

Article

From Mismatch to Smart Match: Artificial Intelligence and Land Resource Misallocation

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Abstract

Optimizing the allocation of national land resources is a crucial measure for safeguarding food security and ecological security, as well as a key pathway for achieving urbanrural integration and coordinated regional development. Against the backdrop of the global digital transformation, artificial intelligence offers new opportunities for intelligent and refined land resource management. However, existing research has not sufficiently explored the impact of AI on land resource allocation. Using panel data of 265 Chinese cities from 2010 to 2023, this study investigates the effect of artificial intelligence level (AIL) on land resource misallocation (LRM) and its underlying mechanisms. The findings demonstrate the key conclusions: (1) AIL significantly reduces urban LRM. This result remains robust after adjusting the sample, accounting for province–time interactions, controlling for other policy effects, excluding outliers, and addressing endogeneity concerns. (2) Mechanism analysis indicates that AIL reduces urban LRM by enhancing government environmental concerns, promoting land transfer marketization and industrial structure upgrading. (3) Heterogeneity analysis indicates that the inhibitory effect of AIL on LRM is more pronounced in non-old industrial base cities, low-population-density cities and strong government intervention cities. These findings suggest that local governments should tailor AI research, development, and application strategies according to their cities' resource endowments and developmental foundations. This study not only enriches empirical evidence on AI's role in reducing LRM but also offers practical pathways and decision-making references for other countries to optimize territorial governance and achieve sustainable land resource utilization through digital and intelligent technologies.

Keywords: artificial intelligence; land resource misallocation; government environmental concern; land transfer marketization; industrial structure upgrading

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1. Introduction

Economic life has always needed a physical stage, and for centuries land has provided exactly that—a foundational asset powering human progress and material expansion. Yet to cast land merely as a platform for activity misses what it has become. In this convergence of cascading global crises, land has been reconstituted from a passive stage to an active strategic instrument [1]. At present, the distribution of land resources

across the planet is under acute, multi-sided strain. The drive to meet rising food demand compels the preservation and, in some regions, the deliberate extension of farmland; simultaneously, rapid industrialization and urban sprawl continue to consume prime agricultural soils at a troubling tempo. Between 1985 and 2020, the outward push of cities is reckoned to have swallowed close to 280,000 km² of cropland across the planet—enough to strip roughly 3 million tons from global grain harvests. The damage fell most heavily on Asia, which alone soaked up 61 per cent of the lost cropland and 64 per cent of the resulting production shortfall [2]. What these figures trace is more than a simple escalation of land-use friction. They signal a steady unravelling of the structural base on which global food security rests. Adding another dimension of vulnerability, climate change operates as a threat multiplier here: it squeezes land availability while simultaneously heightening the susceptibility of what remains to degradation. Globally, coastlines have retreated an average of 31 meters landward [3], with small island states and low-lying coastal areas suffering a disproportionate burden of this retreat. By 2050, sea-level rise and coastal erosion in Caribbean island states alone may inundate some 3,900 km² of land, with concomitant economic damages estimated at USD 624 billion [4]. Such pressures hit directly on territorial security and economic development, bringing real urgency to land adaptation and the deepening of resilience in the global climate governance architecture.

The advance of globalization has seen countries across the world lean ever more heavily on land resources to extract growth momentum. When land is valued almost exclusively for its economic output function, distortions in resource allocation tend to follow. Germany deliberately retooled its land policy to channel 70 per cent of land value gains into public projects [5]. The United States leaned on land as a driver of industrialization [6]; South Korea, for its part, converted land into an alternative conduit for financing public goods [7]. Each path, in a distinctive register, has ended up tightening the friction between finite land endowments and the pursuit of durable economic expansion. Nowhere does this collision register more sharply than in China. There, land resource misallocation has hardened into a decisive bottleneck that undercuts both sustainable resource use and the transition toward high-quality development. The issue is not land scarcity per se. But land finance has long been a lubricant for China's growth [8]. Hemmed in by GDP-obsessed promotion metrics and the centrifugal pull of fiscal decentralization, local authorities have converged around a single playbook: offloading industrial land at rock-bottom prices to hook investment, while bidding up commercial land values to plug the resulting fiscal holes. The outcome is a distorted price structure between commercial and industrial parcels. What sets in is a gradual erosion of aggregate economic efficiency, layered onto a worsening spatial misallocation of urban land [9–12]. Reconciling the competing economic, social, and ecological claims on land—while arresting and then reversing the slide into worse misallocation—has therefore crystallized into a policy conundrum that no longer respects national borders.

In recent years, artificial intelligence has increasingly become a key driver of high-quality economic development, with its potential in real-time processing of massive data, optimizing decision-making models, reducing information asymmetry and improving resource allocation efficiency increasingly prominent [13,14]. Thus, AI is expected to serve as a promising catalyst for effective land resource allocation. In China, the rapid advancement of AI and its extensive application in resource management have opened new technical pathways for land resource management and optimized allocation. In 2017, the Chinese government released the New Generation Artificial Intelligence Development Plan, elevating the construction of smart government to a national strategic priority. The 2025 Government Work Report further emphasized “continuing to advance the ‘AI+’ initiative and supporting the widespread application of large models,” reinforcing AI's strategic role in deeply integrating high-quality development across all sectors [15].

Subsequently, various local governments successively launched pilot projects such as Smart Land and Intelligent Planning. These initiatives aim to enhance the intelligence of land supervision, market transactions, and spatial planning through measures such as constructing intelligent monitoring platforms and implementing big data-based land use performance evaluations [16]. These efforts are expected to alleviate information asymmetry and resource allocation distortions at the technological level, promote precise matching of land supply and demand, and thereby improve the comprehensive governance capacity for LRM.

Regrettably, academic research on the aforementioned issues remains limited to date. The literature on land resource misallocation (LRM) has focused primarily on its measurement and consequences. Proxies for LRM vary widely in what they capture. The commercial–industrial land price spread is perhaps the most commonly used indicator, owing to its simplicity [12,17]. Alternative measures, including transfer price ratios across land types [18], marginal output price ratios [9], and urban green space coverage [19–21], each capture a different dimension of LRM. What links these disparate indicators is their shared pattern of consequences: inhibited green technology innovation [22,23], eroded green total factor productivity [11], faltering sustainable urbanization [24,25], energy inefficiency [26], sluggish green growth [27], and worsening carbon emissions and pollution [28–31]. The question of what drives LRM has not gone unexamined. Industrial land sprawl and special economic zones distort price signals in ways that entrench allocative distortions, patterns made especially conspicuous by China’s rapid urbanization [8,32,33]. A rival strand of work, however, finds room for state intervention to play a genuine corrective role. Information infrastructure investment [34], tighter environmental regulation [35], and government–market coordination [36], emerge, under the right conditions, as levers that can loosen rather than tighten LRM. Absent from these debates is any systematic examination of artificial intelligence. Whether AI compounds or corrects land misallocation remains an open, empirically unaddressed question.

Another strand of the literature is on the impact of the digital economy on land use efficiency. The empirical evidence generally shows that the effect is significantly positive [37–39]. The most identified mechanisms include industrial structural upgrading, green technology progress, digital talent inflow and the alleviation of resource misallocation [40–43]. The improvement of efficiency is also related to digital finance [44], platform business model [45], and the deeper integration of digital technology and real economy [46,47]. However, not all the impacts are positive. The rebound effect and the persistence of the lock-in of industrial structure may offset the potential benefits brought by digitalization [48]. The dependence on land finance further weakens the connection [49]. The linear account, however, has increasingly been called into question. A growing body of research now focuses on threshold effects: the digital economy, green innovation, and industrial structure upgrading yield efficiency gains only after reaching certain critical levels [44,50]. Institutional and regulatory conditions further condition these nonlinearities. Land finance dependence, for instance, exhibits an inverted U-shaped pattern—moderate reliance enhances land use efficiency, yet beyond a tipping point the effect turns detrimental [50]. Environmental regulation follows a J-curve trajectory, constraining efficiency at low intensity and yielding positive effects only after regulatory stringency surpasses a critical threshold [48]. From a spatial perspective, the digital economy generates positive spillovers for land use efficiency, but these effects weaken as geographic distance increases [51]. Although the existing literature has offered a rich discussion of land use efficiency through the lens of the digital economy, most of it looks at the digital economy in a broad sense. Far less attention has been paid to how specific digital technologies, such as artificial intelligence, shape land resource misallocation or land use efficiency.

The third area covers the new research on artificial intelligence governance. Previous studies have mainly focused on the economic and environmental impacts of AI, with particular attention to its positive role in promoting industrial transformation and upgrading and in supporting environmental sustainability. The macro-level effect of AI has been mapped in several fields including green economic growth [52], healthcare service quality [53], and corporate ESG performance [54]. Micro-level studies have focused on AI's capacity to expand employment, with the job creation benefits associated with the digital economy noted [55,56]. Alongside these findings is a cautionary note: AI's pervasive transformation of production and everyday life, it is argued, could exacerbate income inequality by changing skill demands and employment patterns [57]. On the environmental side, several studies have examined the positive role AI plays. This includes environmental performance [58], carbon emission reduction [54,59,60], eco-efficiency [61] and green technology innovation [62]. A few studies have also confirmed, from the angles of government resource allocation and firm investment efficiency, that AI helps to improve the way resources are allocated [63,64]. Yet, for all AI's potential to raise resource allocation efficiency, no study has yet treated it in a systematic way as a governance tool capable of correcting distortions in land factor allocation. The specific effects of AI on land resource misallocation, and the mechanisms behind them, remain largely unexplored.

Given this context, this study investigates the following research questions: (1) Does AIL effectively alleviate urban LRM? (2) Through which channels does AIL affect urban LRM? (3) Does the effect of AIL on LRM vary across different settings? A thorough examination of these questions carries practical significance. It can help promote the more efficient allocation of land resources and support green, low-carbon development in China. It can also offer empirical lessons for other economies and regions that face land resource constraints and governance transitions and seek to use AI technologies to improve their land resource management systems. To this end, we draw on panel data for 265 Chinese cities covering the period 2010 to 2023. We use fixed-effects models, mediation effect models, and instrumental variable methods to identify the causal link between AI and LRM, and provide a full analysis of the underlying mechanisms and heterogeneous effects.

