

Spatial interaction effects of population mobility on the development of urban artificial intelligence industries: A multidimensional test based on the spatial Durbin model

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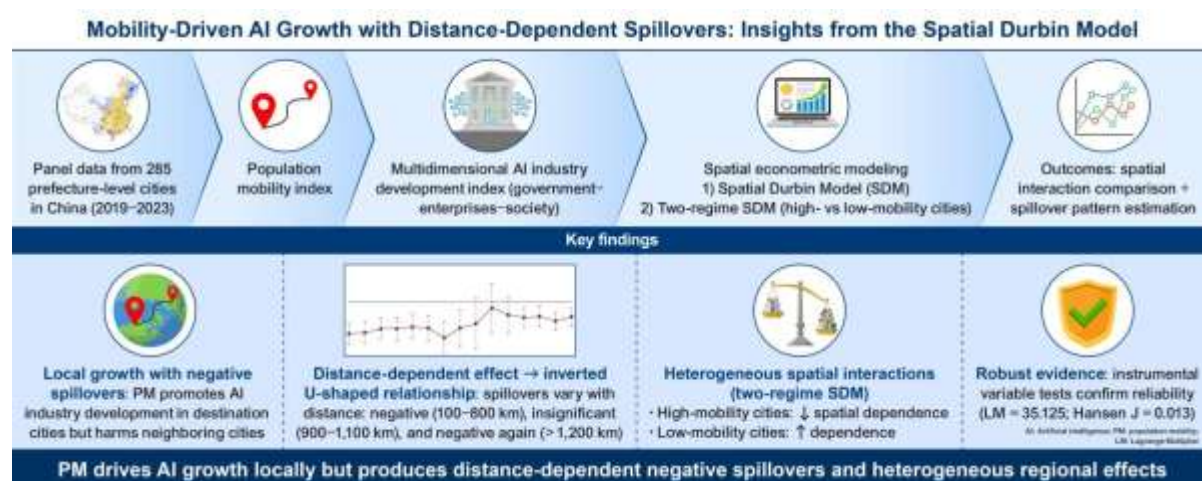
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Abstract: As a vital carrier of the cross-regional reallocation of labour, knowledge, and innovation resources, population mobility plays a key role in shaping the spatial evolution of the artificial intelligence (AI) industry. Drawing on the analytical frameworks of new economic geography, regional innovation system theory, and intergovernmental competition game theory, this study uses panel data from 285 prefecture-level cities in China from 2019 to 2023 to empirically identify spatial spillover effects and the evolving patterns between population mobility and AI industry by employing the spatial Durbin model (SDM). Additionally, a two-regime SDM is applied to reveal the asymmetric interactions among heterogeneous cities. The findings show that population mobility significantly promotes local AI industry development while exerting a negative spatial spillover effect on neighbouring regions. Moreover, this effect exhibits an inverted U-shaped nonlinear pattern as geographic distance increases. Cities with high and low population mobility also display distinct sensitivities to external influences. This study provides theoretical insights and empirical evidence for promoting balanced regional development and high-quality growth in the AI industry.



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Introduction

Artificial intelligence (AI) is the driving force behind a new wave of technological revolution and industrial transformation, which is reshaping the structure of economic and social development (Wang et al., 2023). AI has grown rapidly in recent years and is now broadly recognised for its global economic impact (Aghion et al., 2017; Ernst et al., 2019; Kalai et al., 2024). Globally recognised as a cutting-edge general-purpose technology (Rizvi et al., 2021), AI has sparked extensive academic discussions in areas such as socioeconomic transformation, productivity restructuring, energy transition, and labour market dynamics (Aly, 2022; Entezari et al., 2023; Korinek & Stiglitz, 2021; Shen & Zhang, 2024). Meanwhile, rapid

economic growth has driven large-scale population movements that have significantly reshaped China's regional demographic structure, productivity patterns, and socioeconomic landscape. According to the Seventh National Population Census (2020), interprovincial migration reached 124.84 million, a 45.37% increase over the Sixth Census. Research indicates that population mobility, as a key channel for reallocating regional production factors, restructures labour market dynamics and reshapes the spatial distribution of knowledge dissemination, technological diffusion, and innovation resources. These dynamics raise several critical questions: Can population mobility promote the development of China's AI industry? Does such an effect exhibit spatial spillover characteristics, and what moderating role does geographic distance play? Do cities with varying levels of population mobility display heterogeneous spatial interaction patterns in AI industry development? Systematically addressing these questions holds significant theoretical and practical value for understanding how population mobility influences high-tech industrial development in China—a super-large economy with 1.4 billion people—and for advancing the co-evolution of socioeconomic growth and technological innovation.

