluate the level of balance between supply and demand. The spatial distribution map of the cold island effect supply and demand was obtained by connecting the supply and demand relationship with the spatial location of the units (Figure 14A).

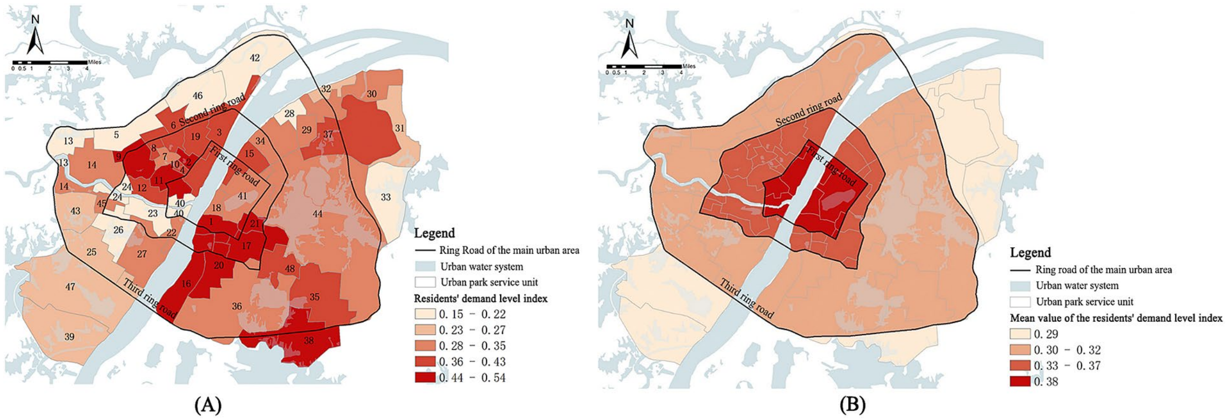

FIGURE 13
(A) Spatial distribution of the cold island demand index; **(B)** The cold island demand capacity within each ring road in the study area.

3.4.1 Supply and demand I: less supply but more demand

There are 19 units in total, showing a spatially clustered distribution in the study area, belonging to regions with high residential density and lacking vegetation cover. Two types are analyzed: the social supply-shortage type (Figure 14B) and the ecological service-shortage type (Figure 14C).

Social supply-shortage type (9 units): The main manifestations of this type lie in the residents' impeded access to the cold island effect, the excessive people cold island supply of urban parks carries, and the not sufficiently complementary built environment around the dominant parks in the unit to the cold island supply. These regions are in the middle of Qiaokou District, Jianghan District, and Jiang'an District. The confluence of the Yangtze River and the Han River has facilitated the gradual development of this area into the commercial and financial center of Wuhan, and a heavily populated zone in the main urban area, which mainly explains its high social demand value. Simultaneously, the existing neighborhoods exhibit a high level of density, resulting in "numerous but small parks" in the region, hence presenting the overloaded supply capacity phenomenon.

Ecological service-shortage type (10 units): The cold island supply of urban parks within the units is insufficient to mitigate the summer heat and the heat island effect caused by urbanization, resulting in extreme heat. Additionally, the continuous distribution of high-temperature heat island patches in some units exacerbates the negative impacts of the heat island effect. These regions are located in Hongshan District and Wuchang District, which include rapidly developing zones such as the East Lake High-Tech Development Zone, Hongshan Square, Zhongnan Road Business District, and Optics Valley University Town. The parks in these units are small and dispersed, resulting in a very weak cooling effect on land surface temperature. Although adjacent to three water bodies-East Lake, South Lake, and the Yangtze River, the connectivity among them is weak, resulting in inadequate dispersion of the cold island effect. This demonstrates that, in addition to park size, landscape connectivity is also a critical factor influencing cold island supply. This finding aligns with previous research, confirming that the mosaic distribution of cold and heat islands and the connectivity of cold island networks play a crucial role in improving thermal environmental issues. A spatially complete and well-structured cooling network can significantly reduce the continuity of negative impacts associated with high-intensity urban development (66–68).

3.4.2 Supply and demand II: relative balance between supply and demand

There are 18 units in total (Figure 14A). These units exhibit a balanced relationship between park cold island supply and residential cold island demand within a specific range. However, given the constant development of the city and the corresponding changes in residents' demands, it is imperative to analyze these units in conjunction with the urban land use plan in order to detect any difficulties possibly requiring early warning.

3.4.3 Supply and demand III: more supply but less demand

There are 11 units in total (Figure 14A), each exhibiting a park vegetation coverage of 0.75 or higher. Additionally, all of these units either contain water bodies or are situated in close proximity to them. The supply capacity of cold islands is strong enough to meet the residents' demand for cold islands within the unit. For example, the East Lake Scenic Area, Longyang Lake-Ink Lake Scenic Area, Moon Lake Scenic Area, Fuhe Ecological Green Wedge, Hanjiang River Ecological Axis, etc., collectively form the ecological framework of the main urban area of Wuhan and designated in the planning as the low development intensity or ecological landscape control zones, which is conducive to the sustainable development of the city and the healthy life of its inhabitants "benign balance.