Unlike previous studies, the potential marginal contributions of this research lie in the following three aspects: (1) Integrating AIL and LRM into a unified analytical framework, scientifically exploring the impact of AI on LRM from both theoretical and empirical perspectives. This advances the theoretical understanding of AI in land resource optimization and provides empirical validation for its application in helping cities overcome resource constraints and achieve green, low-carbon development. (2) From the perspectives of multiple dimensions of government, market, and enterprises, we conduct an in-depth analysis of the impact mechanisms of AIL on LRM, and identify transmission pathways between the two through three aspects: government environmental concerns, land transfer marketization, and industrial structure upgrading. This enriches and supplements previous research on LRM pathways [65–67]. (3) From the perspectives of resource endowment, population agglomeration, and government intervention, we examine the heterogeneous effects of AI on LRM, providing scientific evidence for the differentiated application of AIL in the process of land resource management. Additionally, this study offers new insights for governments worldwide to formulate differentiated and adaptable AI governance policies within diverse institutional environments.

The remainder of this study is structured as follows: Section 2 discusses theoretical mechanisms and research hypotheses. Section 3 details the methodologies and data used. Section 4 reports empirical findings and provides normative analysis. Section 5 discusses

the results. Section 6 concludes the paper and proposes policy implications. The research framework is shown in Figure 1.

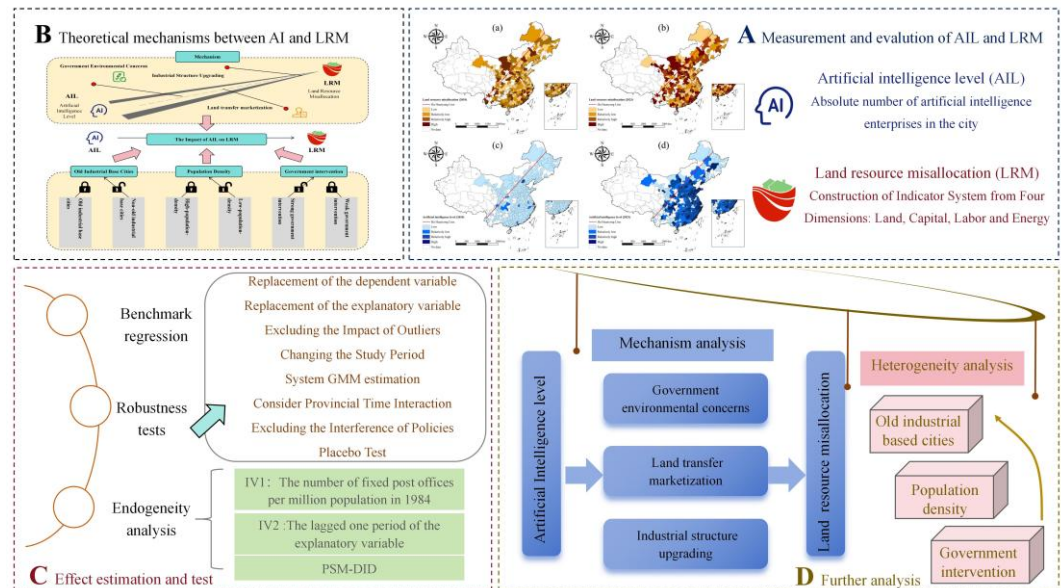


Figure 1. Research framework. Note: (A) Measurement and evaluation of AIL and LRM; (B) Theoretical mechanisms between AI and LRM; (C) Effect estimation and tests, including benchmark regression, robustness tests, and endogeneity analysis; (D) Further analysis, including mechanism analysis and heterogeneity analysis. (a) Spatial distribution of LRM in 2010; (b) Spatial distribution of LRM in 2023; (c) Spatial distribution of AIL in 2010; (d) Spatial distribution of AIL in 2023.

2. Theoretical Analysis and Research Hypotheses

2.1. Theoretical Framework

The main reason for LRM is the deviation of actual land allocation from the efficient state [68]. The theory of factor misallocation explains this as a result of institutional constraints and informational frictions that misallocate land from marginal product-guided patterns [69]. The logic is further developed in the theory of information asymmetry. The information flow between local governments, market participants and land users is fragmented, uneven and poorly transmitted, resulting in misjudgment of supply and demand, which produces flawed allocation decisions [70]. Another perspective is from institutional economics, which suggests that local governments' land allocation decisions are affected by fiscal revenues, economic growth targets and performance assessment regimes, and the incentive distortions they introduce may result in misguided administrative intervention in land supply and utilization [71]. Institutional constraints, informational biases, and misguided administrative intervention thus work together to increase the misallocation of land resources.

The rise of AI is changing the information basis and governance environment of land resource allocation. Based on the theory of digital governance, digital technologies can enhance information collection, real-time monitoring and joint supervision. Through the integration of heterogeneous data—spanning land use, business operations, industrial production, and ecological conditions—AI can support local governments in forecasting land demand, monitoring utilization trends, and evaluating allocation outcomes [72]. This helps to ease information frictions and to make oversight more timely, more precise and easier to trace. At the same time, land use performance and non-compliant behaviour become easier to observe. This can tighten the scrutiny of local governments' land allocation practices and improve the incentives that shape their decisions [73]. The level

of AI development in a city can therefore not only help to curb LRM directly. It can also work through channels such as GEC, LTM and ISU to produce further effects. The theoretical framework of this study is illustrated in Figure 2.

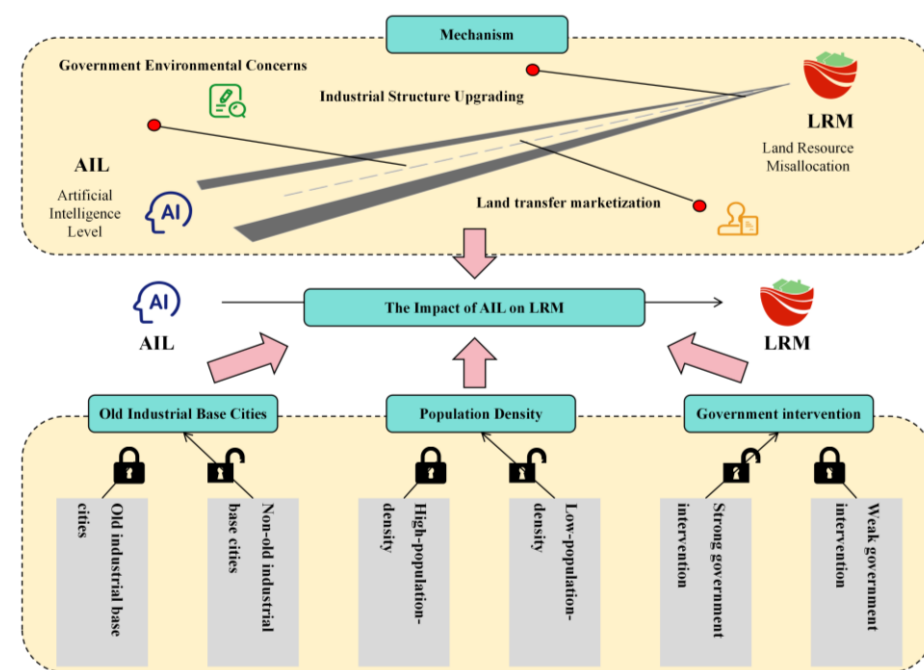


Figure 2. Influence mechanism of AIL on LRM.

2.2. Impact of AIL on LRM

When land is allocated, too little information, distorted market signals and biased administrative intervention can all be present. Together, they make it hard for land input to line up with urban industrial development, spatial expansion and the marginal output of factors. The mismatch leads to LRM [9,11]. In the context of the wide application of artificial intelligence in data recognition, spatial analysis, predictive judgment, and decision support, it provides new technical means to reduce LRM [74]. On the one hand, AI can improve the capacity of information collection and processing in the management of land resources. The allocation of land resources is an information exchange of multiple actors, such as governments, firms and the public. When information is scarce or slow to travel, land supply and demand can be badly mismatched, price signals can be distorted, and the expansion of construction land can be unbalanced [75]. Drawing on big data, machine learning and spatial recognition technologies, AI can make it more efficient to gather, identify and integrate information on land use, industrial demand and spatial development. In turn, this strengthens the capacity to assess land supply–demand conditions and to anticipate future trends [64,75]. Backed by institutional disclosure rules, data access and governance capacity, these information-processing gains can help to ease some of the information frictions in land allocation. They can also improve how efficiently land resources are matched to needs. On the other hand, AI can bring down the costs of decision-making in land management and land transactions. It can also make land allocation decisions and oversight more timely and more precise. Complex approval procedures, high transaction costs and distorted administrative allocation are all important sources of LRM. AI can enhance the efficiency of decision-making in land transfer, land supply and land supervision. It does so through automated approval, intelligent assessment, risk identification and predictive analysis [72,75]. When land allocation decisions can respond more swiftly to changes in industrial demand and spatial development, land is more likely to flow towards sectors and regions where its marginal output is higher. This helps to curb

the LRM that arises from institutional frictions and sluggish decision-making. Moreover, intelligent interpretation of remote sensing images, IoT monitoring, and spatial data analysis allow AI to realize dynamic monitoring of land use conditions and detect land idleness, inefficient land use, illegal occupation, or sprawl development more quickly [16,76]. This dynamic monitoring capability can offer technical support to governments. It can help them promote more intensive use of land, redevelop inefficiently used plots and improve the mix of construction land. All of this can help to ease LRM.

