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The impact of artificial intelligence policy on urban land green use efficiency: a quasi-natural experiment from China

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The question of whether innovations in artificial intelligence (AI) can effectively enhance green land use efficiency is of critical importance. Exploring this issue is essential for uncovering new pathways for green governance and novel approaches to sustainable development in the intelligent age. Utilizing panel data from 286 prefecture-level and above cities in China from 2015 to 2023, this paper employs a multi-period Difference-in-Differences model to examine the impact of the National New Generation AI Innovation and Development Pilot Zones (AIPZ) on urban land green use efficiency (ULGUE). By treating the establishment of these zones as a quasi-natural experiment, we systematically investigate the effects, underlying mechanisms, and heterogeneity from a policy-driven perspective. The findings reveal that: (1) the establishment of AIPZ has significantly enhanced the ULGUE in the pilot cities. This conclusion remains robust after a battery of robustness tests. (2) Mechanism tests indicate that the AIPZ policy elevates ULGUE primarily through three transmission channels: green technology innovation, labor structure optimization, and industrial structure upgrading. (3) Heterogeneity analysis reveals that the impact of the AIPZ is more pronounced in municipalities and provincial capitals, large-scale cities, and those with a high level of digital infrastructure. (4) Furthermore, tests on spatial spillover effects demonstrate that the policy generates significant positive spillovers, simultaneously improving land green use efficiency in both the local and surrounding areas. The findings of this study not only expand the research boundaries regarding the environmental effects of AI policies, but also provide crucial theoretical underpinnings and practical insights for leveraging intelligent policies to enhance land green use efficiency and advance sustainable urban development globally.

KEYWORDS

artificial intelligence policy, green technology innovation, industrial structure upgrading, labor structure optimization, urban land green use efficiency

1 Introduction

As an indispensable material factor of production, land resources serve as a fundamental platform for the flow and integration of various production factors. They underpin the spatial configuration of urban production, living, and ecological functions, whose efficiency directly determines the long-term well-being of urban development (Xu W. et al., 2025). Land use efficiency refers to optimizing economic output while maximizing the intensity of land use. In contrast, land green use efficiency places a greater emphasis on mitigating environmental impacts throughout the utilization process, on the basis of pursuing economic benefits. It thus embodies the dual characteristics of high-intensity utilization and low-carbon sustainability (Ma et al., 2024). By the end of 2023, China's urban built-up area had reached 64,500 square kilometers, with its permanent resident urbanization rate climbing to 66.16%. However, this rapid spatial expansion has also exposed critical issues such as extensive land use and low efficiency. The growing misalignment between this mode of expansion and the urbanization process has become increasingly apparent, subsequently exacerbating multiple challenges, including insufficient economic growth momentum, arable land resource shortages, pressure on food security, and ecological environmental pollution (Liu et al., 2014). Against this backdrop, enhancing the level of green land use has become a crucial lever for promoting the optimal allocation and efficient utilization of urban land resources. Additionally, it is a crucial decision for fully promoting the economy's and society's shift to a low-carbon, green economy.

In recent years, alongside the vigorous growth of the digital economy, artificial intelligence, characterized by its robust capabilities in data processing and intelligent decision-making, has progressively permeated various sectors of economic development. It has emerged as a new engine driving the global economy (Liu B. et al., 2025). AIPZ initiated in 2019 and established across 18 cities in eight batches, represent a concentrated effort by China to enhance its AI innovation and accelerate the commercialization of AI technologies. As the core engine of the latest technological and industrial transformation, AI is fundamentally reshaping industries through groundbreaking breakthroughs, smarter resource allocation, and deep-seated upgrades. It thereby promotes a shift towards intensive, green, and low-carbon land use. This not only effectively curbs high resource consumption and pollution emissions but also ensures the sustainable utilization of land resources (Shen and Lin, 2025; Zhao et al., 2024). Furthermore, AI policy demonstrates significant potential for advancing sustainable development, optimizing resource allocation, and improving social welfare, thereby highlighting its pivotal role in the transition to a green economy (Ren and Wang, 2025). Therefore, a systematic investigation into the impact of AI policy on ULGUE can not only identify its environmental effects but also yield robust empirical evidence for enhancing ULGUE and advancing sustainable development.

Based on the existing literature, two main categories of studies are closely related to this paper. The first category examines the measurement of ULGUE and factors influencing it. Against the backdrop of continuously advancing ecological civilization construction, environmental benefits have received increasing attention as concomitant outputs of land use. Consequently, the theoretical connotation and measurement methods of land use efficiency have been expanded and deepened (Wang et al., 2025). Specifically, early studies measured land use efficiency within a framework that considered land as a foundational input, labor and capital as additional factors, and economic and environmental gains as desirable outputs (Jiao et al., 2020). Building upon this foundation, when scholars further incorporated undesirable outputs like pollution emissions, the idea of land use efficiency evolved into what is now termed ULGUE. ULGUE is defined as the level of green economic output generated per unit of land, representing the spatial manifestation of urban resource inputs and outputs. It is concretely measured by theratio of production inputs (such as labor, land, and capital) to comprehensive outputs, encompassing economic and social benefits, ecological gains, and environmental negative externalities (Tan et al., 2021). The super-efficiency SBM model has become a mainstream efficiency assessment tool in this field, as it improves upon traditional DEA models by incorporating undesirable outputs and effectively resolving the issue of indistinguishable efficiency values among multiple decision-making units. Regarding the driving factors of ULGUE, scholarly discussions have primarily been conducted from the perspectives of natural, economic, and policy factors. From the natural factors perspective, urban ecological resources such as urban landscapes, green spaces, and forest cover have been shown to contribute positively to ULGUE (Zheng et al., 2023). Conversely, pollution emissions exert a significant negative impact on ULGUE (Li et al., 2023). At the economic level, factors such as urban construction, industrial transformation, foreign investment, and market openness significantly influence ULGUE (Zhou and Lu, 2023). Moreover, the effects of these economic factors often exhibit regional heterogeneity and demonstrate significant spatial spillover effects (Zhao et al., 2024). Regarding policy factors, studies have demonstrated that exogenous policy shocks—including low-carbon pilot policies, green fiscal policies, innovative city construction, and innovation-driven policies—contribute positively to the enhancement of ULGUE (Jiang et al., 2023; Wang and Li, 2025; Xu H. et al., 2025; Zuo and Zhang, 2025).

The second category focuses on AI's economic and environmental impacts. Characterized by its strong spillover and driving effects, AI is increasingly central to academic research as a distinct field of study. On one hand, scholars have primarily examined the economic effects of AI through dimensions such as economic growth, employment, income distribution, innovation, and trade. At the macro level, AI not only enhances productivity but also influences economic and even social institutions, thereby fostering inclusive growth within industries (Chen and Qin, 2022). At the micro level, AI optimizes the allocation efficiency and structural composition of labor and capital, consequently improving firms' labor productivity and corporate value (Kromann et al., 2020). On the other hand, scholars hold divergent views regarding the environmental effects of AI. Some pessimistic studies indicate that while the industrial intelligent transformation in developing countries brings scale and efficiency improvements, It also poses challenges such as job displacement, environmental costs, and workplace safety risks (Acemoglu and Restrepo, 2020a; Brevini, 2020; Yang et al., 2022). Particularly in developing countries where environmental regulations are not yet fully established, the industrial intelligent transformation driven by AI technology may not only fail to promote ecological improvement but could potentially lead to more severe environmental pollution. Conversely, a substantial body of scholars maintains a more optimistic perspective, emphasizing that empowering industrial green transformation with AI technology can achieve environmental benefits alongside economic gains, achieving dual economic and environmental benefits (Li et al., 2022). This is because the application of emerging technologies like AI can lead to more intensive utilization of energy and resources, while simultaneously enhancing environmental monitoring and ecological risk prevention through functions such as intelligent detection and real-time early warning, thereby facilitating green economic development and sustainable development (Zhang L. et al., 2022).