4 Discussion

4.1 Urban park planning strategy for matching supply and demand of cold islands

4.1.1 Overall strategy—adaptive planning

Adaptive planning is a spatial feedback process aiming to dynamically adjust planning strategies in response to the evolving requirements of the users (69). To ensure a relative equilibrium between the supply and demand of cold islands in urban parks in the

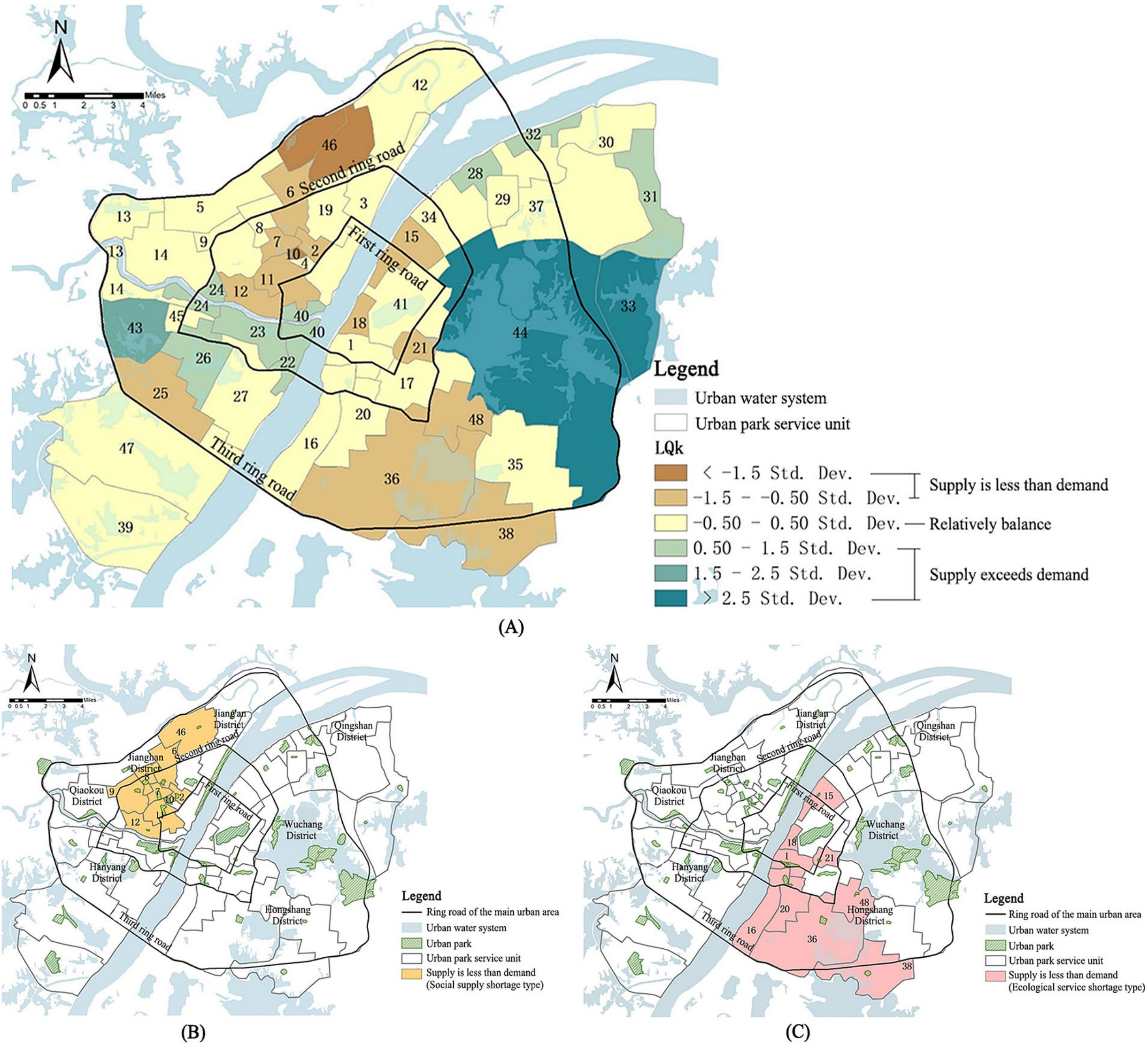

FIGURE 14
(A) Spatial distribution of the supply–demand relationship of cold island effect in the main urban area of Wuhan; **(B)** Spatial distribution of the social supply-shortage type units; **(C)** Spatial distribution of the ecological service-shortage type units.

future, it is imperative to introduce the concept of adaptive planning and conduct prognostic assessments. The operational mechanism of the adaptive planning structure employed in this study is visually depicted in Figure 15. It analyses the intrinsic linkage between urban parks, cold island effects, and people. This analysis is to reveal the problems of the current space in terms of supply and demand and to assess the development potential of the future space. It can guide the adaptive planning process of urban parks, the object of adaptation, and characterize the dynamic demand changes of urban residents, the subject of adaptation (70).