One crucial economic factor is population size, which plays a vital role in economic growth, ecological protection, urban land expansion, and industrial evolution (Khursanaliev, 2023; Mahtta et al., 2022; Rehman et al., 2022; Zeng & Zong, 2023). Using the CiteSpace tool, Zhou et al. (2025) conducted a systematic bibliometric analysis of 1,647 publications indexed in the Web of Science database from 2007 to 2024, revealing that the impact of AI on labour has become a key research frontier and academic focus. Existing research on the relationship between population and the AI industry generally falls into two categories, the first of which is studies focusing on the effects of AI on the labour market. Using provincial panel data from China, Siyao et al. (2024) revealed considerable heterogeneity in the impact of AI development on employment structure. Zhang (2023) analysed this issue from the perspective of Marxist political economy and reached similar conclusions. Murugesan et al. (2023) explored the mechanisms linking AI and labour digital transformation via a survey of 271 human resource specialists from the fields of information technology, manufacturing, and public administration. Their study focused on five key applications of AI and three core HR elements. Zhou et al. (2020) found that the probability of AI-induced labour substitution across various occupations in China was particularly high for women, older workers, and groups with lower education or income levels.

The second category of extant research examines the interactions between AI and population mobility governance. Using Canada and Germany as case studies, Beduschi (2021) explored how AI technologies have transformed the ways governments and international organisations manage international population movement. Bircan and Korkmaz (2021) reflected on the lack of regulatory oversight concerning AI and big data in population mobility management, emphasising that realising the full ethical and effective potential of these technologies requires enhanced collaboration among mobile populations, data scientists, academic researchers, and policymakers. McAuliffe et al. (2021) investigated how the relationship between population mobility and artificial intelligence (AI) evolved during the COVID-19 pandemic, revealing that while AI has promoted human rights protection and international development, its potential benefits are gradually being eroded. This body of research is vital for understanding the multifaceted linkages between demographic dynamics and AI-driven economic transformation.

Although a growing body of research has explored the relationship between population mobility and the AI industry, significant gaps remain owing to limitations such as the scarcity of high-quality micro-level data, lack of empirically grounded mechanism models, and an incomplete understanding of how AI interacts with broader economic dynamics and institutional environments (Frank et al. (2019). Few studies have examined the impact of AI on green transformation from a spatial spillover perspective Zhou et al. (2024),

Chen et al. (2024), and Wang et al. (2025). However, studies examining the spatial effects of population mobility on AI industry development remain scarce. To address this gap, this study draws on new economic geography, regional innovation systems, and regional competition–cooperation theories to systematically investigate the impact of population mobility (PM) on AI industry development and its spatial transmission mechanisms. Using panel data from 285 Chinese cities (2019–2023) and spatial econometric techniques, the study identifies spatial interaction patterns between PM and AI development. Furthermore, a two-regime spatial econometric model is employed to compare effects across different population mobility scales.

This study makes three main contributions. First, it constructs a comprehensive AI industry development index for Chinese prefecture-level cities across three dimensions—government support, enterprise innovation, and social infrastructure—and innovatively incorporates Baidu Migration big data to measure intercity population mobility, enhancing the accuracy and spatiotemporal resolution of core variables. Second, through spatial econometric methods, it reveals spatial spillover effects of population mobility on AI industry development and identifies an attenuation pattern whereby effects diminish with geographic distance. Third, by applying a two-regime spatial Durbin model (SDM), it uncovers heterogeneous spatial interaction patterns between cities with high and low mobility levels, demonstrating that these cities exhibit distinct spatial interaction modes during AI industry evolution. These findings provide empirical support for formulating differentiated regional policies to promote the development of China’s AI industry.