Existing literature has established a solid theoretical and empirical foundation to investigate the relationship between AI and

ULGUE. Nevertheless, certain limitations persist in current research. On one hand, although a mature body of literature exists on the economic impacts of AI, considerable divergence remains regarding its environmental impacts, necessitating further in-depth investigation. Moreover, no study has yet examined the environmental benefits of AI from a policy-driven perspective. On the other hand, the implementation of AIPZ is fundamentally reliant on land as a foundational resource. Both the economic and environmental outcomes of these zones are ultimately reflected in land use patterns, exerting a profound influence on ULGUE. However, the relationship between AI policy and ULGUE remains unexplored in the existing literature. This research gap exists primarily because AI policy represents an emerging frontier within the current digital and intelligent wave, extending beyond the scope of previous academic inquiry. This oversight, in turn, creates a valuable research opportunity for the present study. It is particularly noteworthy that, compared to traditional environmental policies focused on ecological benefits and conventional industrial policies prioritizing economic outcomes, AI policy not only fosters technological advancement but also organically integrates such advancement with mechanisms for energy conservation and emissions reduction. This unique characteristic enables AI policy to generate "positive policy externalities" without incurring additional policy costs. Based on this rationale, this study treats the establishment of AIPZ as an exogenous policy shock. Utilizing panel data from 286 Chinese cities (2015–2023), we theoretically and empirically examine its impact on ULGUE and the underlying mechanisms. Accordingly, this research addresses the following questions: (1) Does the establishment of AIPZ influence ULGUE in pilot cities? (2) Through what mechanisms does the AIPZ policy affect ULGUE? (3) Does the impact of AIPZ on ULGUE vary across different types of cities?

This study contributes to the existing literature in the following ways: (1) This study takes advantage of the AIPZ initiative as a quasi-natural experiment to identify the causal effect of AI policy on urban land use efficiency. This approach not only extends the discourse on AI policy but also enriches the ULGUE literature by introducing a policy-oriented perspective. (2) This research uncovers the underlying mechanisms through which AIPZ enhance ULGUE, specifically focusing on the synergistic effects of green technology innovation, labor structure optimization, and industrial structure upgrading. This addresses a critical gap in understanding how AI policy influences ULGUE. (3) By examining heterogeneity across city administrative levels, city size, and digital infrastructure levels, this study provides crucial insights for tailoring policy implementation to local conditions, thereby offering valuable guidance for optimizing pilot policies and improving ULGUE in diverse urban contexts.

2 Policy background and theoretical analysis

2.1 Policy background

The deep integration of AI technologies with green and low-carbon industries has become one of the important tasks for social and economic development. In 2015, the State Council issued "Made in China 2025," emphasizing the development of intelligent equipment and products, and promoting the intelligentization of production processes and the cultivation of new production methods. Subsequently, the NDRC and three other ministries jointly introduced supporting policies to accelerate the development of the AI industry. In 2017, the State Council issued the "Next Generation Artificial Intelligence Development Plan," elevating AI to a national strategy and establishing a "three-step" development roadmap. This marked China's entry into a phase of systematic advancement in artificial intelligence. In 2019, the Ministry of Science and Technology issued the "Guidance on the Construction of National New Generation AI Innovation and Development Pilot Zones," promoting the application of AI technologies in fields such as manufacturing, logistics, and environmental protection, with the aim of establishing a group of AI innovation hubs with significant leading and driving effects. By the end of 2021, the Ministry of Science and Technology had established National New Generation AI Innovation and Development Pilot Zones in 18 cities across eight batches. These pilot zones were strategically aligned with major regional development strategies, including the Beijing-Tianjin-Hebei coordinated development, the Yangtze River Economic Belt development, the Guangdong-Hong Kong-Macao Greater Bay Area construction, the Yangtze River Delta regional integration, and the Chengdu-Chongqing economic circle. The initiative also balanced synergistic development among western, central, eastern and northeastern cities, positioning AI as a key driver of regional growth. The evolution of China's AI policy development is presented in Figure 1.

2.2 Theoretical analysis

2.2.1 Direct impact of AIPZ on ULGUE

The establishment of AIPZ can enhance both the economic and environmental benefits of urban land, thereby directly improving ULGUE. On one hand, the development of the AIPZ has intensified efforts in pioneering and core technology research, while strengthening the construction of smart infrastructure such as communication networks, big data centers, and computing centers. This enables local governments and enterprises to monitor the flow of production factors in real time, promotes the coordinated coupling of production systems and land use systems (Tian et al., 2022), and enhances the economic output of land. On the other hand, the platform effect and supervisory constraint effect of the AIPZ contribute to precise control of pollutants and carbon emissions (Yang and Liu, 2024). AI technology breaks down data barriers, enabling government environmental agencies to utilize technical monitoring and intelligent tracking to obtain accurate pollution emission data. This allows for the implementation of "rewarding excellence and penalizing inferiority" measures, Incentivizing enterprises to adopt energy-saving and emission-reduction practices (Sun and Zhang, 2020). Additionally, the application of AI in urban land management enhances the precision of land use monitoring and management, as well as the scientific rigor of land use decision-making (Sanchez et al., 2023), thereby contributing to the improvement of comprehensive land use benefits. In summary, through the combined enhancement of economic and environmental benefits, production activities concentrated on limited urban land can achieve dual improvements in pollution reduction and output capacity, thereby ultimately elevating ULGUE. Therefore, the study proposes:

> *Hypothesis 1 (H1)*: The construction of AIPZ can enhance ULGUE.

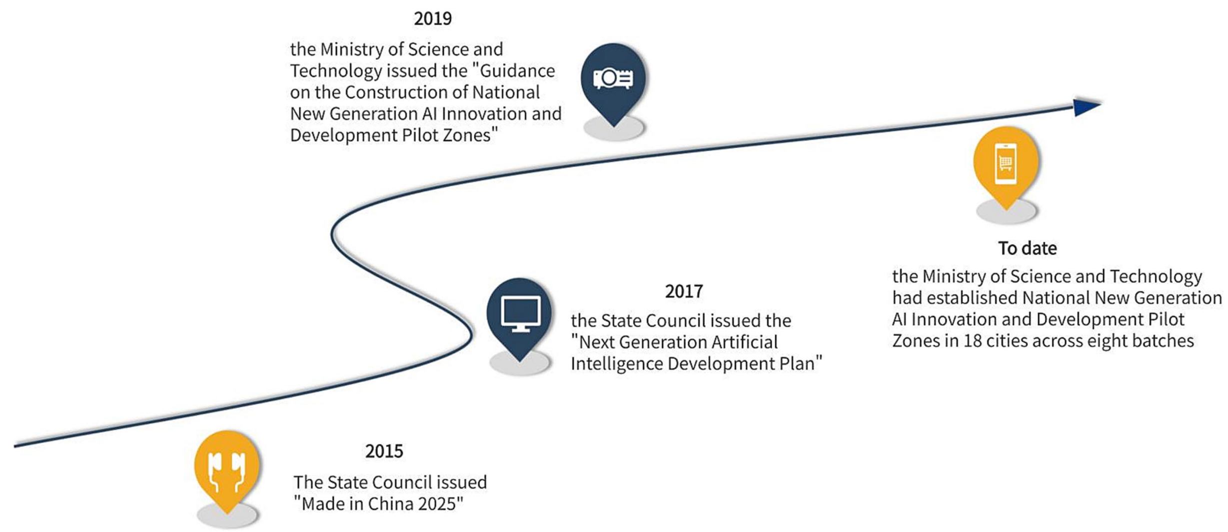

FIGURE 1
Policy evolution.