4.1.2 Typology planning strategy

Taking the evaluated supply and demand relationship as the guide for action, this study presents a set of sub-strategy that exhibit strong feasibility and serve as valuable references. These strategies aim to enhance the cold island supply level of urban parks, bolster their adaptive capacity in the future development process and allocate the limited ecological resources and service functions to the individuals and regions that require them the most.

Strategy 1: During the process of old city reconstruction, it is advisable to plan for wedge-shaped parks and expand the existing parks, thereby enhancing the accessibility to urban parks (for less supply but more demand--social supply-shortage type). Currently, Wuhan is continuously promoting old city reconstruction and gradually and piecewise carrying out scientific planning. Emphasis should be placed on incorporating the consideration of the parks' cold island effect into the renewal planning for Hankou, Qiaokou, and Jiang'an Districts. Liudu Bridge and Unity Street can consider planning city wedge parks to connect with the Yangtze River, when carrying out old city reconstruction. Some neighborhoods in Hanzhong Street, the Friendship Neighborhood, or other neighboring areas can consider connecting with Qiaokou Park to expand the size of Qiaokou Park when undergoing renovation and renewal. Moreover, they should reserve sufficient space for the expansion of city parks to meet the

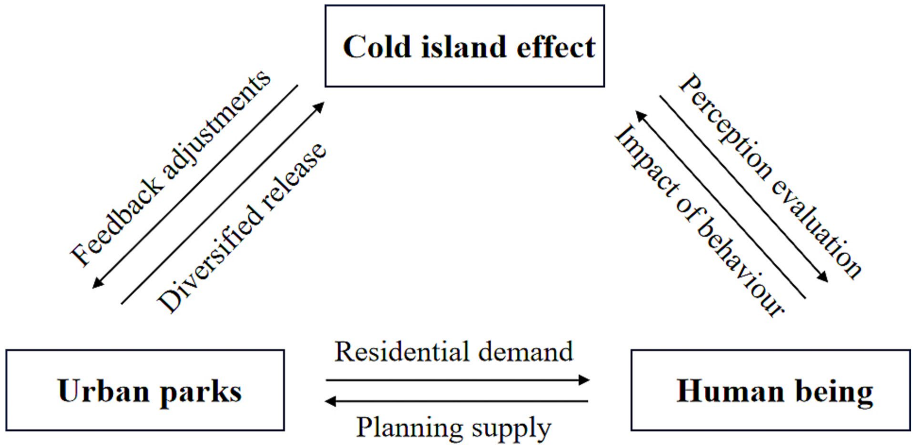

FIGURE 15
Operational mechanism of adaptive planning structures.

future demand for cold islands in the high-density residential neighborhoods. By controlling the building density and architectural form of old renovation communities, and using more point buildings at air intakes, it can promote breeze circulation and effectively form their own fresh air systems. Through the accessibility analysis, the urban-facing joints and pedestrian entrances are increased to achieve the goal that city parks are accessible to more urban residents. For example, Northwest Lake Park, Zhongshan Park, Fountain Park, Minor South Lake Park, Treasure Island Park, Wuhan Youth Palace, and other parks and green spaces are relatively close to each other and they can consider planning the "string of pearls into a chain" of greenways. Planning greenways from residential neighborhoods to parks allows residents to reach urban parks more conveniently, improving the comfort and accessibility of paths leading to the parks. In the old city renovation, green space should be inserted in gaps or white space, and "pocket parks" with recreational and ornamental functions should be established to cover greenfield cold island service blind spots and enhance the cooling radiation effect on the neighborhood.

Strategy 2: Cold island connectivity should be enhanced and blue-green cold island corridors should be built (for less supply but more demand--ecological service-shortage type). Numerous studies have shown that cold island connectivity can improve cooling efficiency. From the southern suburbs of Wuhan along Tangxun Lake, South Lake, and East Lake to Tianxing Sandbar, a cold island corridor running through the north and south of Wuhan is constructed, passing through many heat island areas in the Wuchang and Hongshan Districts. It can cut down on the negative impacts of the heat island effect and alleviate the physical and mental discomfort due to the high temperature in summer. East Lake, South Lake, and Yezhi Lake are several essential waters in Wuchang District. They should reserve the open green space around the waters, enrich the vegetation community level, and play the synergistic cooling effect of the blue-green space to boost the overall cooling of the city.