The remainder of this paper is organised as follows. Section 2 presents the theoretical framework and hypotheses. Section 3 describes the methodology and data. Section 4 reports baseline regression results, robustness checks, and results of tests on distance-based attenuation of spatial spillover effects. Section 5 develops a two-regime model to examine heterogeneous spatial interaction patterns across mobility levels. Section 6 concludes with key findings and policy recommendations. The technical approach implemented in this paper is illustrated in Figure 1.

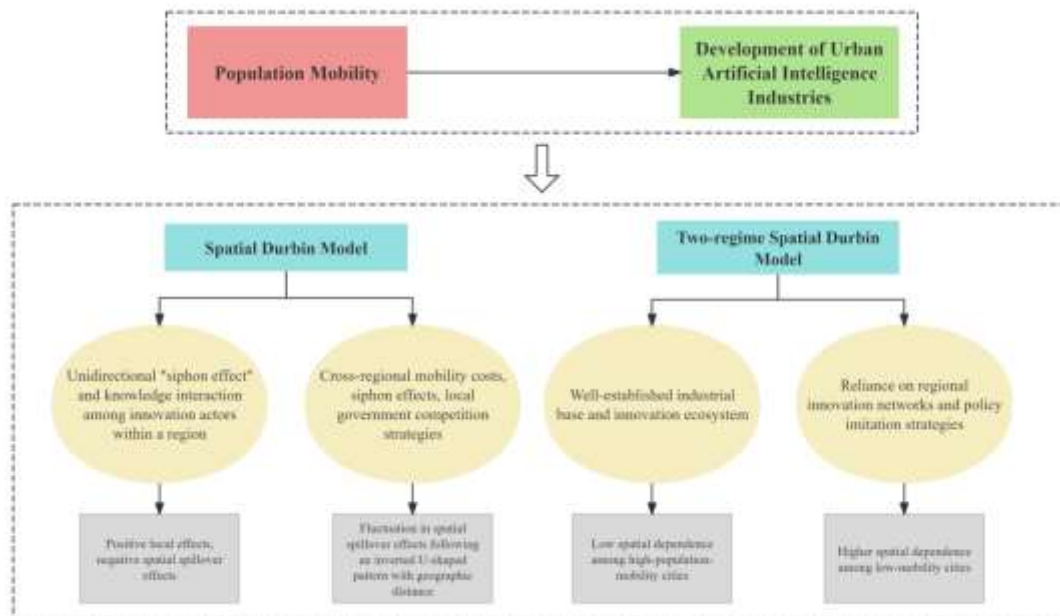


Figure 1. Theoretical mechanism diagram.

Research Hypotheses

Grounded in the core-periphery model proposed by Krugman, new economic geography explains the spatial concentration and dispersion of economic activity (Martin & Sunley, 1996). The model emphasises

the interplay among increasing returns to scale, transport costs, and factor mobility, revealing how initial location advantages are reinforced through positive feedback mechanisms, culminating in a spatial polarisation pattern characterised by agglomeration in core regions and a decline in peripheral ones. When a core city takes the lead in establishing AI industrial clusters, its high-wage jobs, well-developed supply chains, and abundant data resources attract highly talented individuals, creating a unidirectional ‘siphon effect’. Simultaneously, the rapid growth of related urban industries generates employment opportunities that attract large numbers of workers. This core–shell structure tends to increase spatial polarisation (Wei et al., 2020), leaving peripheral cities struggling with a dual shortage of both highly skilled professionals and general labour as they attempt to develop their own AI sectors. Moreover, the cross-regional mobility of talented individuals entails the transfer of tacit knowledge (Lam & Rui, 2023), which is essential for advancing the AI industry. As talent is concentrated in core cities, peripheral regions may still access explicit knowledge through academic publications, open-source code, and similar channels; however, it is often difficult to absorb the tacit, experience-based knowledge that underpins technological adoption and transformation. Within core areas, innovation actors also tend to form closed collaborative networks, reducing knowledge spillover.