2.2.2 Indirect impact of AIPZ on ULGUE

(1) Green Technology Innovation

The establishment of AIPZ provides external driving forces for breakthroughs in green innovation. On one hand, it offers essential technical support for green innovation. Technologies such as big data analytics and digital simulation enable innovation entities to simulate and predict outcomes of green projects, reducing trial-and-error costs. Meanwhile, the creation of intelligent platforms facilitates more efficient knowledge and technology exchange among industry, academia, and research institutions, enhancing collaborative innovation capacity and thereby achieving cross-disciplinary and multi-level breakthroughs in green innovation (Wang et al., 2025). On the other hand, the development of AIPZ facilitates the optimal allocation of green innovation factors. AI accelerates the flow of green innovation resources and expands the scope of resource allocation, enabling innovation entities to integrate resources across broader temporal and spatial dimensions. This creates greater possibilities and growth space for green innovation (Liu et al., 2020). Furthermore, during the development of AIPZ, the pilot cities have actively formulated and implemented incentive policies and promotion measures in areas such as key technology research and development, intelligent terminal development, and industrialization of key new products. This has led to sustained growth in government science and technology expenditures and enterprise R&D investment, continuously elevated urban human capital levels, and consequently driven green technology innovation in fields including clean energy, environmental governance, and resource recycling (Bi et al., 2024). Research shows that technological innovation not only boosts production but also cuts emissions effectively. Particularly, green technology innovation can further reduce energy consumption from both production and consumption ends, promote the efficient utilization of clean energy, and ultimately enable production activities on land to realize substantial gains in both environmental and economic benefits. This comprehensive enhancement consequently elevates ULGUE (Liu and Dong, 2021). Therefore, the study proposes:

> *Hypothesis 2 (H2)*: The construction of AIPZ enhances ULGUE through green technology innovation.

(2) Labor Structure Optimization

The development of AIPZ drives the optimization and reshaping of the labor force skill structure. On one hand, the introduction of AI technologies and smart scenarios within these zones generates demand for advanced skills such as data analytics, machine learning algorithms, and intelligent system management. This prompts the workforce to acquire capabilities in precise planning, simulation forecasting, and dynamic optimization. Consequently, these enhanced skills enable scientific layout decisions in the preliminary stage of land resource allocation, thereby avoiding inefficient urban expansion and ecological conflicts. On the other hand, while the intelligent transformation in pilot cities may reduce labor demand in certain sectors through the "substitution effect," it also generates more employment opportunities via "creative destruction" (Acemoglu and Restrepo, 2020b). This shift in the skill demand landscape compels low-skilled workers to continuously acquire new knowledge and skills to avoid unemployment, while simultaneously incentivizing enterprises to enhance employee training programs (Xie et al., 2021). Consequently, the overall quality of the workforce improves, enabling better adaptation to the labor paradigm shifts brought about by intelligentization. Research confirms that high-quality labor factors can more effectively utilize systems such as smart energy management and environmental monitoring platforms, enabling precise planning, intensive utilization, and ecological management of land resources. This enhances both land productivity and environmental performance, thereby driving improvements in ULGUE (Shen and Lin, 2025). Therefore, the study proposes:

> *Hypothesis 3 (H3)*: The construction of AIPZ enhances ULGUE through labor structure optimization.

(3) Industrial Structure Upgrading

The development of AIPZ facilitates industrial structure upgrading in pilot cities. On one hand, these zones establish an essential institutional environment for building effective collaboration mechanisms within and between industries. This helps accelerate the formation of industrial clusters within their jurisdictions, encompassing AI-related sectors such as algorithms, data, models, talent, and ecosystems. Consequently, resource elements are increasingly invested in and transferred to emerging industrial sectors, moving toward mid-to-high-end, intelligent, and producer service industries. This drives the intelligent, green, and digital transformation of traditional industries (Meng et al., 2022). On the other hand, AIPZ can reorganize production factors through technological innovation, break down industry barriers, and promote diversified integration and collaborative development across different sectors. This not only facilitates optimized reallocation of factors but also catalyzes the emergence of strategic and future industries. By enabling precise matching between enterprise production needs and required technologies, it replaces traditional development models with more efficient scientific and technological innovation paradigms (Zou and Xiong, 2023). Furthermore, the development of AIPZ further clarifies the priority of accelerating AI technology advancement, effectively deepening the integration of AI with traditional industries. This allows advanced elements such as cutting-edge knowledge and sophisticated experience to permeate traditional industrial chains, enhancing coordination among upstream and downstream segments and ultimately strengthening industrial chain resilience (Zhang et al., 2024). Research demonstrates that the Industrial modernization and emerging sector expansion, typically accompanies the adoption of more stricter environmental standards and advanced production technologies. During this process, high-pollution and high-energy-consumption enterprises are compelled to exit the market, replaced by a modern industrial system characterized by higher value-added, intellectualization, and green transformation. Consequently, production factors such as capital and labor are utilized more efficiently, while production activities' dependence on land resources is reduced. This achieves the dual objectives of output increase and pollution diminution within the land use system, ultimately exerting a positive influence on ULGUE (Zhang W. et al., 2022). Therefore, the study proposes:

> *Hypothesis 4 (H4)*: The construction of AIPZ enhances ULGUE through industrial structure upgrading.

Figure 2 outlines the pathways through which AIPZ directly and indirectly affects ULGUE.

3 Materials and methods

3.1 Model specification

This paper adopt a multi-period DID model to assess the effect of AI Pilot Zone establishment on ULGUE. The specific model is:

$$ULGUE_{it} = \beta_0 + \beta_1 AI_{it} + \gamma X_{it} + \mu_i + \lambda_t + \varepsilon_{it} \quad (1)$$

In Equation 1, t denotes the year, i denotes the city, and ULGUE_{it} is the explained variable, namely ULGUE. AI_{it} is the policy shock variable, which takes the value of 1 if the city has been included in the AIPZ by year t. Its coefficient β_1 measures the impact of the AIPZ establishment on ULGUE. X_{it} represents the vector of control variables. μ_i denotes city fixed effects. λ_t represents year fixed effects. ε_{it} is the random disturbance term.

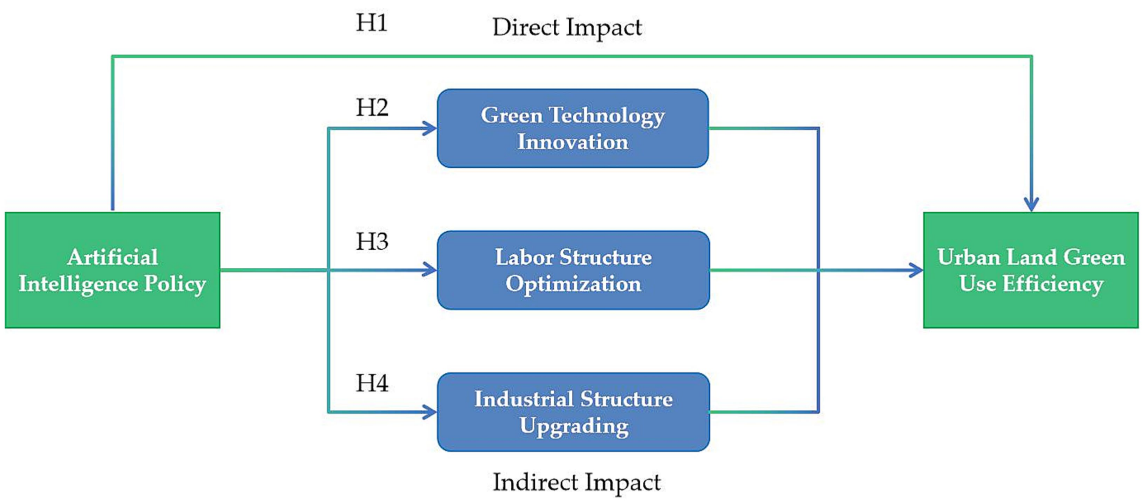

FIGURE 2
The impact mechanisms of the AIPZ on ULGUE.