Strategy 3: The blue-green intertwined ecological background should be restored and protected (for relative balance). It's imperative to restore and protect the blue and green natural ecological background of the parks and to control and prevent the trend of encroachment on green spaces and water areas during urbanization. The blue-green intertwined urban parks, such as Tang Lake Unit, Sand Lake Unit, Yangchun Lake Unit, Wuhan Zoo Unit, etc., should optimize the edge shape of the blue-green space patches and keep the waterfront space with a high degree of vegetation coverage. It can not only better realize the cooling effect of the parks' cold islands, but also provide citizens with better social and sports space thus to cope with the inevitable increase in the demand value of the cold islands in the process of urban development and to maintain the balance of supply and demand as long as possible.

Strategy4: Adequate green space should be reserved (for relative balance). Based on the early warning problems of each research unit in the relative balance zone, combined with Wuhan's territorial spatial planning, the planning early warning strategy for the disorder of supply and demand in the development process are targeted to be proposed. The units with pieces of residential neighborhoods in the future plan, such as Jiangtan Sports Unit, Science Park Unit, Guanshan Unit, etc., should pay more attention to the budget for the number of potential residents, and analyze the accessibility of parks' sites in the planning of urban parks. These units also are required to design community-level parks as a supplement and reserve a sufficient amount of land for green space development. This will prevent future urban area development from attracting too many residents and excessive social demand arising from socio-economic activities which will upset the existing relative balance, and enhance accurate prevention and control capability of urban thermal environmental risks.

4.2 Limitations and insights

This study represents a positive attempt to investigate the cold island effect of urban parks from a dual perspective of supply and demand. However, there are still challenges that require resolution. First of all, the cold island effect of urban parks exhibits significant spatiotemporal complexity; however, due to the inherent limitations of Landsat data, existing research predominantly focused on spatial analysis. Future studies can further investigate daily and seasonal variations in the supply and demand of the urban parks' cold island effect by utilizing data sources with shorter revisit periods, such as MODIS (Moderate Resolution Imaging Spectroradiometer). This would help uncover the interaction mechanisms between park characteristics and meteorological factors across multiple temporal scales. Secondly, the supply and demand of the park cold island effect are influenced by multiple factors, such as internal landscape composition (71) and surrounding urban morphology (18), which were not comprehensively incorporated in the current evaluation system. Additionally, the selected indicators primarily explored urban thermal environment patterns at a two-dimensional level, lacking investigation into three-dimensional factors such as building height (BH), sky view factor (SVF), and frontal area index (FAI) (18). Future research should establish a more holistic evaluation framework for supply and demand to better analyze the complex environmental interactions surrounding urban parks. Finally, with the development of information technology, further investigation of urban parks can be conducted at a more detailed level, which should incorporate the integration of microscopic, mesoscopic, and macroscopic scales. This entails grasping the overall layout at the macroscopic scale, emphasizing the precise adjustments made at the micro level and considering the transitional function of the mesoscopic level. Future research can examine each unit on the grid scale to find the implementation points more precisely.

5 Conclusion

In the process of rapid urban development, the planning and construction of urban parks are prone to be a mismatch between supply and demand. In light of this, this paper selected 60 urban parks in the main urban area of Wuhan that effectively exert the cold island effect as the research subjects. By integrating the Thiessen polygons with the detailed regulatory planning units to delineate research units and developing the supply and demand evaluation model of the cold island effect of urban parks, this research conducted a comprehensive quantitative assessment of cooling services from both supply and demand perspectives. The interaction between the supply and demand perspectives was established by applying the location entropy theory, enabling the proposal of targeted optimization strategy for urban parks in Wuhan to achieve better supply–demand alignment. The main findings are as follows: ① The spatial distribution of cold island supply and demand exhibited significant heterogeneity. High-supply units were strongly correlated with water body distribution, while high-demand units aligned closely with population density and POI density centers, displaying a "scattered overall, locally concentrated" pattern. ② A significant supply–demand mismatch in cold island effects was observed, with 19 units (accounting for approximately 40%) exhibiting insufficient supply relative to demand. These units were predominantly concentrated in areas with complex building environments, high population density, low vegetation coverage, and poor landscape connectivity. To address these challenges, this study proposed the following optimization strategy: optimizing the scale and layout of existing parks, reserving green spaces for ecological restoration, strengthening the protection of blue-green ecological foundations, and establishing a blue-green cold island corridor network to enhance ecological connectivity.

By quantifying the residential cold island demand and the park cold island supply capacity, this study advances research on the cold island effect of urban parks at regional and city scales, offering new insights for sustainable urban development and climate adaptation planning. The findings not only provide a scientific basis for mitigating urban heat island effects but also offer decision-making support for the precise allocation of urban park resources. This research holds significant practical implications for improving urban living environments and enhancing ecological benefits with precision.