Therefore, this study proposes the following hypothesis:

H1. *AIL helps to alleviate urban LRM.*

2.3. Mechanism Pathways Through Which AIL Affects LRM

2.3.1. Government Environmental Concern

Regarding government actors, land development and utilization are regulated through planning guidance, use control and environmental constraint functions [66]. The weight that governments give to environmental issues can therefore affect both the direction and the efficiency of land resource allocation. When governments put too much stress on short-term economic growth and the spread of construction land, while paying too little attention to ecological limits, environmental risks and targets for more compact use, land development tends to drift away from what the resource base and the environment can support. This results in significant land use and misallocation [77,78]. AI can enhance governments' capabilities to identify environmental threats and comprehend the actual use of land, consequently accelerating the rise of environmental issues on the policy agenda [79]. From the point of view of the dynamic capability theory, the ability of the government to govern depends on the ability to sense, identify and respond to changes in the external environment. Digital governance theory posits that digital technology can improve government information collection and governance through information integration, dynamic monitoring, and collaborative oversight [70]. AI can improve the efficiency of governments in the detection of problems such as environmental pollution, ecological degradation, idle land, and sprawling development, relying on ecological environment perception networks, remote sensing monitoring, intelligent identification, and data analysis platforms, and it can also improve their ability to respond quickly and implement decisions in environmental governance [80]. When environmental risks and land use problems are identified and assessed more timely, governments are more likely to pay attention to environmental issues and more likely to put ecological protection, compact land use, and the governance of inefficiently used land on the policy agenda. From an institutional economics point of view, the fact that environmental risks and land use performance become easier to observe has two effects. It strengthens the supervision of local governments and the accountability constraints they face, and increases the institutional cost of ignoring ecological concerns and pursuing extensive land expansion [81,82]. This causes local governments to rebalance their land allocation incentives between economic growth and environmental protection. In turn, increased government attention to the environment helps to further alleviate LRM. First, when governments pay attention to the ecological limits and carrying capacity of resources and the environment, land development is directed to break away from scale-driven expansion and turn to compact use, thus reducing the distortions in land allocation caused by environmental externalities and urban sprawl [66]. Second, governments that pay attention to environmental concerns are more capable of foreseeing the potential environmental risks and long-term ecological costs of land development and use [61]. This induces a change in land management from ex post correction to ex ante prevention and thereby improves the path of land resource allocation.

Therefore, this study proposes the following hypothesis:

H2. *AIL helps to alleviate urban LRM by enhancing government environmental concerns.*

2.3.2. Land Transfer Marketization

The land transfer market performs a number of basic functions for the market participants, which include price discovery, matching supply and demand, and reallocation of resources [83]. Hence, the degree of marketization of this market has implications for the direction and efficiency of land resource allocation. Where administrative intervention plays a dominant role, and the market mechanism is still underdeveloped, land prices cannot reflect the real supply–demand, locational features, or the needs of industrial development [84,85]. As a result, land resources tend to be inefficiently used or by inefficient actors. This aggravates land resource misallocation. AI can enhance the information integration and supply–demand matching capabilities in the land transfer market. In doing so, it can encourage greater reliance on market mechanisms in the allocation of land resources. According to information asymmetry theory, in the process of land transactions, the parties involved have asymmetric information on the quality, locational conditions, development potential, and transaction risks of the land, which causes distorted price signals and poor decision-making [34]. Resource allocation theory adds that, for land resources to be allocated efficiently, market participants need reasonably full information and must be able to make sound decisions based on price signals. AI can integrate and analyse multi-source, heterogeneous data [12]. This allows it to identify more efficiently how land is being used, what industrial land demand looks like, what spatial and locational conditions apply, and what market transaction information reveals. Drawing on deep learning, predictive analysis and intelligent diagnostic models, AI can spot land that is used inefficiently, lies idle or has been misallocated. Then, market participants will be able to dynamically match supply and demand information to improve the efficiency of land reallocation [86]. With the improvement of information disclosure and data access in land transactions, market participants will be able to more accurately judge the land supply–demand conditions and transaction risks [84,87]. This helps to ease some of the information frictions in the land transfer process and to push land transfer towards a higher degree of marketization. The institutional economics literature indicates that more transparency and traceability of land transactions decrease the space for local governments to make use of non-market allocation and unwarranted administrative interference [11]. This further reinforces the role of market rules in guiding land allocation behavior. The more marketized the transfer of land is, the greater the role of price mechanisms and competition mechanisms in the allocation of land resources. Land prices can then reflect supply–demand relationships and differences in marginal land output more fully. This helps to reduce the allocation biases that arise from administrative intervention and distorted price signals. On the other hand, a more marketized land transfer system helps to improve the disclosure of land transaction information and the enforcement of transaction rules. This lowers the risk of irregular transactions, speculative behavior and breaches of regulation. It also helps in curbing the LRM resulting from market failures and regulatory lags.

Therefore, this study proposes the following hypothesis:

H3. *AIL helps to alleviate urban LRM by promoting land transfer marketization.*

2.3.3. Industrial Structure Upgrading

From the perspective of firms, industrial structure shapes the pattern of land use and the efficiency of output [88]. Industrial structure upgrading can therefore affect both the direction and the efficiency of land resource allocation. When the industrial structure stays locked for too long into sectors that are low in value added, heavy in land use and geared towards extensive expansion, land input tends to be poorly matched with industrial output efficiency [68]. This makes LRM worse. By contrast, shifting the industrial structure towards technology-intensive and high-value-added activities can raise the economic output from each unit of land. At the same time, it can reduce the reliance on expanding the supply of new construction land [89]. This encourages the growth of an industrial base that allows for a more efficient allocation of land resources. Factor misallocation theory points out a key risk. If land is not allocated by the marginal output of different industrial sectors, it can become too concentrated in low-efficiency industries. Industrial structure upgrading can change the relative productivity of different industries and their demand for land. This guides land factors to shift from sectors with low marginal output to those with high marginal output. AI can change how firms produce. It can also promote industrial structure upgrading. Innovation-driven theory suggests that AI can help transform firms' production models. This is made possible by technological innovation, process optimization and good management decisions [90]. As AI penetrates deeper into product R&D, process innovation and resource management, firms' production processes and resource allocation patterns are becoming more digital, intelligent and refined [91]. This encourages the intelligent transformation of traditional industries and supports the upgrading of industrial structures [92]. In this process, urban industrial development gradually moves away from low-end capacity expansion. It shifts towards technological innovation and the clustering of high-value-added industries. At the same time, the function of land resources changes. It converts low-efficiency production space into high-efficiency industrial space [93]. Industrial structure upgrading, in turn, helps to ease LRM. On the one hand, it can steer more land towards industrial sectors with higher production efficiency, stronger innovation capacity and greater value added. This helps to reduce the distortions in land allocation caused by low-end industrial lock-in and path dependence [47]. On the other hand, it allows land resources to be reallocated to more efficient market actors and industrial activities. This alters the land use from extensive sprawl to more compact and optimized use.

Therefore, this study proposes the following hypothesis:

H4. *AIL helps to alleviate urban LRM by promoting industrial structure upgrading.*

3. Research Design

3.1. Model Setting

3.1.1. Benchmark Regression Model

The influence of AI on LRM is examined using the following specified model:

$$LRM_{it} = a_0 + a_1 AI_{it} + a_2 X_{it} + \mu_i + \nu_t + \varepsilon_{it} \quad (1)$$

where LRM_{it} denotes the land resource misallocation of city i in year t ; AI_{it} denotes the artificial intelligence level of city i in year t ; X_{it} denotes a series of control variables; μ_i and ν_t are the city and time fixed effects, respectively; and ε_{it} represents random errors.

3.1.2. Mediating Effect Model

To examine the transmission mechanisms through which AI affects LRM, a mediating effect model is employed for empirical analysis. Specifically, the study investigates three

key pathways: first, whether AI reduces LRM by enhancing government environmental concern; second, whether it promotes land transfer marketization to improve land resource allocation efficiency; and finally, whether AI facilitates industrial upgrading to lower LRM. Based on this, the study extends Model (1) to construct a mechanism analysis framework incorporating government environmental concern, land transfer marketization, and industrial structure upgrading. The specific model is as follows:

$$GEC_{it} = \beta_0 + \beta_1 AI_{it} + \beta_2 X_{it} + \mu_i + \nu_t + \varepsilon_{it} \quad (2)$$

$$LTM_{it} = \gamma_0 + \gamma_1 AI_{it} + \gamma_2 X_{it} + \mu_i + \nu_t + \varepsilon_{it} \quad (3)$$

$$ISU_{it} = \delta_0 + \delta_1 AI_{it} + \delta_2 X_{it} + \mu_i + \nu_t + \varepsilon_{it} \quad (4)$$

where GEC_{it} , LTM_{it} and ISU_{it} denote mechanism variables, including government environmental concerns, land transfer marketization and industrial structure upgrading; the definitions of the other variables are consistent with those in the previous section.

3.2. Variable Selection

3.2.1. Explained Variable

The dependent variable of this paper is land resource misallocation (LRM). LRM is defined as the distance between the actual land input of a city and its contribution to economic output and its marginal land output, guided by resource misallocation theory. The objective of land resource allocation is to make land input match its contribution to production. It is also to steer land factors towards regions and uses where marginal output is higher [94]. The core concern of LRM is therefore whether the match between land factor input and urban production efficiency is a reasonable one.

Existing studies often measure land resource misallocation by the ratio of industrial land area to construction land area. Yet this indicator struggles to capture differences across cities in economic output capacity, factor input structure and resource allocation efficiency. In practice, some local governments expand land supply and land conveyance to ease fiscal spending pressures. This can fuel an excessive expansion of industrial parks and construction land. The result is a gap between land input and economic output efficiency [95]. Using only the ratio of industrial land to construction land, therefore, is not enough to fully capture the degree of urban land resource misallocation. Following the approach of Han and Huang [28], this study uses a resource misallocation model to calculate the land resource misallocation index for each city.

First, we construct the production function as follows:

$$Y_{it} = A_{it} \times K_{it}^{a_s} \times L_{it}^{b_s} \times LD_{it}^{c_s} \quad (5)$$

Among them, Y represents actual output, A denotes total factor productivity, K stands for capital input, L indicates labor input, and LD signifies land resource input. Actual output is measured using nominal GDP deflated by constant 2000 prices. We choose the year 2000 as the base period for prices. This makes sure that output data for all years in the sample are measured at the same price level. It stops changes in the general price level from distorting the estimates of real economic output. The price deflation we refer to here means stripping out the effect of general price movements from nominal GDP. It does not involve any adjustment to land prices. Capital input is measured by the stock of fixed assets. Labor input is measured by the number of employees at the end of the year. Land resource input is measured by the area of urban construction land. a , b , and c represent the output elasticities of capital, labor, and land, respectively, with their sum equal to 1. By taking the natural logarithm of Model (5), the output elasticity of each input factor is calculated.