3.2 Variable definition

3.2.1 Explanatory variable

The explanatory variable is the development of the AI Pilot Zone (AI_{it}). This study constructs a quasi-natural experiment based on the approval of AIPZ, which is denoted by the interaction term between a regional dummy variable (*Treat*) and a time dummy variable (*Time*), denoted as ($AI = Treat \times Time$). If a city is designated as a pilot area, its Treat value is set to 1, indicating the treatment group; non-pilot cities are assigned a Treat value of 0, representing the control group. The Time variable is set to 0 for the pre-policy period and 1 for the post-policy period. Thus, the coefficient of the interaction term (*AI*) captures the net effect of the AI Pilot Zone development on ULGUE.

3.2.2 Explained variable

The explained variable is ULGUE ($ULGUE_{it}$). From an input–output perspective, this paper adopts the super-efficiency SBM model under the assumption of constant returns to scale, implemented via MATLAB, to measure land green use efficiency. This model not only comprehensively accounts for undesirable outputs and corrects for slack variables but also overcomes the limitation of conventional SBM models that often generate numerous efficiency scores of 1, thereby significantly enhancing accuracy and practicality (Tone, 2002; Liu C. et al., 2025). Details of each indicator are presented in Table 1.

TABLE 1 The input–output index system of ULGUE.

Layer of criteria	Factors	Indicators	Unit
Input indicators	Land	Built-up area	Km^2
	Labor	Employees in secondary and tertiary industries	10,000 persons
	Capital	Fixed capital stock (calculated using the perpetual inventory method with 2006 as the base period)	10,000 Yuan
	Energy	Total annual electricity consumption	10,000 kWh
Desired outputs	Economic benefits	Real added value of secondary and tertiary industries	10,000 Yuan
	Social benefits	Urban resident income	Yuan
	Environmental benefits	Per capita park green space area	m^2/person
Undesired outputs	Pollution emissions	Industrial sulfur dioxide emissions	10,000 t
		Industrial wastewater emissions	*t*
		Industrial soot emissions	*t*

3.2.3 Control variables

The selection of control variables draws from prior studies (Wang et al., 2025; Wang and Li, 2025), encompassing factors identified as influential to ULGUE. These include: Economic Development Level (ECO): This is measured by the natural logarithm of real GDP per capita; Financial Development Level (FE): Measured by the natural logarithm of the sum of deposits and loans balances per 10,000 people in financial institutions at year-end; Urbanization Rate (UR): The share of urban population in the total population; Education Level (EDU): Measured as the ratio of scientific research expenditure to GDP; Government Intervention Intensity (GOV): The expenditure-to-revenue ratio of government fiscal accounts; Openness Level (OP): Measured as the natural logarithm of the actual utilized foreign direct investment.

3.3 Data description

Based on data availability, the study covers a panel of 286 prefecture-level cities in China from 2015 to 2023. The data are primarily obtained from the China Statistical Yearbook, Statistical Bulletin of National Economic and Social Development, China City Statistical Yearbook, China Urban Construction Statistical Yearbook, provincial and municipal statistical yearbooks, as well as WIND and EPS databases. The data undergo the following preprocessing procedures: missing values are imputed using linear interpolation, continuous variables were log-transformed to mitigate skewness, and to mitigate the influence of outliers, all continuous variables are winsorized at the 1 and 99% levels. Table 2 presents the descriptive statistics of the main variables.

4 Results

4.1 Baseline regression

Table 3 presents the baseline regression results examining the relationship between the establishment of AIPZ and ULGUE. Column (1) includes control variables but does not account for fixed effects; the results show a significantly positive coefficient for the AI variable. Columns (2) and (3) build upon Column (1) by incorporating city fixed effects and year fixed effects, respectively. In both cases, the coefficient of AI remains significantly positive. Column (4) simultaneously controls for both city and year fixed effects, yielding an AI coefficient of 0.0638, which is statistically significant and positive. These findings consistently demonstrate that the development of AIPZ enhances ULGUE, thereby validating Hypothesis 1 of this study.

4.2 Parallel trends test

The validity of the DID methodology requires satisfaction of the parallel trends assumption. This implies that, prior to the official approval of the AIPZ, there should be no systematic differences in the time trends of ULGUE between the treatment and control groups. To test this assumption, we employ an event study approach, focusing on

TABLE 2 Descriptive statistics.

Variable type	Variable	Obs	Mean	SD	Min	Max
Explained variable	ULGUE	2,574	0.5640	0.2883	0.0114	1.9379
Explanatory variable	AI	2,574	0.0287	0.1671	0	1
Control variables	ECO	2,574	10.9347	0.5236	9.3045	12.4863
	FE	2,574	17.7909	1.0764	15.5246	21.9733
	UR	2,574	0.5982	0.1381	0.2503	0.9980
	EDU	2,574	0.0352	0.0174	0.0021	0.1486
	GOV	2,574	3.1448	1.9739	0.9211	17.8950
	OP	2,574	6.9548	2.1432	0.1247	12.0420

TABLE 3 Benchmark regression results.

Variables	(1)	(2)	(3)	(4)
	ULGUE	ULGUE	ULGUE	ULGUE
AI	0.1140** (0.0556)	0.0592** (0.0256)	0.1193** (0.0544)	0.0638** (0.0255)
ECO	0.3689*** (0.0415)	0.1475*** (0.0385)	0.4278*** (0.0442)	0.1929*** (0.0421)
FE	−0.1370*** (0.0176)	−0.0651** (0.0297)	−0.1159*** (0.0188)	0.0337 (0.0425)
UR	0.3716** (0.1558)	−0.3289** (0.1540)	0.3400** (0.1566)	−0.1825 (0.1770)
EDU	4.7561*** (1.3265)	−0.1123 (1.2178)	4.8964*** (1.3027)	0.5196 (1.2654)
GOV	0.0229*** (0.0087)	−0.0080 (0.0077)	0.0334*** (0.0086)	−0.0001 (0.0081)
OP	0.0028 (0.0060)	−0.0014 (0.0038)	−0.0073 (0.0065)	−0.0018 (0.0038)
City FE	No	Yes	No	Yes
Year FE	No	No	Yes	Yes
N	2,574	2,574	2,574	2,574
R^2	0.2637	0.8286	0.2960	0.8335

*, **, and *** denote significance at the 10, 5, and 1% levels; Robust standard errors clustered at the city level are reported in parentheses.

a five-year window before and after the policy implementation. The following econometric model is specified:

$$ULGUE_{it} = \alpha_0 + \sum_{k=-5}^{5} \beta_k \times D_{i,t_0+k} + \alpha_2 x_{it} + \mu_i + \tau_t + \varepsilon_{it} \quad (2)$$

In Equation 2 D_{i,t_0+k} represents a set of dummy variables indicating the periods before and after policy implementation, t_0 denotes the year when the pilot policy was initiated, and $k = t - t_0$. This study uses the year of AI policy enactment as the baseline period for analysis. A negative value of k indicates k years before the implementation of the pilot city policy, while a positive value of k denotes k years after the policy implementation, with k = −5, −4, −3, −2, −1, 0, 1, 2, 3, 4, 5. Figure 3 plots the results of the parallel trends test. Before the official approval of the AIPZ, there was no significant difference in the green land use efficiency between the treatment and control groups. As the AIPZ were successively established, their positive effect on enhancing green land use efficiency has persisted.