Regional innovation system theory illuminates the mechanisms that underlie this phenomenon. The theory posits that systemic interactions among innovation actors within a region are essential to the creation, diffusion, and application of knowledge (Cooke et al., 2004), and that innovation is a complex process involving collaboration among multiple agents within specific institutional and social networks (Asheim et al., 2011). As a general-purpose technology (Rizvi et al., 2021), AI depends heavily on cross-disciplinary and cross-domain knowledge integration and application. The selective mobility of highly skilled, younger talent may deplete the stock of innovation-oriented human capital necessary for AI development in certain regions, weakening their capacity for industrial recovery and catch-up. Consequently, regional innovation networks in AI may become structurally unbalanced, leading to negative spatial spillover effects.

New economic geography reveals the mechanism by which spatial polarisation in innovation resources occurs given a core-periphery structure, driven by cumulative causation. In turn, regional innovation systems theory highlights the systemic disruption of knowledge production and diffusion resulting from the breakdown of interactive networks among innovation actors. Accordingly, Hypothesis H1 was proposed.

H1: Population mobility facilitates the development of AI industry in this region, but may lead to negative spatial spillover effects.

New economic geography and regional innovation system theories jointly identify the structural roots of negative spatial spillovers. Given China’s vast territory and pronounced regional disparities, examining how geographical distance moderates these effects is important. According to new economic geography, the cost of cross-regional factor mobility is a key determinant of the spatial economic structure (Fingleton & Fischer, 2010). At shorter distances, lower transport costs enable both forward and backward linkages to drive the population and economic activity toward core cities. Under these conditions, the siphon effect on peripheral regions is amplified, resulting in negative spillovers. As intercity distance increases, rising transportation and information dissemination costs diminish the attractiveness of core regions. Simultaneously, the Internet-based nature of the AI industry and its innovation modularity create conditions for cross-regional collaboration, thus mitigating the negative spillover effects of core cities. As geographic distance increases, differences in knowledge, culture, and institutional contexts emerge as barriers to innovation diffusion. While more distant regions may avoid direct competition with core cities, they also struggle to benefit from the knowledge spillovers originating in these centres.

Similarly, research by Polenske (2012) and Malecki (2004) on regional competition and cooperation

helps explain how geographic distance shapes strategic interactions among governments, firms, and innovation actors under conditions of limited resources and open markets. Within China's political-economic institutional environment, the complex interplay between state and market actors influences both labour mobility and the development of the AI industry. Geographically proximate cities or regions often share highly similar labour markets, financing channels, and policy environments, making firms and talent more substitutable across locations and prone to zero-sum competition. This is further intensified by China's unique tournament-style promotion system for local officials (You et al., 2019), in which subnational governments compete vigorously to meet economic performance targets. As AI emerges as a new growth driver, local governments, acting in their own interests, deploy policy incentives, tax breaks, and infrastructure investments to attract AI talent and labour, often at the expense of neighbouring regions, which then face a dual drain of skilled professionals and workers. In this context, peripheral areas may hastily replicate policies from other regions to stay competitive, leading to resource misallocation and intensified interjurisdictional rivalry, which further entrenches the problem. As geographic distance increases, regional disparities in industrial structure and resource endowments become more pronounced, and the intensity of intergovernmental competition tends to decline, opening up possibilities for more effective cooperative game mechanisms. Local governments may engage in cross-regional information exchange and industrial collaboration to coordinate the spatial distribution of industries, and limit redundant construction and destructive competition. Greater geographic scale also increases the likelihood of intervention by higher-level authorities, which can facilitate semi-open knowledge flows and learning spillovers driven by population movement. Ultimately, this helps mitigate the negative effects of labour mobility by reducing the overall operating costs of the economy. However, as geographic distance increases, communication costs, institutional divergence, and cultural barriers accumulate, creating delays in the transmission of innovation across regions. Factor mobility costs may also fragment government-industry networks, increasing collaboration costs. Further, widening regional gaps can facilitate local protectionism, institutional barriers that hinder the free flow of production factors, distort market signals, and undermine trust-building (Bai et al., 2004). Under such conditions, cross-regional government exchanges are more likely to devolve into inefficient, non-cooperative dynamics, causing the negative effects of labour mobility to resurface.