Second, based on the results obtained from Model (5), the relative distortion coefficient of land factors is further calculated.

$$s_{it} = Y_{it}/Y_t \quad (6)$$

$$\bar{c}_{it} = \sum_{i=1}^N s_{it} c_s \quad (7)$$

$$Mis_{it} = \frac{(LD_{it} / LD_t)}{(s_{it} c_s / \bar{c}_{it})} \quad (8)$$

where s_{it} is the share of city i 's output in total output across all cities. The term $\bar{c}_{it}$ is the output elasticity of land, weighted by economic output. Mis_{it} is the relative distortion coefficient of land factors. When Mis_{it} is greater than 1, it indicates that the city's actual land input is relatively high relative to its contribution to economic output and its marginal land output level, suggesting a tendency towards excessive land allocation. When Mis_{it} is less than 1, it indicates that the city's actual land input is relatively low relative to its contribution to economic output and its marginal land output level, suggesting a tendency towards under-allocation of land. When Mis_{it} equals 1, it indicates that land input matches the capacity for economic output and the marginal land output level, and land resource allocation is in a relatively efficient state. This benchmark of fairly efficient allocation does not require different cities to have the same scale of land input or the same output ratio. The model takes into account each city's contribution to economic output and its marginal land output at the same time. Cities with different industrial structures and functional roles can therefore have different reasonable levels of land input. For example, industrial cities, commercial centers and tourist cities differ in how intensively they use land and in their output patterns. But as long as their land input matches their own output contribution and marginal output, they can be seen as being in a fairly efficient allocation state. LRM can thus, to some extent, pick up relative over-allocation or under-allocation of land while still allowing for differences in cities' specializations.

To ensure the interpretability of the model results, we apply inverse processing to Mis_{it} as follows:

$$LRM_{it} = |Mis_{it} - 1| \quad (9)$$

Here, LRM_{it} is the land resource misallocation index for city i in year t . A larger value of LRM_{it} means that urban land input deviates more from the fairly efficient allocation state. It therefore signals more severe land resource misallocation. This indicator mainly captures the overall extent of land resource misallocation. It places greater weight on measuring how far land input has moved away from the efficient allocation state. It is worth noting that Mis_{it} is used chiefly to identify the direction of the deviation. By contrast, LRM_{it} is the final land resource misallocation index, built on the basis of Mis_{it} . All later baseline regressions and robustness checks use this LRM_{it} to measure the degree of urban land resource misallocation.

In practice, land reserves or temporary idleness are not necessarily considered as LRM. LRM is not simply based on whether the land is in immediate use. It considers the match between the city's overall land input and its contribution to economic output and the marginal land output [96]. Land set aside for future industrial expansion therefore needs to be assessed in the round. This means looking at the city's scale of development, its production capacity and how the land is later used. When land reserves are in line with urban development needs, their temporary non-use is, to some extent, reasonable [97]. However, when land input stays out of step with the city's contribution to economic

output and its marginal land output over a long period, it can show up as too much or too little land allocation.

To visually depict the spatiotemporal distribution characteristics of LRM, we present the calculation results for 2010 and 2023, as shown in Figure 3a,b. From a temporal perspective, the range of high-value LRM zones has significantly expanded, indicating a continuously intensifying trend of LRM in Chinese cities. Spatially, LRM exhibits significant regional heterogeneity, with an overall distribution pattern characterized by Southeast > Central > West. Clearly, the land management model to facilitate a more efficient allocation of land resources remains a critical issue that requires urgent attention and action.

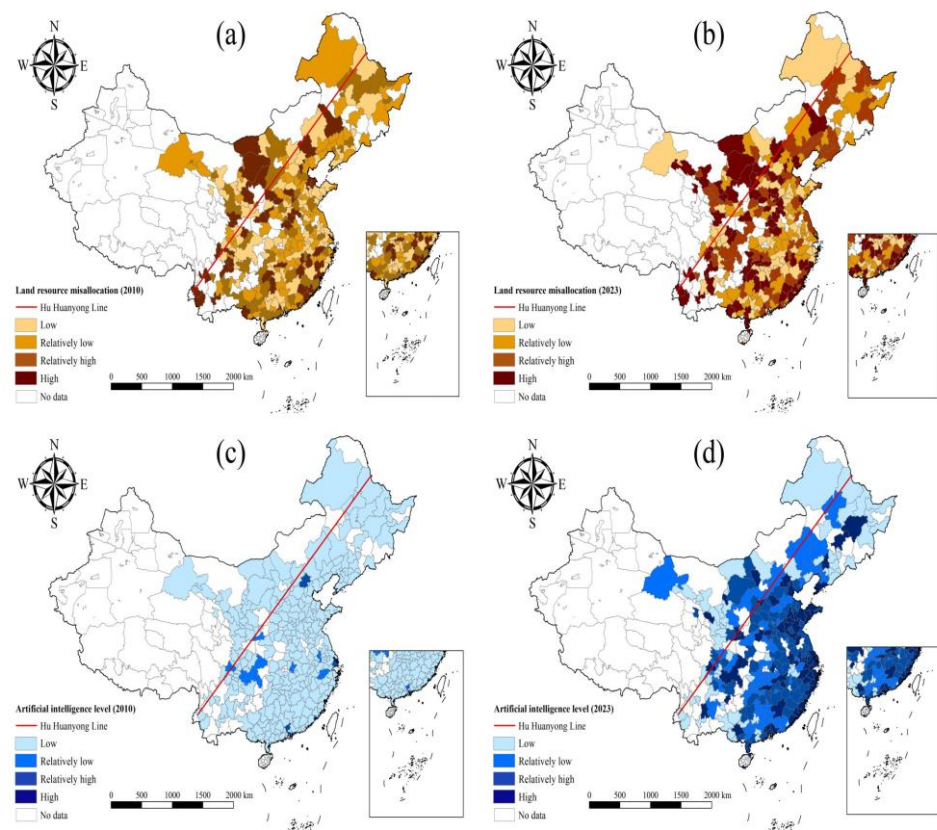


Figure 3. Spatial and temporal differentiation of AIL and LRM. Note: (a) Spatial distribution of LRM in 2010; (b) Spatial distribution of LRM in 2023; (c) Spatial distribution of AIL in 2010; (d) Spatial distribution of AIL in 2023.

3.2.2. Explanatory Variable

AIL is the explanatory variable in this study. Following the approach of Zeng and Zhang [98], we first identify AI enterprises using a feature keyword extraction method. Specifically, companies whose business scope includes AI-related keywords such as voice interaction, image recognition, computer vision, or sensors are classified as AI enterprises, resulting in a final dataset of over 3.68 million companies. These enterprises are then mapped to 265 cities based on their registered locations. Finally, to eliminate the influence of scale and reduce the impact of heteroscedasticity on the model results, the number of AI enterprises in each city is logarithmically transformed to obtain the final variable.

It is usually AI companies that conduct the R&D, industrialization and diffusion of AI technologies. Thus, they are a prime vehicle of urban AI development [99,100]. On the one hand, these firms promote industrialization and the spread of AI applications. They do so through algorithm development, product commercialization, scenario adaptation, data processing and technical services [101]. On the other hand, the clustering of AI firms

makes it easier for AI-related professionals to move around. It also encourages knowledge spillovers, boosts technology supply and helps supporting services to grow [102,103]. A larger number of AI firms thus means that a city has a richer set of market actors involved in AI R&D, industrialization and application services. It also signals a denser supply of services in algorithms, data analytics and intelligent decision-making [104]. This suggests that the number of AI firms can effectively capture the level of urban AI development. It does so by reflecting the breadth of the industrial ecosystem, the capacity to supply technology and the conditions for spreading applications.

The AI capabilities in urban public administration depend on two things. One is the digital infrastructure of government institutions. The other is the technical capacity of local firms in algorithm development, data analytics and system integration [105]. AI firms can promote the use of AI technologies in land resource management. They do so through government procurement, public–private partnerships, service outsourcing and joint platform development [106,107]. This provides the basis for looking at how the clustering of urban AI firms affects land resource allocation.

AI firms differ in their specialist fields, capital scale, ability to absorb employment and capacity for innovation. Relying only on the number of firms may therefore bring in some measurement bias. To deal with this, we re-measure the level of urban AI development in the robustness checks. We do so from three angles: AI efficiency, AI development momentum and AI development quality. This helps to reduce the effect that measurement error in the core explanatory variable might have on the estimates.

To visualize the spatiotemporal distribution of AI, we present the estimated results for 2010 and 2023, as shown in Figure 3c,d. From a temporal perspective, the extent of high-value AI zones has significantly expanded, indicating a marked improvement in China's urban AI capabilities. Spatially, while high-value AI zones were sparsely distributed in 2010 without forming contiguous clusters, by 2023 they had clearly concentrated in contiguous areas along the eastern coastal regions. The overall distribution exhibits a gradient pattern of "East > Central > West." Therefore, coordinating balanced regional development of AI and fully leveraging its enabling role in land resource allocation have become critical issues requiring in-depth research to advance the modernization of national territorial governance and achieve sustainable land resource utilization.

3.2.3. Mechanism Variables

(1) Government environmental concerns (GEC): Shuai et al. confirmed that government environmental concerns can significantly enhance the efficiency of land resource allocation [108], providing a basis for this study to examine whether AI can reduce LRM by increasing government environmental concerns. Referring to existing research [109,110], we first extract keywords related to environmental protection from the existing literature and government environmental reports to create an environmental concern lexicon [111]. This lexicon includes keywords across dimensions such as air environment, water environment, ecological environment, sustainable development, and general environmental management. Specifically, air environment keywords include haze, smog control, SO₂, CO₂, PM₁₀, PM_{2.5}, air, dust, exhaust, emissions, blue skies, and VOCs; water environment keywords include aquatic ecology, chemical oxygen demand (COD), scattered pollution, discharges, water environment, water security, water quality, clear waters, black and odorous water, sewage, and COD; ecological environment and sustainable development keywords include environmental protection, green development, new energy, low-carbon, environmental quality, reforestation, ecological environment, ecological conservation, and ecological damage. General environmental management keywords encompass pollution, energy consumption, pollution control, emission reduction, waste discharge, waste residue, coal-fired environmental violations,

environmental crimes, environmental cases, environmental penalties, and environmental governance. Second, this study collects annual government work reports from 265 Chinese cities via official local government websites for the period 2010 to 2023. Python 3.12 software is used to convert the reports into text format, and the environmental concern lexicon is applied for information matching. Finally, the environmental concern index for each local government is calculated by determining the proportion of words from the environmental concern lexicon within the sentences of the government work reports and multiplying this value by 100.