4.3 Robustness checks

4.3.1 Placebo test

Following the actual approval pattern of national AIPZ, multiple virtual treatment groups were randomly generated, and regression analyses identical to Model (1) were conducted to provide robustness verification for the baseline findings. After 500 random samplings of the policy variable AI, the distribution of *p*-values and kernel density distribution of the regression coefficients between AI and ULGUE were obtained. As shown in Figure 4, the coefficients of the randomly generated virtual policy variables are distributed around zero and are distinctly separated from the baseline regression coefficient. This indicates that the research findings are not coincidental but are indeed driven by the establishment of AIPZ.

4.3.2 PSM-did

The selection of cities for the AIPZ policy is not entirely random but is based on comprehensive factors such as economic conditions, geographical location, and manufacturing development levels. To address potential selection bias arising from this non-random assignment, this study adopts a PSM-DID approach. Table 4 reports the matching results, where columns (1) and (2) correspond to radius matching and kernel matching, respectively. The results show that the coefficients for AI remain significantly positive across different matching methods, confirming the robustness of the baseline regression findings.

4.3.3 Exclusion of municipalities

Since the unique political status of municipalities directly under the central government in China may affect the accuracy of the AI pilot zone effect estimations, this paper excludes samples from the four cities of Beijing, Tianjin, Shanghai, and Chongqing and re-estimates the model. Column (3) of Table 4 reports the estimates after excluding the municipalities. The significantly positive coefficient for AI at the 1% level, even after excluding municipalities, affirms the robustness of our core findings.

4.3.4 Anticipation effect test

To rule out potential interference from policy anticipation on the estimation results, we conduct an anticipation effect test by artificially advancing the implementation time of the AIPZ. Specifically, we construct policy variables that assume the pilot zones were established 1 year and 2 years earlier than the actual dates, and incorporate these into the baseline model. The regression results in Column (4) of Table 4 show that the coefficient for AI remains significantly positive at the 1% level, indicating the absence of a significant anticipation effect in the AI Pilot Zone policy.

4.3.5 Mitigating interference from other concurrent policies

To address potential confounding effects from other policies implemented during the sample period that might influence ULGUE, we control for several concurrent initiatives, including the "Made in China 2025" National Demonstration Zones (MIC 2025), the Tradable

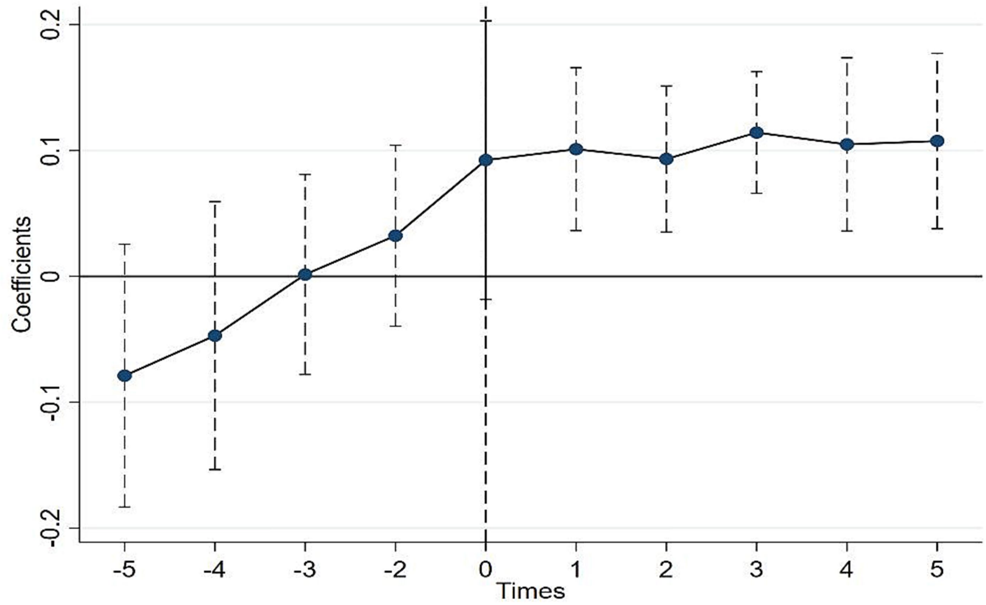

FIGURE 3
Parallel trend test.

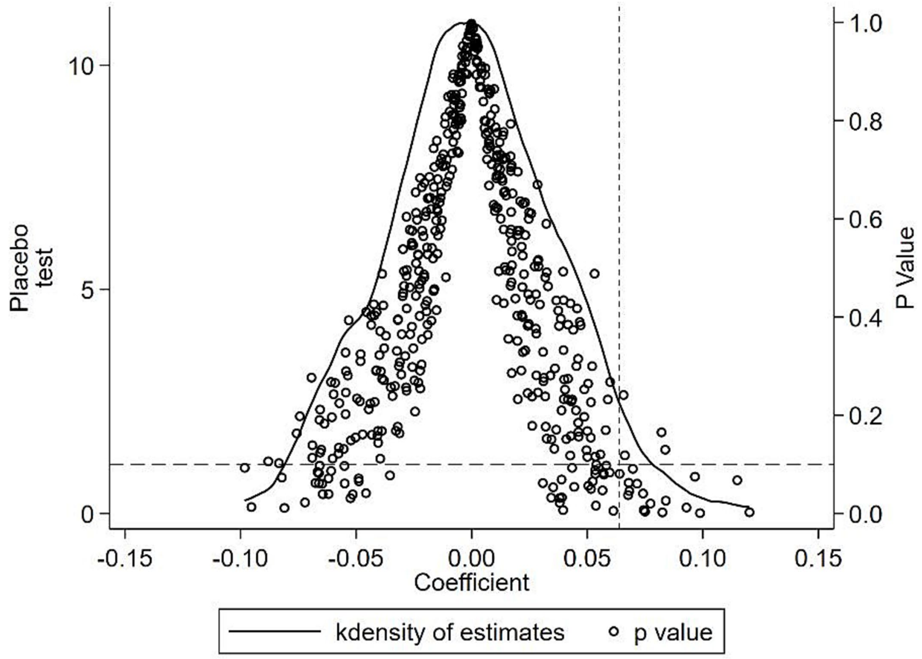

FIGURE 4
Placebo Test.

Energy Consumption Rights Pilot (ECR Pilot), and the Digital Economy Innovation and Development Pilot Zones (NDEI Pilot). To isolate the potential impact of these policy variables, we incorporate them into the baseline regression model. The results in Table 5 (columns 1–3) confirm that the positive effect of AIPZ on ULGUE is robust to the inclusion of controls for other major policy pilots, affirming the uniqueness of the AIPZ impact.