In summary, new economic geography and theories of regional competition and cooperation collectively suggest that geographic distance shapes spatial spillovers through its effects on the costs of economic exchange and strategic interaction mechanisms, characterised by nonlinear evolutionary characteristics and an inverted U-shaped negative spillover pattern. Accordingly, Hypothesis H2 was proposed.

H2: The spatial spillover effect of population mobility on AI development exhibits an inverted U-shaped pattern of negative spillover that varies with geographic distance.

An analysis of cities with different levels of population mobility reveals a polarisation trend among those with high mobility, split primarily between developed and underdeveloped cities, while most cities with low population mobility tend to be at medium levels of development. This pattern provides a basis for examining spatial interaction dynamics in the AI industry across cities with varying scales of population mobility.

Regional innovation systems theory emphasises the networked interactions that define innovation systems, including knowledge flow networks, the interplay among innovation actors, and the connectivity between internal and external innovation linkages (Huggins & Thompson, 2015). In cities with high population mobility, the frequent inflow and outflow of labour, capital, and knowledge promote highly open factor networks. This high mobility means that knowledge acquisition and technological advancement in the

AI industry are no longer dependent on external nodes in specific regions, but rather increasingly rely on the cumulative circulation generated within the cities' own internal innovation networks. Consequently, the AI industry's development structure in these cities exhibits characteristics of open multi-node innovation systems. Within such open innovation ecosystems, each node city possesses its own capacity for cumulative innovation and demonstrates a high degree of economic resilience (Du et al., 2025; Zhang et al., 2026). Even if an external shock disrupts the industry in one location, the system as a whole can absorb and regenerate through internal connectivity. In contrast, another category of high-mobility cities, namely those that are underdeveloped, tends to have a weak talent base and limited economic foundation in AI. As an emerging industry, AI in these cities tends to follow the objective laws of industrial development and is likely to be at an early stage, focusing primarily on assimilating and applying mature technologies. As such, these cities are relatively less susceptible to fluctuations in the AI industry of neighbouring regions. Among cities with relatively low population mobility, constrained by their comparatively limited talent pools and economic foundations, the AI industry tends to be at an intermediate stage of development. Owing to constraints in human capital and labour conditions in these cities, advancing the industry may depend on cross-regional collaboration and the regional innovation systems formed through such linkages. This reliance on networked regional systems makes these cities potentially more sensitive to changes in the AI industries of nearby cities. Moreover, in low-mobility environments, cities within the same regional innovation system are prone to forming imitation-based cooperative relationships (Zhou et al., 2019): when one city achieves a technological breakthrough or gains preferential policy support, other cities, prompted by these signals, quickly make parallel adjustments. This type of follow-the-leader behaviour in intergovernmental policy increases the sensitivity of cities within the system.

In summary, cities with high population mobility demonstrate strong resilience to external shocks through the construction of open and dynamic innovation networks, whereas cities with low population mobility rely on regional cooperation networks and exhibit external sensitivity, making them more vulnerable to negative spatial spillovers. Accordingly, Hypothesis H3 was proposed.

H3: Cities with different levels of population mobility exhibit significant differences in the responsiveness of AI industry development to similar industrial changes.

Econometric Model and Data Description

Model Setting and Variable Selection

Dependent Variable: AI Development Index

Previous studies have primarily used robot installation density or AI-related patents as single proxy variables to represent the level of AI application (Liu et al., 2020; Liu et al., 2022a; Wang et al., 2024a; Yang & Liu, 2024). However, this approach has several limitations. First, it adopts an overly narrow conceptual scope, equating 'AI application' merely with 'industrial automation'. Second, industry coverage is largely skewed towards manufacturing, leading to sectoral imbalance. Third, geographic and statistical biases may arise, as robots installed in one region might produce goods or services for other regions or even the global market. To overcome these shortcomings, this study follows the indicator framework proposed by Wang et al. (2025) by constructing a comprehensive AI development index tailored to the study's objectives, which integrates three dimensions: government, enterprise, and society.

Regarding the government dimension, following the computational method developed by Hine and Floridi (2024), Python was employed to analyse government work reports, aggregating 73 AI-related keywords, and obtaining word-frequency statistics to measure direct policy support for AI development. Additionally, the ratio of government expenditure on science, technology, and education to total public budget spending was calculated to capture indirect government support for AI development.