(2) Land transfer marketization (LTM): Jiang et al. confirmed that land transfer marketization can significantly improve land utilization efficiency [83], providing literature support for this study to examine whether AI reduces LRM by promoting land transfer marketization. Following the research of Lu et al. [112], LTM is measured using the price-weighted ratio of revenues from land tenders, auctions, and listings to total land transfer revenues.

(3) Industrial structure upgrading (ISU): Liu et al. demonstrated that industrial structure upgrading can significantly enhance land use efficiency [88], providing literature support for this study's investigation into whether AI promotes industrial structure upgrading to reduce LRM. Following the methodology of Zheng et al. [113], the industrial structure upgrading index is measured using the industrial structure hierarchy coefficient method. We construct an industrial structure upgrading index. It is based on the shares of value added of the primary, secondary and tertiary industries in GDP. We assign weights of 1, 2 and 3 to each of them. A larger value of this index means that the tertiary industry occupies a higher relative position in the city's industrial structure. It thus signals a greater degree of industrial structure upgrading.

3.2.4. Control Variables

Considering that urban characteristics also influence LRM, the following control variables have been added to the model:

(1) Fiscal decentralization (FD). The degree of fiscal decentralization influences the fiscal incentives and behavioral patterns of local governments in land resource allocation [114], potentially exerting latent effects on LRM. Therefore, drawing on existing research [115,116], this study measures urban fiscal decentralization using the ratio of general government revenue to general government expenditure.

(2) Human capital (HC). Human capital is a crucial factor driving the transformation of land resources from factor input to high-value-added utilization, directly influencing the efficiency of land market allocation [117]. Therefore, this study adopts the method of Kuzmin et al. [118], using the ratio of the number of students enrolled in regular universities to the year-end total population.

(3) Economic development (PGDP). As economic development progresses, land use patterns gradually shift from extensive expansion to intensive optimization, promoting more efficient utilization of land resources [119]. Therefore, the method proposed by Yu et al. [120] is adopted to measure the level of urban economic development using per capita GDP.

(4) Infrastructure level (IL). Gu et al. confirmed that robust infrastructure reduces factor mobility and transaction costs, effectively mitigating LRM [121]. Thus, the method of Jubiz-Diaz et al. [122] is employed to measure the infrastructure level using the per capita highway freight volume.

(5) Financial development (FID). Financial development optimizes capital supply and facilitates the transformation of land resource allocation toward marketization and financialization [123], which may potentially have an impact on LRM. Therefore,

following the methodology of Fan et al. [124], this study measures the level of financial development by the ratio of year-end deposits and loans of financial institutions to GDP.

(6) Trade openness (TO). Trade openness facilitates the introduction of international market competition and price signals, correcting distortions in domestic land factor markets and thereby enhancing the efficiency of land resource allocation [125]. Consequently, this study adopts the methodology of He and Wang [15] and measures trade openness by the proportion of total import and export trade to GDP.

3.3. Data Sources

In this study, we select panel data from 265 cities in China (excluding Tibet, Qinghai, Hainan, Hong Kong, Macau and Taiwan) as samples, and the data are primarily from the China City Statistical Yearbook and statistical bulletins from provinces and cities. Some missing individual data have been supplemented by linear fitting or interpolation. The descriptive statistics for all the variables are presented in Table 1.

Table 1. Descriptive statistics.

Variables		Obs	Mean	SD	Min	Max
Explained variable	LRM	3710	0.921	2.614	0.000	41.621
Explanatory variable	AIL	3710	5.181	1.947	0.000	11.540
	GEC	3710	15.304	7.519	0.000	87.000
	LML	3710	0.902	0.121	0.000	1.000
Mechanism variables	ISU	3710	2.310	0.144	1.831	2.846
	FD	3710	0.453	0.220	0.056	1.541
	HC	3710	0.024	0.065	0.000	1.000
	PGDP	3710	5.678	3.510	0.530	26.470
Control variables	IL	3710	0.315	0.423	0.000	11.214
	FID	3710	2.610	1.219	0.588	14.420
	TO	3710	0.199	0.381	0.000	6.956

4. Empirical Results and Analysis

4.1. Benchmark Regression

According to Model (1), we examine the direct impact of AIL on LRM. The results in columns (1) to (5) of Table 2 demonstrate that, regardless of whether control variables and fixed effects are included, the estimated coefficient for AIL is significantly negative at the 1% level. A one-unit increase in AIL is linked, on average, to a fall of 0.373 units in LRM. This suggests that a stronger AIL industrial base and a better environment for technology supply in a city can help to bring down urban LRM. Therefore, Hypothesis 1 is verified.

The direct impact of AIL on reducing LRM stems from its enhanced ability to improve the precision of national land allocation and the efficiency of factor mobility. On one hand, through big data analytics, machine learning, and spatial optimization algorithms, AI enables intelligent matching and dynamic monitoring of land resource supply and demand, thereby reducing resource idleness and misallocation caused by information asymmetry or improper planning at the source. On the other hand, AI-enabled technologies such as smart contracts and blockchain promote transparency in land transaction information and automate processes, lowering transaction costs and minimizing risks of human intervention, thus directing land factors more efficiently toward high-value-added sectors. Simultaneously, AI-driven remote sensing monitoring and illegal land use detection systems facilitate real-time supervision, effectively curbing non-compliant land practices and correcting LRM at the institutional implementation level. Several studies support our findings, confirming the positive role of AI. For instance,

Wang et al. demonstrated that AI-centric digital infrastructure significantly enhances land use efficiency [64]. Gu et al. found that AI-supported digital economies effectively mitigate the adverse impacts of LRM on ecological resilience [50]. Furthermore, Li et al. revealed that AI-centric digital technologies significantly improve land resource allocation efficiency [88], thereby alleviating the negative effects of LRM on food security. Therefore, promoting the deep integration and scenario-based innovation of AI in land spatial governance represents a crucial pathway to systematically address the challenges of land resource allocation and achieve regional sustainable development.

Table 2. Benchmark regression results of AI on LRM.

Variable	(1)	(2)	(3)	(4)
	LRM	LRM	LRM	LRM
AIL	−0.057 *** (−4.47)	−0.340 *** (−4.76)	−0.159 *** (−4.60)	−0.373 *** (−4.92)
FD			−0.173 *** (−6.15)	0.086 *** (3.15)
HC			−0.016 (−1.03)	−0.136 *** (−2.63)
PGDP			0.202 *** (4.07)	−0.107 *** (−3.16)
IL			0.015 (1.19)	−0.025 (−1.22)
FID			0.088 *** (3.35)	−0.029 (−1.50)
TO			−0.026 (−2.20)	−0.025 * (−1.91)
City/Year FE	No	Yes	No	Yes
R ²	0.003	0.792	0.030	0.794
N	3710	3710	3710	3710

Note: *** and * denote significance at the 1% and 10% levels, respectively, with t-values in parentheses.

4.2. Robustness Tests

4.2.1. Replacement of the Dependent Variable

To deal with possible estimation bias from measurement error in the core dependent variable, we first replace the LRM measure. We use the ratio of industrial, mining and warehousing land to state-owned construction land instead. This allows us to check the causal link between AIL and LRM [34]. The regression results are shown in column (1) of Table 3. The estimated coefficient on AIL is significantly negative at the 5% level. This tells us that the positive effect of AIL in easing LRM is not unduly affected by measurement error tied to the choice of variable. Second, we replace the core dependent variable altogether. We switch from LRM to land use efficiency, and re-examine the causal link between AIL and LRM. Following Wang et al. [126], we use a stochastic frontier production function (SFA) to measure urban land use efficiency. The results are shown in column (2) of Table 3. The estimated coefficient on AIL is significantly positive at the 1% level. This again confirms that the baseline regression results are robust.

Table 3. Robustness test results.

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
	LRM	LRM	LRM	LRM	LRM	LRM	LRM	LRM	LRM	LRM	LRM
AIL	−0.192 ** (−2.01)	0.087 *** (4.41)	−0.021 ** (−2.47)	−0.092 ** (−1.98)	−0.009 * (−1.92)	−0.339 *** (−4.82)	−0.335 *** (−3.85)	−0.166 ** (−1.99)	−0.381 *** (−4.51)	−0.278 *** (−3.08)	−0.373 *** (−4.92)
L.LRM								0.659 *** (9.00)			
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Province FE	No	No	No	No	No	No	No	No	Yes	No	No
Province-Year FE	No	No	No	No	No	No	No	No	No	Yes	No
AR(1)-P								0.002			
AR(2)-P								0.784			
R ²	0.713	0.985	0.793	0.793	0.792	0.795	0.800	0.784	0.822	0.828	0.794
N	3710	3710	3710	3710	3710	3710	2915	3445	3710	3710	3710

Note: *** denote significance at the 1% level, ** denote significance at the 5% level, * denote significance at the 10% level, respectively, with t-values in parentheses.

4.2.2. Replacement of the Explanatory Variable

To rule out measurement bias in the core explanatory variable, we re-measure the level of urban AIL from three angles: efficiency, momentum and quality. First, we follow Li et al. [127] and use the SBM model to measure AI efficiency. The initial inputs are the level of scientific expenditure and human capital. The intermediate outputs are the number of AI patents and the number of newly established AI firms. The final output is the level of economic development. The results are shown in column (3) of Table 3. The estimated coefficient on AIL is significantly negative at the 5% level. This backs up the robustness of the baseline regression results. Second, we follow Fang et al. [128] and use Baidu Index search engine data. From these, we construct a city-level measure of sentiment towards AI. This captures the enthusiasm and momentum for AI development in each city. The results are shown in column (4) of Table 3. The estimated coefficient on AIL is significantly negative at the 5% level. This again reinforces the robustness of the baseline results. Finally, we follow Zhou et al. [129] and compute the AI innovation bubble. We take the difference between the number of AI invention applications and the number of AI invention grants in a given year. This serves as a measure of AI quality. To make the direction of the regression coefficient easier to interpret, we standardize the indicator and reverse-code it before estimation. The results are shown in column (5) of Table 3. The estimated coefficient on AIL is significantly negative at the 10% level. This, too, confirms the robustness of the baseline regression results.