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

JS: Conceptualization, Data curation, Formal analysis, Funding acquisition, Methodology, Supervision, Writing – original draft, Writing – review & editing. YQ: Conceptualization, Formal analysis, Methodology, Visualization, Writing – original draft, Writing – review & editing. YL: Data curation, Formal analysis, Visualization, Writing – original draft.

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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.2025.1523210/full#supplementary-material

References

1. Ouyang WL, Morakinyo TE, Ren C, Ng E. The cooling efficiency of variable greenery coverage ratios in different urban densities: a study in a subtropical climate. *Build Environ*. (2020) 174:106772. doi: 10.1016/j.buildenv.2020.106772

2. Li XM, Zhou YY, Asrar GR, Imhoff M, Li XC. The surface urban Heat Island response to urban expansion: a panel analysis for the conterminous United States. *Sci Total Environ*. (2017) 605-606:426–35. doi: 10.1016/j.scitotenv.2017.06.229

3. Garrett JK, White MP, Huang J, Ng S, Hui Z, Leung C, et al. Urban blue space and health and wellbeing in Hong Kong: results from a survey of older adults. *Health Place*. (2019) 55:100–10. doi: 10.1016/j.healthplace.2018.11.003

4. Liu HM, Huang B, Zhan QM, Gao SH, Li RR, Fan ZY. The influence of urban form on surface urban Heat Island and its planning implications: evidence from 1288 urban clusters in China. *Sustain Cities Soc*. (2021) 71:102987. doi: 10.1016/j.scs.2021.102987

5. Amani-Beni M, Zhang B, Xie GD, Xu J. Impact of Urban Park's tree, grass and waterbody on microclimate in hot summer days: a case study of Olympic Park in Beijing, China. *Urban For Urban Green*. (2018) 32:1–6. doi: 10.1016/j.ufug.2018.03.016

6. Park YJ, Guldmann JM, Liu DS. Impacts of tree and building shades on the urban Heat Island: combining remote sensing, 3D Digital City and spatial regression approaches. *Comput Environ Urban Syst*. (2021) 88:101655. doi: 10.1016/j.compenvurbsys.2021.101655

7. Xiong JH. An investigation of the impact of ecological landscape shaping in urban public spaces on urban climate. *Chin Bull Bot*. (2023) 58:671.

8. You HY. Characterizing the inequalities in urban public green space provision in Shenzhen, China. *Habitat Int*. (2016) 56:176–80. doi: 10.1016/j.habitatint.2016.05.006

9. Zhong XH, Jin HX, Li S, Ji R, Bao ZH. Cold Island effect of Park green space and its influencing factors in Hangzhou. *Chin Landsc Archit*. (2022) 38:75–80. doi: 10.19775/j.cla.2022.09.0075

10. Algretawee H. The effect of graduated Urban Park size on Park Cooling Island and distance relative to land surface temperature (LST). *Urban Clim*. (2022) 45:101255. doi: 10.1016/j.uclim.2022.101255

11. Yao X, Yu KY, Zeng XJ, Lin YB, Ye BJ, Shen XB, et al. How can urban parks be planned to mitigate urban Heat Island effect in "furnace cities"? An accumulation perspective. *J Clean Prod*. (2022) 330:129852. doi: 10.1016/j.jclepro.2021.129852

12. Kong FH, Yin HW, James P, Hutyra LR, He HS. Effects of spatial pattern of greenspace on urban cooling in a large metropolitan area of eastern China. *Landsc Urban Plan*. (2014) 128:35–47. doi: 10.1016/j.landurbplan.2014.04.018

13. Xie QJ, Li J. Detecting the cool island effect of urban parks in Wuhan: a City on Rivers. *Int J Environ Res Public Health*. (2021) 18:15. doi: 10.3390/ijerph18010132

14. Di JN, Su T, Lei B, Liu XB, Meng C, Xu LQ, et al. Analysis of urban Heat Island effect and influencing factors based on the "source-sink" landscape pattern: a case study of Hefei. *China Environ Sci*. (2023) 43:6039–50. doi: 10.19674/j.cnki.issn1000-6923.20230609.001

15. Chen Z, Chen FM, Zhu FG, Cao L, Shen XH, Li JX. Effects of Park size and plant community structure on Urban Park air temperature. *Chin J Ecol*. (2011) 30:2590–6. doi: 10.13292/j.1000-4890.2011.0377

16. Zhang CS, Xie GD, Lu CX, Liu CL, Li N, Wang S, et al. The mitigating effects of different urban green lands on the Heat Island effect in Beijing. *Resour Sci*. (2015) 37:1156–65.