Regarding the enterprise dimension, indicators at the enterprise level include the stock of AI enterprises, robot installation density, and the total number of authorised AI patents, representing corporate-level AI activity. Robot installation density was calculated using methods proposed by Wang et al. (2024b) and Lv (2024).

At the societal level, indicators include regional entrepreneurial vitality, public attention to AI, the number of mobile-phone users at year-end, telecommunications business revenue, and human capital level, which collectively reflect socioeconomic factors that facilitate AI development.

All indicators are positively oriented. An entropy weighting method was used to compute the composite AI development index. The direction and weight of each indicator are shown in Figure 2.

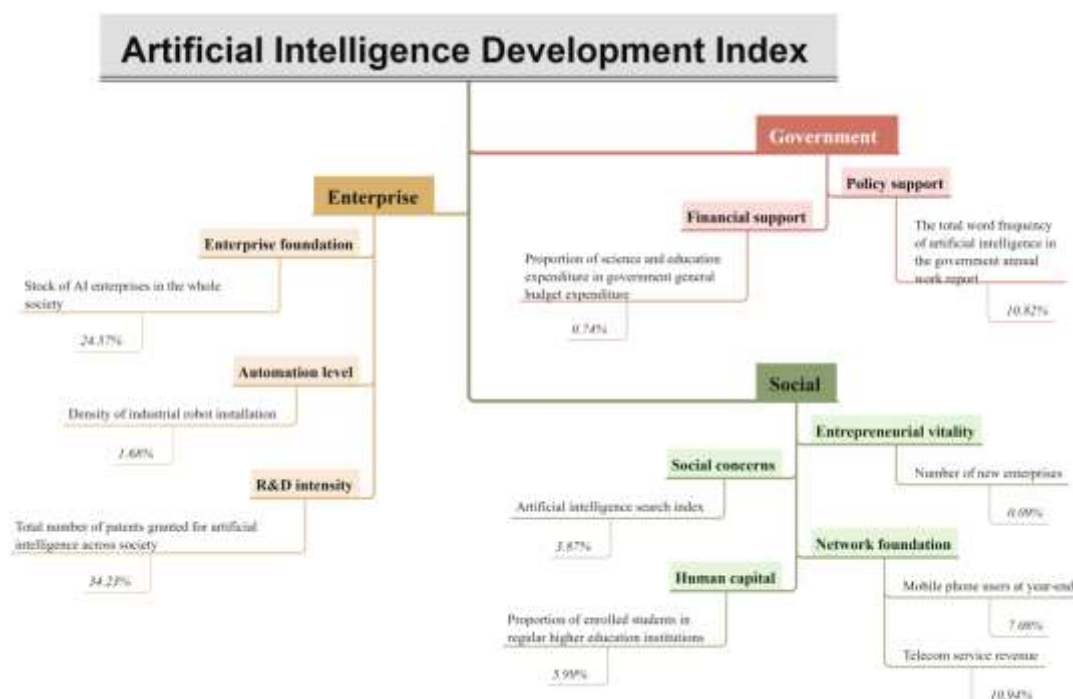


Figure 2. Composition and Weighting of the Artificial Intelligence Development Index Indicator System
 Note: The three distinct colour zones in this diagram represent three primary dimensions: government, enterprise, and society. Each dimension comprises secondary dimensions as its components, and the tertiary and quaternary dimensions within these secondary dimensions specify the calculation methods for the individual indicators and their weights derived from the entropy method.

Explanatory Variable: Population Mobility (PM)

Baidu, which is recognised as one of the world's four leading AI enterprises, leverages its strong foundation in the Chinese Internet ecosystem with core products including Baidu Search, Baidu Cloud, and Baidu Maps (Chen et al., 2022b). The population mobility index used in this study was derived from the Baidu Migration Big Data Platform, an application developed based on Python and an important data product under Baidu Maps, which relies on Baidu's Location-Based Service (LBS) technology, which captures real-time positioning information from user devices to dynamically visualise the spatiotemporal patterns of population migration across cities. Given that the migration scale index effectively quantifies the intensity of intercity population flows in China, it provides a robust basis for horizontal comparison among cities. This dataset was successfully utilised in related studies on intercity migration in China by Wei and Wang (2020) and Yangtianzheng and Ying (2024). As the Baidu population mobility index is released as daily data and no corresponding annual data are officially provided, this study aggregated the daily observations for

each year and computed the annual averages for all prefecture-level cities in China. The derived annual mobility indicators were employed as key variables in the empirical analysis.