4.2.3. Excluding the Impact of Outliers

Sample data containing extreme values may lead to biased estimation results; therefore, this paper re-estimates the model after trimming 1% from both ends of all variables. As shown in column (6) of Table 3, even after addressing extreme values, the AIL coefficient remains significantly negative at the 1% level, further validating the robustness of the baseline regression findings.

4.2.4. Changing the Study Period

In 2020, the COVID-19 pandemic impacted adjustments to China's land management policies and the application of AI [121]. To assess the robustness of the results, data from

2020 to 2022 are excluded for a baseline regression. The results in column (7) of Table 3 show that the estimated coefficient of AIL is -0.335 , and it is significant at the 1% level, indicating that AIL contributes to improving LRM, verifying the robustness of the baseline regression results.

4.2.5. System GMM Estimation

LRM may show path-dependent features. That is, LRM in the previous period may affect LRM in the current period. There may also be two-way causality between AIL and LRM. To address these concerns, we use the system GMM estimator to reassess the robustness of the results. This helps to rule out the effect of model specification bias. The results are shown in column (8) of Table 3. The estimated coefficient on L.LRM is 0.659 and is significant at the 1% level. This tells us that LRM shows clear path dependence. LRM in the previous period has a significant positive effect on LRM in the current period. The estimated coefficient on AIL is -0.166 and is significant at the 5% level. This suggests that the finding that AIL helps to ease LRM is robust. Turning to the model diagnostics, the p -value of the AR(1) test is 0.002 . This rejects the null hypothesis of no autocorrelation. The p -value of the AR(2) test is 0.784 . This fails to reject the null hypothesis. It tells us there is no second-order serial correlation in the residuals. The system GMM estimates are therefore reliable. They further confirm the robustness of the baseline regression findings.

4.2.6. Consider Provincial Time Interaction

As a key administrative level in China, provinces are fundamental to the country's governance system; their inner cities exhibit commonalities in policy orientation and cultural background [92]. Therefore, this study incorporates province–time interaction fixed effects into the baseline regression to control for time-varying influences across different provinces. Even after accounting for the correlated characteristics of cities within the same province, the impact of AIL on LRM remains significantly negative at the 1% level (Column (9) of Table 3), confirming the robustness of the original conclusion. We also add province-by-year interaction fixed effects to the baseline regression. This helps to control for time-varying confounding factors at the provincial level. The results are shown in column (10) of Table 3. The estimated coefficient on AIL remains significantly negative at the 1% level. This once more confirms that the baseline regression results are robust.

4.2.7. Excluding the Interference of Policies

To eliminate the potential impact of relevant macro policies during the study period on the estimation results, digital technology policies such as Smart City and Broadband China that were implemented in 2012 and 2014, respectively, are incorporated into the baseline model for re-estimation. This approach allows for a more accurate identification of the causal relationship between AIL and LRM. The results in column (11) of Table 3 show that the estimated coefficient of AIL remains significantly negative at the 1% level, confirming that the positive effect of AIL on LRM is not confounded by other policies.

4.2.8. Placebo Test

We run a placebo test to rule out the chance that unobserved confounders or pure randomness are driving the positive effect of AILL on LRM. We randomly shuffle the AILL variable across cities within each year. This ensures there is no systematic link between the placebo AIL and LRM. We then re-estimate the baseline model using the placebo AIL. We repeat the process 1000 times. This gives us a distribution of 1000 placebo coefficients. Figure 4 shows the result. The distribution of the 1000 placebo coefficients is centered around zero and roughly follows a normal distribution. The true estimated coefficient is marked by the red vertical line. It lies in the left tail of the distribution. This

further confirms the robustness of our findings that the positive effect of AIL on LRM is not due to omitted variable bias or random chance.

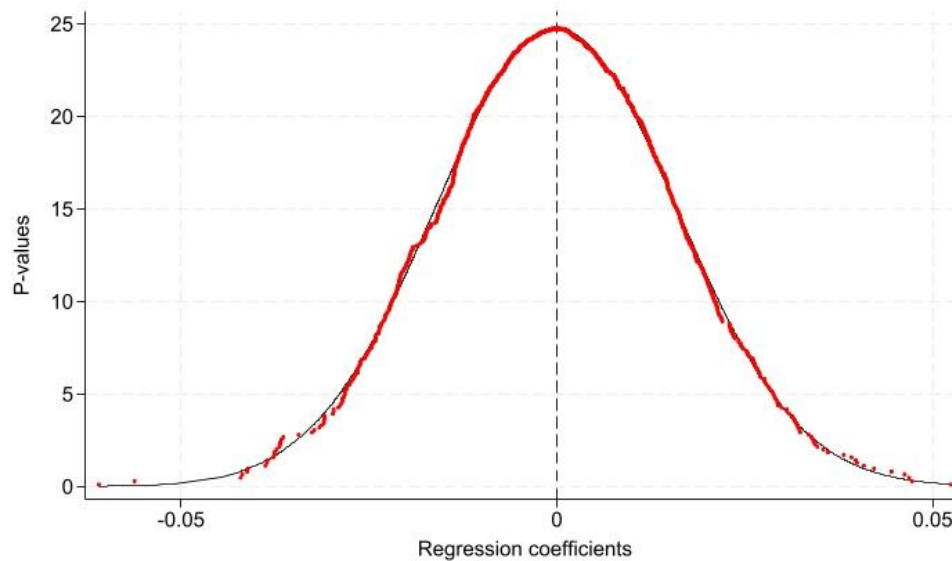


Figure 4. Placebo test. Note: Red curve: Joint distribution of all coefficient-p values obtained from multiple random placebo simulations (falsified treatments); Black thin line: Fitted kernel density envelope; Black vertical dashed line ($x = 0$): Zero-effect line, indicating the position where the policy has no effect at all.

4.3. Endogeneity Analysis

Endogeneity issues pose a significant methodological challenge to the validity of causal inference, potentially arising from omitted variables, reverse causality, and sample selection bias. To address these concerns, this study employs instrumental variables and propensity score matching for re-analysis, thereby improving the consistency and robustness of the estimation results.

4.3.1. Instrumental Variable Method

Relevance and exogeneity are essential prerequisites for the use of the instrumental variables (IV) approach [130]. Relevance refers to the requirement that instrumental variables must be strongly correlated with the core explanatory variable, while exogeneity demands that the instrumental variables have no direct relationship with the dependent variable. The instrumental variables employed in this study include the number of fixed post offices per million population in 1984 (IV1) and the one-period lag of the explanatory variable (IV2).

(1) IV1. Information transmission and communication in early societies primarily relied on post offices, making their number a reflection of a city's foundational communication technology and development level [131], which correlates with contemporary urban AIL levels. The results are shown in column (1) of Table 4. The instrumental variable is strongly correlated with AIL. The first-stage F-statistic is 18.900, well above the critical value from the Stock–Yogo weak instrument test. This tells us that weak instrument bias is not a concern. In theory, the number of historical post offices in 1984 affects current AI development mainly through its influence on cities' long-run accumulation of information infrastructure, the process of digitalization and the capacity to adopt technology. More importantly, the 1984 data come well before the sample period of this study. They have no direct bearing on current land resource misallocation. The exogeneity requirement of the IV is therefore met. In addition, we include year fixed

effects and city fixed effects in our model. These control for unobserved city-specific factors that do not change over time, as well as for common macroeconomic shocks. We also interact the number of post offices in 1984 with year dummies. This allows the instrumental variable to vary over time, making it suitable for panel data analysis. The instrument we use, IV1, therefore meets both the relevance condition and the exogeneity condition. This helps to ensure that our estimates are reliable. The results in column (2) show that, after taking into account possible endogeneity from omitted variables and reverse causality, AIL still significantly reduces LRM. The Kleibergen–Paap LM statistic is 17.838 ($p = 0.000$). This rejects the null hypothesis that the instrument is under-identified. Both the Cragg–Donald Wald F statistic and the Kleibergen–Paap F statistic exceed the critical values. This confirms that the instrumental variable is valid. Therefore, the causal relationship that AIL can effectively reduce LRM is robust.

(2) IV2. The one-period lag of the explanatory variable is generally considered to have no direct correlation with the current error term, which helps mitigate bidirectional causality and reduces endogeneity concerns [132]. Therefore, this study employs the lagged period of AIL as an instrumental variable for endogeneity testing. The results are shown in column (1) of Table 4. The instrumental variable is strongly correlated with AIL. The first-stage F-statistic is 18.900, well above the critical value from the Stock–Yogo weak instrument test. This tells us that weak instrument bias is not a concern. In theory, the number of historical post offices in 1984 affects current AI development mainly through its influence on cities' long-run accumulation of information infrastructure, the process of digitalization and the capacity to adopt technology. More importantly, the 1984 data come well before the sample period of this study. They have no direct bearing on current land resource misallocation. The exogeneity requirement of the IV is therefore met. In addition, we include year fixed effects and city fixed effects in our model. These control for unobserved city-specific factors that do not change over time, as well as for common macroeconomic shocks. The instrument we use, IV2, therefore meets both the relevance condition and the exogeneity condition. This helps to ensure that our estimates are reliable. The results in column (2) show that, after taking into account possible endogeneity from omitted variables and reverse causality, AIL still significantly reduces LRM. The Kleibergen–Paap LM statistic is 17.838 ($p = 0.000$). This rejects the null hypothesis that the instrument is under-identified. Both the Cragg–Donald Wald F statistic and the Kleibergen–Paap F statistic exceed the critical values. This confirms that the instrumental variable is valid. Therefore, this further confirms that the causal relationship through which AIL can effectively reduce LRM is robust.

Table 4. Endogeneity test results.

Variable	(1) AIL	(2) LRM	(3) AIL	(4) LRM	(5) PSM-DID
IV1	0.053 *** (6.11)				
IV2			0.431 *** (49.62)		
AIL		−1.523 ** (−2.46)		−0.430 *** (−5.27)	−0.372 *** (−4.88)
Controls	Yes	Yes	Yes	Yes	Yes
City/Year FE	Yes	Yes	Yes	Yes	Yes
R ²	0.988	0.778	0.996	0.826	0.794
N	3710	3710	3445	3445	3657

Note: *** and ** denote significance at the 1% and 5% levels, respectively, with t-values in parentheses.