17. Qiu KB, Jia BQ. The roles of landscape both inside the Park and the surroundings in Park cooling effect. *Sustain Cities Soc*. (2020) 52:101864. doi: 10.1016/j.scs.2019.101864

18. Han DR, Xu XL, Qiao Z, Wang F, Cai HY, An HM, et al. The roles of surrounding 2D/3D landscapes in Park cooling effect: analysis from extreme hot and Normal weather perspectives. *Build Environ*. (2023) 231:110053. doi: 10.1016/j.buildenv.2023.110053

19. Aram F, Solgi E, García EH, Mosavi A, Várkonyi-Kóczy AR. The cooling effect of large-scale urban parks on surrounding area thermal comfort. *Energies*. (2019) 12:21. doi: 10.3390/en12203904

20. Shi LJ, Zhao MD. Cool island effect of urban parks and impact factors in summer: a case study of Xi' An. *J Arid Land Resour Environ*. (2020) 34:154–61. doi: 10.13448/j.cnki.jalre.2020.139

21. Li MT, Yang LB, Wei Y. Improved Gaussian based 2-step floating catchment area method:a case study of green space accessibility in Shanghai. *Prog Geogr*. (2016) 35:990–6. doi: 10.18306/dlkxjz.2016.08.008

22. Pietil M, Neuvonen M, Borodulin K, Korpela K, Tyrvinen L. Relationships between exposure to urban green spaces, physical activity and self-rated health. *J Outdoor Recreat Tour*. (2015) 10:44–54. doi: 10.1016/j.jort.2015.06.006

23. Tamosiunas A, Grazuleviciene R, Luksiene D, Dedele A, Reklaitiene R, Baceviciene M, et al. Accessibility and use of urban green spaces, and cardiovascular health: findings from a Kaunas cohort study. *Environ Health*. (2014) 13:1–11. doi: 10.1186/1476-069X-13-20

24. Sun YW, Tan SH, Shen JZ. Research on influence of Park green coverage rate on crowds emotional recovery. *Landsc Archit*. (2021) 28:85–91. doi: 10.14085/j.fjyl.2021.04.0085.07

25. Zhang Q, Zhou D, Xu D, Rogora A. Correlation between cooling effect of green space and surrounding urban spatial form: evidence from 36 urban green spaces. *Build Environ*. (2022) 222:109375. doi: 10.1016/j.buildenv.2022.109375

26. Xie QJ, Yang CZ, Ren L. Scale effect of regulating mechanism of urban water bodies in improving thermal environment in Wuhan, China. *Chin J Ecol*. (2024) 43:2325–33. doi: 10.13292/j.1000-4890.202408.003

27. Fan HY, Yu ZW, Yang GY, Liu TY, Liu TY, Hung CH, et al. How to cool hot-humid (Asian) cities with urban trees? An optimal landscape size perspective. *Agric For Meteorol*. (2019) 265:338–48. doi: 10.1016/j.agrformet.2018.11.027

28. Gunawardena KR, Wells MJ, Kershaw T. Utilising green and Bluespace to mitigate urban Heat Island intensity. *Sci Total Environ*. (2017) 584-585:1040–55. doi: 10.1016/j.scitotenv.2017.01.158

29. Weng QH, Rajasekar U, Hu XF. Modeling urban Heat Islands and their relationship with impervious surface and vegetation abundance by using Aster images. *IEEE Trans Geosci Remote Sensing*. (2011) 49:4080–9. doi: 10.1109/tgrs.2011.2128874

30. Wilson JS, Clay M, Martin E, Stuckey D, Vedder-Risch K. Evaluating environmental influences of zoning in urban ecosystems with remote sensing. *Remote Sens Environ*. (2003) 86:303–21. doi: 10.1016/s0034-4257(03)00084-1

31. Bowler DE, Buyung-Ali L, Knight TM, Pullin AS. Urban greening to cool towns and cities: a systematic review of the empirical evidence. *Landsc Urban Plan*. (2010) 97:147–55. doi: 10.1016/j.landurbplan.2010.05.006

32. Chen HY, Deng QL, Zhou Z, Ren ZG, Shan XF. Influence of land cover change on Spatio-temporal distribution of urban Heat Island -a case in Wuhan Main urban area. *Sustain Cities Soc*. (2022) 79:103715. doi: 10.1016/j.scs.2022.103715

33. Li XX, Li WW, Middel A, Harlan SL, Brazel AJ, Turner BL. Remote sensing of the surface urban Heat Island and land architecture in Phoenix, Arizona: combined effects of land composition and configuration and cadastral-demographic-economic factors. *Remote Sens Environ*. (2016) 174:233–43. doi: 10.1016/j.rse.2015.12.022

34. Santamouris M, Ban-Weiss G, Osmond P, Paolini R, Synnefa A, Cartalis C, et al. Progress in urban greenery mitigation science - assessment methodologies advanced technologies and impact on cities. *J Civ Eng Manag*. (2018) 24:638–71. doi: 10.3846/jcem.2018.6604