4.3.6 Endogeneity treatment

Although the AI Pilot Zone policy serves as a quasi-natural experiment with relative exogeneity, the approval of pilot cities may still correlate with local AI development levels and be subject to potential omitted variable bias, leading to non-random selection issues. To further mitigate endogeneity concerns, this study employs the interaction term between the number of landline telephones per 100 people at the

TABLE 4 Robustness test 1.

Variables	(1)	(2)	(3)	(4)
	ULGUE	ULGUE	ULGUE	ULGUE
AI	0.0822* (0.0474)	0.0805* (0.0470)	0.0829*** (0.0306)	0.1060*** (0.0340)
CV	YES	YES	YES	YES
City FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
N	758	768	2,538	2,574
R^2	0.8264	0.8288	0.8305	0.8344

*, and *** denote significance at the 10%, and 1% levels.

prefecture-level city level in 1984 and a time dummy variable as an instrumental variable for the AI Pilot Zone policy (Huang et al., 2019). On the one hand, the historical distribution of landline telephones reflects the development level of a city's early information infrastructure. Cities with a higher number of landline telephones may have held a first-mover advantage in the process of digitalization and informatization, laying the groundwork for subsequent AI development. These cities are thus more likely to be selected as AIPZ pilot cities, which ensures the instrumental variable satisfies the relevance condition. On the other hand, landline telephones have been largely replaced by modern digital communication technologies, meaning that the historical number of landline telephones is unlikely to directly affect current ULGUE, thus satisfying the exogeneity assumption of the instrumental variable. The results from the two-stage instrumental variables regression are presented in columns (4) and (5) of Table 5. The test results indicate that, after accounting for endogeneity, the establishment of AIPZ continues to significantly enhance ULGUE.

4.3.7 Bacon decomposition

Given the staggered implementation of the policy across different regions, the two-way fixed effects estimator equals a weighted average of all possible two-group or two-period DID estimators in the data. The average treatment effect estimated using two-way fixed effects in a multi-period DID design may suffer from heterogeneity bias due to "forbidden comparisons" or "bad controls" (Goodman-Bacon, 2021). To address this, we conduct a Bacon decomposition, which provides a formal diagnosis by precisely identifying the weight and coefficient of each pairwise comparison. The results in Table 6 indicate that the "bad controls" have an estimated coefficient of −0.030 and a negligible weight of only 0.5%. This indicates that the bias caused by heterogeneous treatment effects is minimal, thus confirming the robustness of our regression results.

4.4 Mechanism analysis

Existing studies have confirmed the promoting effects of green technology innovation (Zuo and Zhang, 2025), labor structure optimization (Shen and Lin, 2025), and industrial structure upgrading (Wang et al., 2025) on ULGUE. This section aims to verify the impact of AIPZ development on these three mechanisms—green technology innovation (GTI), labor structure optimization (LSO), and industrial structure upgrading (IS)—to precisely reveal the logical chain through which AIPZ influence ULGUE. As shown in Equation 3 M_{it} represents the proxy variables for the three mechanisms:

$$M_{it} = \beta_0 + \beta_1 AI_{it} + \rho X_{it} + \mu_i + \lambda_t + \varepsilon_{it} \tag{3}$$

First, green technology innovation is proxied by the natural logarithm of the number of green patents granted within a region. Table 7 shows in column (1) that the coefficient for GTI is 0.189, statistically significant at the 1% level. This indicates that the establishment of AIPZ effectively stimulates green technology innovation in pilot cities, thereby enhancing ULGUE. Thus, Theoretical Hypothesis 2 is validated. Second, this study defines workers with associate degrees or higher as high-skilled laborers and uses the natural logarithm of the number of high-skilled workers to measure Labor Structure Optimization. Table 7 shows in column (2) that the coefficient for LSO is 0.1076, statistically significant at the 1% level. This indicates that the establishment of AIPZ effectively enhances the labor skill structure in pilot cities, thereby improving ULGUE. Therefore, Theoretical Hypothesis 3 is validated. Finally, this paper classifies the economy into three sectors based on their contributions to GDP. The proportion of each sector's value-added in GDP is sequentially taken as a component in a spatial vector, thereby forming a set of three-dimensional industrial structure spatial vectors $X_0 = (x_{0,1}, x_{0,2}, x_{0,3})$. The basic unit vector set $X_1 = (1, 0, 0)$, $X_2 = (0, 1, 0)$, and $X_3 = (0, 0, 1)$ is selected as the reference vectors. The angles $\vartheta_j = (1,2,3)$ between the industrial structure spatial vector X_0 and each of these reference vectors are calculated sequentially as follows:

$$\vartheta_j = \arccos\left[\frac{\sum_{i=1}^{3}\left(x_{j,i} \cdot x_{0,i}\right)}{\left(\sum_{i=1}^{3} x_{j,i}^2\right)^{1/2} \cdot \left(\sum_{i=1}^{3} x_{0,i}^2\right)^{1/2}}\right] \tag{4}$$

In Equation 4, $x_{j,i}$ refers to the i-th component of the basic unit vectors x_j (j = 1,2,3), and $x_{0,i}$ refers to the i-th component of vector x_0.

$$IS = \sum_{j=1}^{3} W_j \times \vartheta_j \tag{5}$$

In Equation 5, W_j represents the weight of ϑ_j, and IS denotes the degree of industrial structure optimization and upgrading. The magnitude of the IS value reflects the degree of industrial structure advancement. Considering the monotonically decreasing nature of the inverse cosine function, it can be inferred that larger values of both ϑ_j and *IS* indicate a higher degree of industrial structure optimization and upgrading (Liu et al., 2021). Table 7 shows in column (3) that the coefficient for *IS* is 0.1076, statistically significant at the 1% level. This indicates that the establishment of AIPZ effectively drives industrial structure upgrading in pilot cities, thereby enhancing ULGUE. Thus, Theoretical Hypothesis 4 is validated.

4.5 Heterogeneity analysis

4.5.1 Administrative level heterogeneity

Cities with higher administrative levels enjoy greater voice and decision-making power in policy formulation and resource allocation.

TABLE 5 Robustness test 2.

Variables	(1)	(2)	(3)	(4)	(5)
	ULGUE	ULGUE	ULGUE	ULGUE	ULGUE
AI	0.0498** (0.0247)	0.0629** (0.0255)	0.0608** (0.0263)		0.0628** (0.0261)
MIC 2025	0.1029*** (0.0308)				
ECR Pilot		0.0245 (0.0250)			
NDEI Pilot			0.0225 (0.0211)		
IV				0.0899*** (0.0016)	
CV	Yes	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
N	2,574	2,574	2,574	3,718	3,718
Kleibergen–Paap rk LM statistic				20.791 (0.0000)	
Kleibergen–Paap rk Wald *F* statistic				2966.225 {16.38}	
R^2	0.8352	0.8337	0.8338		0.0338

The *p*-value is reported in parentheses for the Kleibergen–Paap rk LM statistic; the critical value at the 10% significance level is reported in curly brackets {} for the Kleibergen–Paap Wald rk *F* statistic. **, and *** denote significance at the 10%, and 1% levels.

TABLE 6 Robustness test 3.

Bacon decomposition	Weight	Estimated coefficient
Earlier group treatment vs. later group control	0.006	−0.051
Later group treatment vs. earlier group control	0.005	−0.030
Treatment vs. never treated	0.989	0.038

TABLE 7 Analysis of influence mechanisms.

Variables	(1)	(2)	(3)
	GTI	LSO	IS
AI	0.1891*** (0.0548)	0.1076* (0.0618)	0.0029*** (0.0007)
CV	YES	YES	YES
City FE	YES	YES	YES
Year FE	YES	YES	YES
N	2,574	2,574	2,574
R^2	0.9159	0.9683	0.9747

*, and *** denote significance at the 10%, and 1% levels.