4.3.2. Propensity Score Matching

This study employs propensity score matching to address endogeneity issues caused by sample self-selection bias [133]. Specifically, we use whether a city is designated as a National Pilot City for New Generation AI Innovation and Development as the treatment variable, thereby dividing the sample into treatment and control groups. Based on this, we select a series of control variables reflecting urban characteristics. We estimate the propensity scores for each city using a Logit model and perform 1:1 nearest-neighbor matching within the mixed-year sample to construct a comparable analytical sample. Column (5) of Table 5 reports the regression results based on the matched sample. The coefficient for AIL is significantly negative at -0.372 , with significance at the 1% level. This finding suggests that our benchmark results are robust.

Table 5. Mechanism analysis results.

Variable	(1)	(2)	(3)
	GEC	LTM	ISU
AIL	0.229 ** (1.99)	0.301 ** (2.07)	0.414 *** (8.31)
Controls	Yes	Yes	Yes
City/Year FE	Yes	Yes	Yes
R ²	0.438	0.391	0.934
N	3710	3710	3710

Note: *** and ** denote significance at the 1% and 5% levels, respectively, with t-values in parentheses.

4.4. Mechanism Analysis

The benchmark regression results provide evidence that AI significantly curbs LRM; however, the mechanism through which AIL affects LRM still requires further investigation. Based on the previous theoretical analysis, we further examine the mechanism by which AIL reduces LRM from a multidimensional perspective, including the government, the market, and enterprises.

Results in column (1) of Table 5 show that the estimated coefficient for AIL on government environmental concerns is 0.229, significant at the 5% level, indicating that AIL effectively enhances government environmental concerns. At the local level, the degree of government attention to the environment reflects their attention to ecological limits and environmental risks, and compact land use targets [111,134]. When the government attaches importance to environmental issues, land development decisions are more likely to be constrained by a number of factors, including the carrying capacity of resources and the environment, ecological protection requirements and targets for combating inefficient land use [135,136]. Therefore, it is less likely for governments to promote economic growth by expanding construction land and increasing land conveyance. Moreover, Shuai et al. confirmed that government environmental concerns can significantly improve land resource allocation efficiency [108]. Therefore, AIL can reduce LRM by enhancing government environmental concerns, supporting Hypothesis 2.

Furthermore, AIL can strengthen the capacity to spot environmental risks and to monitor land use. In doing so, it can help turn government environmental concerns into more binding land governance actions. On one hand, the ecological perception networks and intelligent supervision platforms established by AI enhance the dynamic capabilities of government environmental governance [80]. This facilitates the translation of environmental concerns into concrete conservation actions, creating sustained environmental constraints that drive the transition toward sustainable land use models

and ultimately optimize the efficiency of land resource allocation. On the other hand, AI employs intelligent early warning and scenario simulation technologies to assist governments in precisely identifying potential ecological risks during land development. This shifts land management from post-event correction to preemptive prevention, thereby optimizing land resource allocation pathways and effectively preventing structural misallocation of land resources.

The results in column (2) of Table 5 show that the estimated coefficient of AIL on land transfer marketization is 0.301, which is significant at the 5% level. This indicates that AIL effectively promotes land transfer marketization. Land transfer marketization reflects how far price mechanisms, competition mechanisms and supply–demand matching mechanisms are at work in land resource allocation. When the degree of marketization is higher, land prices can more readily capture the true supply–demand relationship, locational conditions and differences in marginal land output. Land factors can also flow more easily towards market actors and industrial activities with higher production efficiency [83]. Therefore, AIL can reduce LRM by promoting land transfer marketization, thereby verifying Hypothesis 3.

Furthermore, AIL can strengthen the capacity to integrate information and match supply with demand in the land market. In doing so, it can encourage greater reliance on market mechanisms in land resource allocation. Based on the theory of resource allocation, AI possesses strong capabilities in multi-source data fusion and analysis [86], enabling the identification of inefficient land use and the precise matching of market demands through deep learning models. This facilitates the optimized reallocation of existing land resources. Additionally, integrating AI into the national land space monitoring platform can provide real-time warnings of market violations and help curb land speculation. By reducing information asymmetry and maintaining transaction order, these processes promote a more efficient flow of land factors [137].

The results in column (3) of Table 5 show that the estimated coefficient of AIL on industrial structure upgrading is 0.414, which is significant at the 1% level. This indicates that AIL effectively promotes industrial structure upgrading. Industrial structure shapes the pattern of land use and the efficiency of output. When a city's industrial structure stays locked for too long into sectors that are low in value added, heavy in land use and geared towards extensive expansion, land input tends to be poorly matched with industrial output efficiency. This makes the distortion of land resource allocation worse [138]. By contrast, upgrading the industrial structure towards more technology-intensive and higher value-added sectors can boost the economic output from each unit of land. It can also reduce the reliance of economic growth on expanding the supply of new construction land [139,140]. Moreover, Liu et al. confirmed that industrial structure upgrading significantly enhances the efficiency of land resource allocation [88]. Therefore, AIL can reduce LRM by promoting industrial structure upgrading, thereby verifying Hypothesis 4.

Furthermore, AIL can promote industrial structure upgrading. This, in turn, can ease LRM by reshaping the industrial structure that land resources are expected to support. On one hand, AI drives the intelligent transformation of traditional industries through technology spillover effects [92], prompting the urban land carrying function to shift from low-end production capacity to high-value-added innovation clusters [93], thereby achieving structural optimization of land utilization. On the other hand, AI raises industry efficiency standards, prompting inefficient production capacity to orderly exit the land market [47], releasing existing space and reallocating it to more efficient entities. This process eliminates LRM caused by industrial path dependence and improves the efficiency of urban land utilization.

4.5. Heterogeneity Analysis

4.5.1. Old Industrial Base Cities

The National Adjustment and Transformation Plan for Old Industrial Bases (2013–2022) released a list of cities designated as old industrial bases. These bases are typically important energy cities experiencing rapid development; however, their development models remain relatively extensive [141]. Generally, these bases face significant challenges, such as low efficiency in land resource utilization and a rigid industrial land-use structure, which urgently require technological empowerment and institutional innovation to address resource misallocation. Therefore, this study divides the total sample into old industrial base cities and non-old industrial base cities to further examine the heterogeneous impact of AIL on LRM. The results in columns (1) and (2) of Table 6 indicate that AIL has a significant inhibitory effect on LRM in non-old industrial base cities, whereas its effect on LRM in old industrial base cities is insignificant.

This difference suggests that the effect of AIL on LRM is held back by a city's industrial base and by the room it has for institutional change. Old industrial base cities carry a heavy industrial structure that has been in place for decades. Their established patterns of industrial land use, along with entrenched interest networks, reinforce path dependence in both industrial structure and land use. As a result, converting land to new uses, redeveloping underused industrial land and reallocating the existing land stock all meet with greater resistance. These structural constraints weaken what AI can do in identifying land information, matching supply with demand and improving governance. The technological strengths of AI are thus hard to convert fully into gains in land allocation efficiency [142]. Non-old industrial base cities, by contrast, face less path dependence in their industrial structures and fewer institutional barriers in land resource allocation. They enjoy more room to adjust their structures and respond more quickly to market signals [143]. This flexibility gives more scope for trial-and-error and for step-by-step improvement as AI is applied to land resource management. At the same time, it helps AI to build up governance support more rapidly in areas such as land information integration, dynamic matching of supply and demand, and the assessment of use efficiency. AI is therefore better placed in non-old industrial base cities to steer land factors towards high-efficiency uses and high-efficiency users, and in this way to ease LRM.

4.5.2. Population Density

Population density is not only a key indicator characterizing urban spatial form and agglomeration intensity but also profoundly influences the supply–demand structure and utilization intensity of land resources [144]. Therefore, this study divides the total sample into high-population-density and low-population-density cities to further examine the heterogeneous effects of AIL on LRM. The results in columns (3) and (4) of Table 6 indicate that AIL significantly suppresses LRM in low-population-density cities but has no significant impact on high-population-density cities.

This difference suggests that the effect of AIL on LRM is held back by how strongly a city's population clusters together and by the intensity of its land development. In high-population-density cities, people and economic activity are highly concentrated. Construction land has also been developed with great intensity. This has created fairly strong structural lock-in in how land resources are allocated [145]. In this setting, AI tends to be used more for fine-grained management of the existing land stock and for keeping track of land use conditions. Yet the scope for developing new land is limited, and the costs of changing existing land uses are high. Both factors can narrow AI's room to ease land resource misallocation. Low-population-density cities, by contrast, generally have more plentiful land resources and greater leeway for spatial adjustment. Even so, they often

struggle with extensive land use, poor matching of supply and demand, and low allocation efficiency [146]. This gives AI more room to bring its technical strengths into play in identifying land information, carrying out spatial monitoring and matching supply with demand in a dynamic way. AI can help such cities to spot idle land, underused land and tendencies towards unwarranted expansion more quickly. It can also help steer land resources towards higher-efficiency uses and higher-efficiency users. As a result, the easing effect of AI on LRM comes through more clearly in low-population-density cities.

4.5.3. Government Intervention

The intensity and effectiveness of government intervention in land markets and resource allocation vary across regions. To protect local economic development and gain promotion opportunities, local government officials may implement intervention measures that subsequently affect factor prices and allocation efficiency [147]. In this study, government intervention is measured using the method proposed by Gou et al. [148], specifically through the ratio of general public budget expenditures to GDP. This ratio directly and clearly reflects the scale of government fiscal expenditures and the intensity of economic intervention. A higher value indicates greater government market intervention, while a lower value indicates less. Therefore, this study divides the total sample into cities with strong government intervention and those with weak government intervention based on the median of government intervention, and further examines the heterogeneous impact of AI on LRM. Results in columns (5) and (6) of Table 6 indicate that AI significantly suppresses LRM in cities with strong government intervention, whereas its effect on LRM in cities with weak government intervention is insignificant.

Table 6. Heterogeneity analysis results.

Variable	(1) Old Industrial Based Cities	(2) Non-Old Industrial Based Cities	(3) High Population Density	(4) Low Population Density	(5) Strong Government Intervention	(6) Weak Government Intervention
AIL	0.015 (0.57)	−0.601 *** (−5.00)	0.067 (1.48)	−0.629 *** (−5.40)	−0.565 *** (−4.29)	−0.075 (−1.04)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
City/Year FE	Yes	Yes	Yes	Yes	Yes	Yes
R ²	0.645	0.794	0.681	0.801	0.810	0.760
N	1218	2492	1855	1855	1847	1843

Note: *** denote significance at the 1% level, respectively, with t-values in parentheses.