35. Zhou W, Shen X, Cao FL, Sun Y. Effects of area and shape of greenspace on urban cooling in Nanjing, China. *J Urban Plan Dev*. (2019) 145:9. doi: 10.1061/(asce)up.1943-5444.0000520

36. Yue WZ, Qiu SS, Xu H, Xu LH, Zhang LL. Polycentric urban development and urban thermal environment: a case of Hangzhou, China. *Landsc Urban Plan*. (2019) 189:58–70. doi: 10.1016/j.landurbplan.2019.04.008

37. Tao ZL, Cheng Y. Research Progress of the two-step floating catchment area method and extensions. *Prog Geogr*. (2016) 35:589–99. doi: 10.18306/dlkxjz.2016.05.006

38. Chen X, Dong YK, Wang QS. Evaluation of seasonal supply and demand for urban parks based on improved 2SFCA model. *J Shenyang Jianzhu Univ Nat Sci*. (2022) 38:504–11. doi: 10.11717/j.issn:2095-1922.2022.03.15

39. Wu KY, Jin JL. Attribute recognition method of regional ecological security evaluation based on combined weight on principle of relative entropy. *Geogr Sci*. (2008) 28:754–8. doi: 10.3969/j.issn.1000-0690.2008.06.007

40. Feng L, Ll XD. Effects of heat waves on human health:a review of recent study. *J Environ Health*. (2016) 33:182–8. doi: 10.16241/j.cnki.1001-5914.2016.02.025

41. Mavrogianni A, Davies M, Batty M, Belcher SE, Bohnenstengel SI, Carruthers D, et al. The comfort, energy and health implications of London's urban Heat Island. *Build Serv Eng Res Technol*. (2011) 32:35–52. doi: 10.1177/0143624410394530

42. Bokaie M, Zarkesh MK, Arasteh PD, Hosseini A. Assessment of urban Heat Island based on the relationship between land surface temperature and land use/land cover in Tehran. *Sustain Cities Soc*. (2016) 23:94–104. doi: 10.1016/j.scs.2016.03.009

43. Zhao HB, Zhang H, Miao CH, Ye XY, Min M. Linking heat source-sink landscape patterns with analysis of urban Heat Islands: study on the fast-growing Zhengzhou City in Central China. *Remote Sens*. (2018) 10:22. doi: 10.3390/rs10081268

44. Yu GL, Chen TT, Zhao FQ. The influence of air temperature and temperature variability on mental health. *Adv Psychol Sci*. (2020) 28:1282–92. doi: 10.3724/SP.J.1042.2020.01282

45. Yue YF, Zhan QM, Wang J. Optimizing the urban thermal environment: a case study in Wuhan, China. *Resour Environ Yangtze Basin*. (2018) 27:286–95. doi: 10.11870/cjlyzyyhj201802007

46. Li X. Recognition of urban polycentric structure based on spatial aggregation characteristics of poi elements: a case of Zhengzhou City. *Acta Sci Nat Univ Pekin*. (2020) 56:692–702. doi: 10.13209/j.0479-8023.2020.044

47. Tang ZL, Chen S. An evaluation of social justice performance in the distribution of metro networks in the Central City of Shanghai. *Shanghai Urban Plann Rev*. (2016) 1:102–8. doi: 10.3969/j.issn.1673-8985.2016.02.020

48. Estoque RC, Ooba M, Seposo XT, Togawa T, Hijioka Y, Takahashi K, et al. Heat health risk assessment in Philippine cities using remotely sensed data and social-ecological indicators. *Nat Commun*. (2020) 11:12. doi: 10.1038/s41467-020-15218-8

49. Dou WS, Wang CX, Xue MY, Wang ZH. Ldentification and evaluation of urban functional land based on pol data–a case study of five districts in Jinan. *World Reg Stud*. (2020) 29:804–13. doi: 10.3969/j.issn.1004-9479.2020.04.2019186

50. Luan XL, Wei S, Han SR, Li XT, Yang WY, Liu MS, et al. A multi-scale study on the formation mechanism and Main controlling factors of urban thermal field based on urban big data. *Chin J Appl Ecol*. (2018) 29:2861–8. doi: 10.13287/j.1001-9332.201809.015

51. Yang AS, Juan YH, Wen CY, Chang CJ. Numerical simulation of cooling effect of vegetation enhancement in a subtropical Urban Park. *Appl Energy*. (2017) 192:178–200. doi: 10.1016/j.apenergy.2017.01.079

52. Zhao B, Ll LL, Cao L. Gis-based analysis of City Park green space service range and layout optimization–a case study in Huaqiao international Business City. *Chin Landsc Archit*. (2015) 31:95–9. doi: 10.3969/j.issn.1000-6664.2015.06.024