TABLE 8 Heterogeneity analysis.

Variables	(1)	(2)	(3)
	ULGUE	ULGUE	ULGUE
AI × Level	0.0547* (0.0318)		
AI × Scale		0.0638** (0.0255)	
AI × Infra			0.0638** (0.0255)
CV	YES	YES	YES
City FE	YES	YES	YES
Year FE	YES	YES	YES
N	2,574	2,574	2,574
R^2	0.8336	0.8335	0.8335

*, and ** denote significance at the 10%, and 1% levels.

This disparity leads to heterogeneity in the impact of AI Pilot Zone development on ULGUE (Deng and Zhao, 2018). To examine these differential effects, the sample is stratified into two groups according to the cities' administrative level: municipalities and provincial capitals, and non-municipal non-provincial capital cities. This classification allows for an exploration of how the establishment of AIPZ differentially influences ULGUE across cities of varying administrative ranks. Specifically, this study creates an administrative level dummy variable (*Level*), which is set to 1 for municipalities and provincial capitals, and 0 for non-municipal and non-provincial capital cities. We further incorporate an interaction term (*AI*×*Level*) into the regression model. Table 8 shows in column (1) that the development of AIPZ has a more significant effect on upgrading ULGUE in municipalities and provincial capitals. The underlying reasons for this may include the following: Compared to non-municipal and non-provincial capital cities, municipalities and provincial capitals possess stronger fiscal capacity, a higher concentration of scientific and technological innovation talent, and more advanced intelligent infrastructure. These advantages provide strong backing for the advancement and deep integration of AI technologies. Additionally, municipalities and provincial capitals face more severe land resource constraints and environmental pressures, which creates stronger internal motivation for industries to transition toward green development. As a result, AI policies can more rapidly and efficiently unleash their enabling effects in the optimization of land resource allocation and the enhancement of land use efficiency in these cities.

4.5.2 City size heterogeneity

Different city sizes imply varying capacities for resource agglomeration, levels of socioeconomic vitality, and distinct patterns of land allocation, all of which may influence the effectiveness of policy implementation and land use outcomes (Jiang et al., 2023). Therefore, in accordance with the Notice on Adjusting the Standards for Classifying City Sizes issued by the State Council in 2014, this study categorizes the sample into two groups for examination: small and medium-sized cities (with a permanent resident population in the urban district of less than 1 million) and large cities (with a permanent resident population in the urban district of 1 million or more). Specifically, this study creates a city size dummy variable (*Scale*), which is set to 1 for large cities and 0 for small and medium-sized cities. We further incorporate an interaction term (*AI*×*Scale*) into the regression model. Table 8 shows in column (2) that the development of AIPZ has a more significant effect on upgrading ULGUE in large cities. The underlying reasons for this may include the following: Large cities, characterized by dense population distribution and intensive economic activities, face greater urgency in managing pollutant emissions. Coupled with their strong capacity to agglomerate talent, technology, and resources, these factors enable the AI policy effects to manifest more distinctly. Conversely, small and medium-sized cities, constrained by limitations in economic resources, technological capability, and funding, exhibit reduced motivation for engaging in innovation activities and pursuing industrial upgrading. Consequently, the impact of AI policies on ULGUE is less evident in these cities.

4.5.3 Digital infrastructure level heterogeneity

Digital infrastructure can facilitate the green and low-carbon transformation of industrial structures by aggregating data elements and attracting innovation resources, which may lead to heterogeneous effects of the pilot zone policy on ULGUE (Wang et al., 2025). Therefore, this study measures the urban digital infrastructure level from both input and output dimensions using the entropy method. Based on the mean value, cities are stratified into high and low digital infrastructure groups for examination. Specifically, this study creates an urban digital infrastructure level dummy variable (*Infra*), which is set to 1 for cities above the mean value and 0 for cities below the mean value. We further incorporate an interaction term (*AI*×*Infra*) into the regression model. The results in column (3) of Table 8 indicate that the enhancing effect of AI Pilot Zone development on ULGUE is more significant in cities with high levels of digital infrastructure. The underlying reasons may include the following: In cities with advanced digital infrastructure, the establishment of AIPZ can more fully unleash the technology-enabled effects. The synergy between digital infrastructure and AI technologies—manifested through functions such as intelligent traffic dispatch and dynamic energy consumption management—effectively curbs environmental pollution and resource waste in land development, thereby more significantly improving ULGUE. In contrast, cities with low digital infrastructure are constrained by data silos and computational bottlenecks, making it difficult to deeply integrate AI technologies into the land management chain. Consequently, the green efficiency gains of AI in these cities remain relatively limited.

4.6 Spatial spillover effects analysis

To examine whether AI policy generates spillover effects across spatial dimensions—specifically, to test if the policy triggers "imitation" and "contagion" among neighboring regions—this study further extends the DID model to a SDID model (Jia et al., 2021). Given the staggered timing of the AI Pilot Zone approvals, a general form of the multi-period Spatial DID model is constructed as follows:

$$ULGUE_{it} = \theta_0 + \rho W \times ULGUE_{it} + \theta_1 AI_{it} + \delta_1 W \times AI_{it} + \theta_2 X_{it} + \delta_2 W \times X_{it} + \mu_i + \lambda_t + \varepsilon_{it} \tag{6}$$

In Equation 6, W represents the spatial weight matrix. $W \times ULGUE_{it}$ is the spatially lagged dependent variable, and ρ is its spatial autocorrelation coefficient, indicating the impact of the dependent variable in neighboring regions on the local area. $W \times AI_{it}$ is the spatially lagged independent variable, where δ_1 represents the policy's indirect effect, and θ_1 denotes the policy's direct effect. X_{it} represents other control variables influencing the explained variable, while$W \times X_{it}$ represents the spatially lagged control variables, with δ_2 indicating the impact of exogenous variables from neighboring cities on the dependent variable of the local city. All other variables remain the same as in Equation 1.

First, prior to applying the spatial econometric model, this study employs the Moran's I index to calculate the spatial effects under the spatial geographic weight matrix for each year. The results in Table 9 show that ULGUE exhibits significant positive spatial autocorrelation from 2015 to 2023 (I values range between 0.018 and 0.041, $p < 0.01$). This confirms the agglomeration characteristics of ULGUE in geographical space, providing an empirical basis for adopting spatial econometric methods.

Second, this study employs three spatial weight matrices to assess the spillover effects of the AIPZ policy: a spatial geographic distance matrix (calculated based on longitude and latitude coordinates), a spatial economic-geographic nested matrix (incorporating regional GDP and geographic coordinates), and a spatial contiguity matrix (based on administrative boundary adjacency). Through a series of specification tests—including the Hausman test, Likelihood Ratio test, and Wald test—the optimal model selection was determined. The results indicate that the SAR model is most appropriate for both the geographic distance and economic-geographic nested matrices, while the SDM is the optimal choice for the contiguity matrix (Elhorst, 2014). According to the spatial spillover effects test results in Table 10, the spatial autoregressive coefficient ρ is significantly positive at the 1% level, and the estimated coefficient of the AI policy spatial interaction term W × AI is also significantly positive at the 5% level. This finding suggests that the AIPZ policy generates positive spatial spillovers on ULGUE in neighboring cities.