This difference is due to the constraints of the effect of AIL on LRM from the intervention of the government and the pattern of land resource allocation. This is because in cities where government intervention runs deep, the government has greater administrative power over the land supply, land transactions and the allocation of resources. This makes allocation of land resources more vulnerable to administrative bias, local development goals, and ties to special interests. This leads to distorted factor prices and misallocation of land [34]. In this context, AI can improve information processing and enhance traceability in land supply, land transfer and land use oversight through data integration, process recording, risk identification and dynamic monitoring. This provides technical support that could reduce some of the bias embedded in administrative allocation. Therefore, the alleviating effect of AI on LRM is more obvious in cities with strong government intervention. In contrast, the land resource allocation in cities with less government intervention depends more on market mechanisms. Land factors are more

sensitive to price signals and competition, and institutional misallocation opportunities are smaller due to administrative action [83]. AI still has potential to improve the ability to identify land information, match supply and demand, and monitor land use here. But the scope for correcting administrative distortions is relatively narrow. Thus, the marginal improvement effect on LRM is not significant.

5. Discussion

5.1. Study Significance

First, this study provides empirical evidence for understanding how AI contributes to improving the allocation of urban land resources. Existing research on land resource misallocation has largely been conducted through the lens of fiscal incentives, government intervention, land marketization, and industrial structure. Relatively limited attention has been devoted to how digital technologies, and AI in particular, affect land resource allocation. This study integrates AI development and land resource misallocation within a single analytical framework. The results indicate that AI development helps alleviate urban LRM. This finding suggests that AI is not only a technological force driving industrial innovation and the growth of the digital economy, but also a source of technical support that can raise the efficiency of land resource allocation by strengthening capabilities in information identification, spatial monitoring, risk early warning, and decision support [12]. In the context of smart governance, AI can assist local governments in integrating land use information, industrial land demand data, and spatial development information. In this way, land governance can gradually shift from experience-based, fragmented management toward data-driven, integrated governance. This conclusion broadens the perspective of research on how digital technologies improve urban land resource allocation, and aligns with previous work on the role of digital technologies in enhancing land management and environmental monitoring [16,149].

Second, this study carries implications for carbon neutrality targets and sustainable urban development. The efficiency of land resource allocation is closely connected to urban spatial expansion, industrial layout, energy use, and ecological stress. When land resource misallocation is severe, construction land may expand excessively, inefficient industrial land may become locked in, and the spatial layout may become increasingly unbalanced, all of which can increase resource consumption and environmental pressure [31,150,151]. This study finds that AI can alleviate urban LRM through three channels: strengthening the environmental focus of government, advancing the marketization of land transfers, and promoting industrial structure upgrading. This suggests that AI-enabled land governance not only improves land allocation efficiency but also supports urban green transformation and the pursuit of carbon neutrality by encouraging more intensive land use, the redevelopment of underused land, and industrial structure upgrading [152,153]. In advancing the digitalization of territorial spatial governance, therefore, the application of AI technologies should be integrated with ecological red lines, economical and intensive land use, the treatment of inefficient land, and the greening of industry. This would help move land governance beyond a narrow focus on development efficiency toward a broader governance model that balances economic efficiency, ecological limits, and low-carbon development.

Third, this study also offers policy lessons for land system reform. Urban land resource allocation in China has long been shaped by government intervention, land finance, land transfer systems and the institutional divide between urban and rural land regimes [87,112,153]. Land resource misallocation is not just a technical problem. It is also closely tied to institutional arrangements and governance incentives. AI, therefore, cannot take the place of land system reform. What it can do is provide a data foundation and a

set of governance tools to support that reform. On the one hand, mechanisms for disclosing land market information and sharing land transaction data should be strengthened. This would make information more available and easier to trace across the whole chain—land supply, land transfer, land use and the disposal of inefficient land. It would, in turn, create the institutional conditions that allow AI to work well. On the other hand, AI technologies should be woven more tightly into the marketization of land transfers, the redevelopment of existing land stocks, the treatment of inefficient industrial land and the reform of territorial spatial planning. This would make land resource allocation more responsive to industrial demand, demographic shifts and ecological limits. For developing economies that face similar institutional transition challenges and land resource constraints, the Chinese experience carries a clear message. AI-enabled land governance needs to move forward hand in hand with institutional innovation. Only then can it deliver better digital governance and a more precise allocation of land resources.

5.2. Limitations and Future Prospects

This study still has a number of limitations. First, on the measurement side, we use widely adopted methods to gauge LRM. Even so, it remains difficult to capture the full complexity of LRM. Future work could bring in further dimensions—such as land use intensity, land vacancy rates, spatial misallocation and the loss of ecological value—to build a more rounded indicator system. In addition, this study measures urban AI level by the number of AI firms. This mainly reflects the breadth of AI development and the state of technology supply. It cannot, however, fully capture how firms differ in size, specialist fields and innovation capacity. Future research could combine data on AI patents, R&D spending and actual application to obtain a fuller picture. Second, as regards mechanisms, this study focuses on three channels—GRC, LTM and ISU—viewed through the lenses of government, market and firms. Future work could look further into multi-actor interactions, spatial heterogeneity and network effects. Third, in terms of scale, this study works mainly at the city level. It has not yet dug into the behavioral logic of micro-level actors, such as firms, in land resource allocation. Future research could explore land use efficiency, location choices and factor inputs more closely at the firm level.

6. Conclusions and Implications

6.1. Conclusions

Based on balanced panel data of 265 Chinese cities from 2010 to 2023, this study employs fixed-effect models, mediating effect models, and instrumental variable methods to examine the impact and mechanisms of AIL on LRM. The main findings are as follows: (1) AIL has a positive effect in reducing urban LRM. This conclusion remains robust after adjusting the research sample, accounting for province–time interactions, controlling for other policy impacts, excluding outliers, and conducting endogeneity analyses. (2) Mechanism analysis indicates that AIL reduces urban LRM by enhancing government environmental concerns, promoting land transfer marketization, and facilitating industrial structure upgrading. (3) Heterogeneity analysis reveals that in non-old industrial base cities, low-population-density cities, and cities with strong government intervention, the inhibitory effect of AIL on LRM is more pronounced. Therefore, local governments should tailor AI research, development and application strategies based on cities' resource endowments and developmental foundations.

6.2. Management Implications

Drawing on the results, this study proposes the following implications and suggestions.

First, promote the construction of AI-enabled smart land governance systems to improve the efficiency of urban land resource allocation. This study confirms the positive role of AI in reducing urban LRM. Therefore, local governments should encourage the deep integration of AI technologies into national land spatial planning and resource management systems, prioritizing large-scale applications in key areas such as intelligent land monitoring, the development of digital platforms for market transactions, and dynamic assessment and supervision of industrial land efficiency. Specifically, efforts should be made to accelerate the construction of smart land monitoring platforms that integrate multi-source data on land use, industrial land demand, spatial planning, ecological environment, and market transactions. This would enhance the capacity to identify problems such as idle land, inefficient development, illegal occupancy, and unreasonable expansion, and provide technical support for optimizing land supply, redeveloping existing land stocks, and adjusting territorial spatial planning. At the same time, AI-enabled land governance should be aligned with carbon neutrality goals and urban green transformation, guiding the allocation of land resources towards industrial activities with high efficiency, low energy consumption, and low environmental pressure. This would help to steer land use patterns from extensive expansion towards intensive and optimized development.

Second, strengthen the participation of multiple stakeholders in land governance to fully activate the enabling mechanisms of AI. Mechanism analysis indicates that enhancing government environmental concerns, promoting land transfer marketization, and advancing industrial structure upgrades are primary pathways through which AI can mitigate LRM. Accordingly, on one hand, an AI-based intelligent monitoring and risk assessment system for territorial space should be established to shift land management from reactive post-event correction to proactive prevention. Through cross-departmental data sharing and coordinated land policies, government environmental concerns can be effectively translated into concrete protective actions, thereby enhancing the sustainability of land resource allocation. On the other hand, the use of AI should be promoted side by side with land system reform. Mechanisms for disclosing land market information and sharing transaction data should be strengthened. This would make information more accessible and easier to trace across land supply, land conveyance, land transfer and the disposal of inefficient land. It would, in turn, create the institutional conditions needed for the marketization of land transfers. Additionally, enterprises should be encouraged to accelerate the intelligent and green transformation of production processes using AI technology. By optimizing talent recruitment and training mechanisms as well as the vocational education system, the adaptability of the labor force's skill structure to industrial upgrading demands can be improved, enhancing the synergy between industrial structure upgrading and land use structure optimization, thereby improving the overall effectiveness of AI in land resource allocation.

Third, formulate differentiated AI application strategies tailored to the characteristics of urban development. Heterogeneity analysis reveals that the inhibitory effect of AI on LRM is stronger in non-old industrial base cities, low-population-density areas, and cities with strong government intervention. Local governments should therefore avoid applying a one-size-fits-all model of AI land governance. Instead, they should devise differentiated strategies. These strategies need to reflect the city's industrial base, the degree to which its population is concentrated, the stage its land development has reached, and the intensity of government intervention. Therefore, in non-old industrial base cities, leveraging their industrial foundations and economic advantages, the focus should be on building intelligent systems that cover the full life cycle management, expanding smart land use management scenarios, and promoting the deep integration of AI with modern services and advanced manufacturing to establish a precise and intelligent land

governance model. In low-population-density cities, priority should be given to deploying digital infrastructure, establishing regional integrated spatial information platforms, and enhancing local intelligent governance capabilities. Simultaneously, in high-population-density cities, AI should be deeply integrated with traditional land use management processes to promote land conservation, intensive utilization, and functional structure optimization. Furthermore, in cities with strong government intervention, combining local government goals and leveraging policy implementation advantages, AI should be used to strengthen land supply regulation and usage supervision, promote the precise revitalization and efficient reconfiguration of existing land, and optimize the land management system and spatial governance efficiency, thereby effectively improving LRM. For old industrial base cities and high-population-density cities, AI applications should be woven together with urban renewal, the redevelopment of inefficient industrial land, the revival of existing land stocks and industrial transformation policies. This would make AI technologies work better with local institutional settings and spatial constraints.

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