53. Du HY, Cai YL, Zhou FQ, Jian H, Jiang WY, Xu YQ. Urban blue-green space planning based on thermal environment simulation: a case study of Shanghai, China. *Ecol Indic*. (2019) 106:105501. doi: 10.1016/j.ecolind.2019.105501

54. Wu D, Wang YF, Fan C, Xia BC. Thermal environment effects and interactions of reservoirs and forests as urban blue-green infrastructures. *Ecol Indic*. (2018) 91:657–63. doi: 10.1016/j.ecolind.2018.04.054

55. Lin WQ, Yu T, Chang XQ, Wu WJ, Zhang Y. Calculating cooling extents of green parks using remote sensing: method and test. *Landsc Urban Plan*. (2015) 134:66–75. doi: 10.1016/j.landurbplan.2014.10.012

56. Tan XY, Sun X, Huang CD, Yuan Y, Hou DL. Comparison of cooling effect between green space and water body. *Sustain Cities Soc*. (2021) 67:102711. doi: 10.1016/j.scs.2021.102711

57. Shi DC, Song JY, Huang JX, Zhuang CQ, Guo R, Gao YF. Synergistic cooling effects (Sces) of urban green-blue spaces on local thermal environment: a case study in Chongqing, China. *Sustain Cities Soc*. (2020) 55:102065. doi: 10.1016/j.scs.2020.102065

58. Zhou WQ, Huang GL, Cadenasso ML. Does spatial configuration matter? Understanding the effects of land cover pattern on land surface temperature in urban landscapes. *Landsc Urban Plan*. (2011) 102:54–63. doi: 10.1016/j.landurbplan.2011.03.009

59. Xin RH, Zeng J, Li K, Shen ZJ. Identifying the key areas and management priorities of the imbalance between supply and demand in urban thermal environment regulation. *Geogr Res*. (2022) 41:3124–42. doi: 10.11821/dlyj020210757

60. Oke TR. The energetic basis of the urban Heat-Island. *Q J R Meteorol Soc*. (1982) 108:1–24. doi: 10.1002/qj.49710845502

61. Feyisa GL, Dons K, Meilby H. Efficiency of parks in mitigating urban Heat Island effect: An example from Addis Ababa. *Landsc Urban Plan*. (2014) 123:87–95. doi: 10.1016/j.landurbplan.2013.12.008

62. Cheela VRS, John M, Biswas W, Sarker P. Combating urban Heat Island effect-a review of reflective pavements and tree shading strategies. *Buildings*. (2021) 11:24. doi: 10.3390/buildings11030093

63. Yao L, Sun S, Song CX, Wang YX, Xu Y. Recognizing surface urban heat 'Island' effect and its urbanization Association in Terms of intensity, footprint, and capacity: a case study with multi-dimensional analysis in northern China. *J Clean Prod*. (2022) 372:18. doi: 10.1016/j.jclepro.2022.133720

64. Yu XY, Liu Y, Zhang ZH, Xiao R. Influences of buildings on urban Heat Island based on 3d landscape metrics: An investigation of China's 30 megacities at Micro grid-cell scale and Macro City scale. *Landsc Ecol*. (2021) 36:2743–62. doi: 10.1007/s10980-021-01275-x

65. Huang JM, Chang HY, Chen LC, Wang YS. Canopy-scale built-environment characteristics and urban Heat Island effect in a tropical medium-Sized City. *Sustain For*. (2021) 13:17. doi: 10.3390/su13020868

66. Zhang WP, Zhuang ZX, Xie MQ, Hu Y, Wang QN. Construction and pattern optimization of multiscale urban Thermalenvironment network based on circuit theory: a case study of the central urban area of Chengdu. *Chin Landsc Archit*. (2023) 39:103–8. doi: 10.19775/j.cla.2023.04.0103

67. Peng J, Cheng XY, Hu YX, Corcoran J. A landscape connectivity approach to mitigating the urban Heat Island effect. *Landsc Ecol*. (2022) 37:1707–19. doi: 10.1007/s10980-022-01439-3

68. Debbage N, Shepherd JM. The urban Heat Island effect and City contiguity. *Comput Environ Urban Syst*. (2015) 54:181–94. doi: 10.1016/j.compenvurbsys.2015.08.002

69. Li YH, Fan XY, Ma QW. Adaptive planning of recreational space from the view of the balance of supply and demand: a case study of Xixi National Wetland Park in Hangzhou City. *Econ Geogr*. (2018) 38:204–11. doi: 10.15957/j.cnki.jjdl.2018.01.026

70. Fan XY. Adaptive planning of Wetland Park from the perspective of supply and demand [Master's degree]. Zhejiang, China: Zhejiang University (2018).

71. Cai XY, Yang J, Zhang YQ, Xiao XM, Xia JH. Cooling Island effect in urban parks from the perspective of Internal Park landscape. *Hum Soc Sci Commun*. (2023) 10:12. doi: 10.1057/s41599-023-02209-5

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