Finally, since the simple regression estimates of spatial spillover effects may lead to biased estimation, this study further decomposes the spatial spillover effects into direct and indirect effects using the partial differentiation method. The indirect effects capture the impact of AI Pilot Zone development in pilot cities on the ULGUE of neighboring cities. The results in Table 11 show significantly positive indirect effects across all three spatial weight matrices at the 1% level, demonstrating that the AIPZ generates positive spatial spillovers on ULGUE in surrounding cities. The underlying reasons may be explained as follows: On one hand, policy instruments implemented by the government may become models for other cities to emulate, creating a "peer effect" (Deng and Zhao, 2018). The convenience brought by informatization, intellectualization, and high-speed rail connectivity facilitates policy imitation among cities through economic and trade linkages, leading to

TABLE 9 Moran's I statistic.

Year	Geographic distance matrix		Economic-geographic nested matrix		0–1 contiguity matrix	
	Moran's I index	*P*	Moran's I index	*P*	Moran's I index	*P*
2015	0.027	0.000	0.031	0.000	0.010	0.000
2016	0.038	0.000	0.041	0.000	0.008	0.002
2017	0.024	0.000	0.027	0.000	0.003	0.048
2018	0.018	0.000	0.018	0.001	0.005	0.015
2019	0.024	0.000	0.024	0.000	0.007	0.005
2020	0.034	0.000	0.036	0.000	0.008	0.003
2021	0.027	0.000	0.030	0.000	0.006	0.012
2022	0.027	0.000	0.031	0.000	0.007	0.007
2023	0.026	0.000	0.027	0.000	0.003	0.055

TABLE 10 Spatial econometric estimation results.

Variables	(1)	(2)	(3)
	Geographic distance matrix	Economic-geographic nested matrix	0–1 contiguity matrix
AI	0.0624*** (0.0196)	0.0625*** (0.0197)	0.0798*** (0.0207)
rho	0.4310*** (0.1149)	0.3162*** (0.1216)	0.4376*** (0.1174)
W × AI			0.5825** (0.2663)
CV	YES	YES	YES
City FE	YES	YES	YES
Year FE	YES	YES	YES
N	2,574	2,574	2,574
R^2	0.0117	0.0125	0.2579

, and * denote significance at the 10%, and 1% levels.

TABLE 11 Estimation results of direct and indirect effects based on the spatial Durbin model.

Variable	Direct effects	Indirect effects	Total effects
AI	0.0829*** (0.0213)	1.1545** (0.5140)	1.2374** (0.5162)

, and * denote significance at the 10%, and 1% levels.

policy diffusion effects that enhance land green use efficiency across municipalities. On the other hand, AI exhibits a selective preference for emerging and future industries, which can trigger the agglomeration of urban innovation factors. This promotes economic exchanges, resource sharing, and cooperation among city clusters, forming scale effects and consequently generating knowledge and technology spillovers across cities (Wang et al., 2022). In summary, AIPZ can accelerate the transition from traditional extensive development models to clean, green, and low-carbon approaches through spatial spillover effects of policies, thereby promoting the improvement of ULGUE in various cities.

5 Discussion and conclusions

With the booming development of the digital economy, AI leveraging its powerful data processing and intelligent decision-making capabilities, is progressively permeating various sectors of economic development and exerting a profound impact on the input–output dynamics of urban land use. This study investigates the impact of AIPZ on ULGUE. The findings demonstrate that: (1) The AIPZ policy has significantly enhanced ULGUE in the pilot cities. This conclusion remains robust after a series of tests including placebo tests, PSM-DID, exclusion of municipalities, anticipation effect tests, controlling for concurrent policies, endogeneity treatment, and Bacon decomposition. This demonstrates that the development of AIPZ can not only drive economic growth in pilot cities but also deliver environmental benefits by guiding these cities toward green development. (2) The development of AIPZ enhances ULGUE through three transmission channels: green technology innovation, labor structure optimization, and industrial structure upgrading. This finding not only validates the theoretical framework proposed in this study but also provides a clear elucidation of the green development effects associated with the establishment of AIPZ. (3) The positive effect of AIPZ on ULGUE is more pronounced in municipalities and provincial capitals, large-scale cities, and cities with advanced digital infrastructure. This finding underscores the practical significance of tailoring the implementation of AI policies to the specific characteristics of different cities. (4) The development of AIPZ demonstrates significant spatial spillover effects, simultaneously enhancing ULGUE in both local and surrounding areas. This indicates that the establishment of AIPZ can generate policy diffusion effects and scale economies, facilitating the transition from traditional extensive development patterns to cleaner, greener, and low-carbon alternatives.

The findings lead to several actionable policy implications: (1) Proactively advance AIPZ to continuously enhance land green use efficiency. On one hand, systematically document the effective models and institutional innovations developed by pilot cities in promoting manufacturing transformation, summarize replicable practical experiences, and prudently expand the scope of pilot cities on this basis. On the other hand, improve supporting mechanisms—including tax incentives, land use guarantees, and financing support—and incorporate land green use outcomes into policy performance evaluations to strengthen their role in promoting sustainable urban development. (2) Strengthen transmission channels by refining institutional arrangements for green technology innovation, labor structure optimization, and industrial structure upgrading. First, pilot city governments should further guide the construction of AI infrastructure and boost investment in AI technology R&D, creating a favorable environment for AI research and application. Second, pilot cities should enhance the quality of education and skills training for the labor force, improving overall competency to adapt to labor paradigm shifts driven by intelligentization, thereby achieving intensive utilization and ecological management of land resources. Third, pilot governments should strengthen policy guidance to steer traditional industries toward high-end, digital, and intelligent transformation and upgrading, coordinate industrial structure adjustments, and attract more enterprises to participate in the development of AIPZ. (3) Formulate differentiated development strategies based on the specific conditions of each pilot zone to guide cities toward intelligent and green transformation, continuously advancing and expanding green intelligent manufacturing practices, thereby better promoting the enhancement of ULGUE. On one hand, emphasize the systematic summarization and dissemination of experiences from AIPZ. Strategies for expanding the pilot scope should be more orderly and prudent, fully considering local conditions to ensure more significant effects when scaling up the AIPZ. On the other hand, regions demonstrating notable policy outcomes should be actively rewarded to incentivize their industrial transformation efforts. For areas where policy effects are less evident, focused attention should be given to addressing shortcomings in the pilot zone construction, thereby effectively unleashing their policy dividends. (4) Enhance economic exchange and cooperation among AIPZ across cities to fully leverage the benefits of knowledge and technology spillovers. Cities should capitalize on the knowledge and technological externalities generated by the pilot policy, strengthen resource sharing among municipalities, and foster synergistic effects within the entire region. Establish cross-city collaboration mechanisms to effectively integrate innovation resources from different regions, enhance the aggregation and transformation functions of innovation resources, and build a collaborative innovation ecosystem. This will better unleash the policy vitality of AIPZ and promote the improvement of ULGUE.

This study has certain limitations. When applying the super-efficiency SBM model to measure ULGUE, continuous city-level carbon emission data in China are not publicly available. Consequently, undesirable outputs do not include carbon dioxide emissions but incorporate more readily available indicators—industrial sulfur dioxide emissions, industrial soot emissions, and industrial wastewater emissions—to ensure the robustness and reliability of our analysis. Therefore, developing more accurate and scientific measurement approaches for ULGUE remains an important direction for future research.

Data availability statement

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

Author contributions

SZ: Conceptualization, Methodology, Validation, Visualization, Writing – original draft, Writing – review & editing. YZ: Data curation, Methodology, Software, Validation, Visualization, Writing – original draft. ZW: Formal analysis, Funding acquisition, Project administration, Supervision, Validation, Writing – review & editing.

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Conflict of interest

The author(s) declared that this work 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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