Control Variables

To adjust the analyses for the influence of other socioeconomic factors, the analysis utilised the research and computational methods provided by Wang et al. (2024a) and Chen et al. (2022b) to select a set of control variables representing key dimensions of urban economic and infrastructural conditions. Specifically, the variables were total annual electricity consumption (ELC), reflecting the overall level of urban energy use and economic activity; industrial structure (IND), calculated as the ratio of the tertiary to secondary sectors, capturing the degree of industrial upgrading and service-sector dominance; road area (ROD), representing city-scale transportation infrastructure, indicating the accessibility and spatial connectivity of urban areas; digital infrastructure level (DIG), derived using Python-based data processing techniques to quantify the development of information and communication technology facilities; fixed asset investment in municipal public facilities (CAP), measuring the scale of capital input in urban infrastructure construction and public service provision; and government fiscal debt (GOV), reflecting the fiscal capacity and debt level of local governments, which potentially influence regional investment and technology adoption. These control variables were included to ensure that the estimated relationships between population mobility and AI industry development were not confounded by broader socioeconomic and infrastructural differences across cities.

Model Construction

Spatial Econometric Model

Spatial econometrics incorporates spatial autocorrelation methods and considers heterogeneity. The key features and advantages of this approach are explicitly considering spatial interdependence and variability between different analytical units and employing high-precision, high-reliability maximum likelihood estimation (MLE) methods. In this study, the spatial econometric model proposed by Luo et al. (2023) was improved and STATA 18 software was used to examine the effect of AI on urban IGT.

$$AI_{it} = \alpha_1 + \rho \sum_{j=1}^N W_{ij} AI_{it} + \beta_1 PM_{it} + \beta_2 \sum_{j=1}^N W_{ij} PM_{it} + \beta_3 X_{it} + \omega_i + \mu_t + \varepsilon_{it};$$

$$\varepsilon_{it} = \lambda \sum_{j=1}^N W_{ij} \varepsilon_{it} + v_{it} \quad (1)$$

In Equation (1), AI_{it} represents the AI development index, PM_{it} represents population mobility, and X_{it} denotes control variables, while $W_{ij} AI_{it}$ and $W_{ij} PM_{it}$ represent the spatial lags of the dependent and independent variables, with ρ being the spatial autoregressive coefficient. $\omega_i, \mu_t, \varepsilon_{it}$ represent the individual fixed-effects, time fixed-effects, and random error term, respectively. β_n represents the coefficients for the individual variables and spatial error coefficients. W_{ij} is the spatial weighting matrix.

An economic geographic gravity matrix was constructed based on Rao et al. (2025) to improve the analysis of spatial spillover effects. After excluding regions with severe data gaps, such as Ali, Aksu, Turpan, and Bijie, a spatial matrix for 285 prefecture-level cities in China was constructed to assess the interaction and cooperation between two regions with similar geographical proximity and economic strength.

$$W_{ij}^1 = \frac{pgdp_i \times pgdp_j}{d_{ij}^2} \quad (2)$$

Here, $pgdp$ represents the average per capita GDP from 2008 to 2022.

Following LeSage and Pace (2009), Equation (1) was decomposed to further distinguish and quantify the direct, indirect, and total spatial effects, allowing the model to separately capture (i) the direct effects of a city's own variables on its outcome, (ii) the indirect effects (spatial spillovers) transmitted through neighbouring cities via the spatial weighting matrix, and (iii) the total effect, which combined both mechanisms. This approach helped reveal how changes in local population mobility influence AI

development within a city and across its spatial network. The general form of the SDM was rewritten as follows:

$$\begin{bmatrix} \frac{\partial E(Y)}{\partial x_{1t}} & \dots & \frac{\partial E(Y)}{\partial x_{Nt}} \end{bmatrix} = \begin{bmatrix} \frac{\partial E(y_1)}{\partial x_{1t}} & \dots & \frac{\partial E(y_1)}{\partial x_{Nt}} \\ \vdots & \ddots & \vdots \\ \frac{\partial E(y_N)}{\partial x_{1t}} & \dots & \frac{\partial E(y_N)}{\partial x_{Nt}} \end{bmatrix} (I - \rho W)^{-1} \begin{bmatrix} \beta_t & \dots & \omega_{IN} \theta_k \\ \vdots & \ddots & \vdots \\ \omega_{NI} \theta_k & \dots & \beta_t \end{bmatrix} \quad (3)$$

The partial derivative matrix of $E(Y)$ with respect to the explanatory variables shows that a change in one explanatory variable affects its own dependent variable and alters the other dependent variables. These effects can be categorised as direct, indirect, and total effects.

Data Sources and Descriptive Statistics

The data used in this study, covering the period 2008–2022, were primarily drawn from the following sources: China Urban Statistical Yearbook, China Urban–Rural Construction Statistical Yearbook, China Science and Technology Statistical Yearbook, the International Federation of Robotics (IFR), the National Intellectual Property Administration, the Tianyancha Enterprise Information Database, and data provided by Baidu, including the Baidu Maps and AI Search Index datasets. These data collectively offer comprehensive coverage of urban economic development, industrial dynamics, technological progress, and AI-related activities across Chinese cities. Descriptive statistics for all the variables used in this study are presented in Table 1.

Table 1. Variable sources and descriptive statistics.

Variable	Mean	Std. dev.	Min	Max
AI	0.058	0.067	0.005	0.797
PM	2.482	2.858	0.142	25.448
ELC	257.264	254.392	0.000	1848.810
IND	1.395	0.710	0.313	6.387
ROD	2896.390	3615.105	0.000	27582.200
DIG	19.459	10.178	0.000	93.000
CAP	68.171	160.419	0.000	1501.900
GOV	3.249	2.091	0.964	17.895

Note: AI stands for AI Development Index, PM for Population Mobility, and ELC, IND, ROD, DIG, CAP, GOV are the selected control variables in this study, which are respectively total annual electricity consumption (ELC), industrial structure (IND), road area (ROD), digital infrastructure level (DIG), fixed asset investment in municipal public facilities (CAP), government fiscal debt (GOV).

Empirical Results

Spatial Autocorrelation Test

Before constructing a spatial econometric model, it was necessary to test whether the explained variable, namely the urban–rural income disparity indicator, exhibited spatial autocorrelation. Using panel data from 285 prefecture-level cities in China from 2008 to 2022, the global Moran’s I index was obtained for the corresponding years as follows:

$$\text{Moran's } I = \frac{\sum_{i=1}^m \sum_{j=1}^n W_{ij} (x_i - \bar{x})(x_j - \bar{x})}{s^2 \sum_{i=1}^m \sum_{j=1}^n W_{ij}} \quad (4)$$

Here, $m = n = 285$; x_i and x_j represent the sample values of space i and space j , respectively; $\bar{x}$ is the mean of x ; S^2 is the variance of x ; and W_{ij} is the spatial weighting matrix. Global Moran’s I indices for the corresponding years are presented in Table 2.

Table 2. Moran's I index of green transition efficiency by city (2008–2020).

Variable	AI		PM	
Year	Moran's I	Z	Moran's I	Z
2019	0.0933***	5.2977	0.2309***	12.5033
2020	0.0903***	5.1392	0.2434***	13.1802
2021	0.0992***	5.6414	0.2541***	13.7437
2022	0.0871***	4.9745	0.2879***	15.5467
2023	0.0774***	4.4584	0.2516***	13.6038

Note: ***, **, and * indicate significance at the 1 %, 5 %, and 10% levels, respectively. AI stands for AI Development Index, PM for Population Mobility.

The economic geography gravity matrix analysis indicates that both AI and PM exhibit significant positive correlations between 2019 and 2023, with p-values all below 0.01. Moran's I test confirmed the presence of significant spatial autocorrelation between the variables, justifying the use of spatial econometric analysis. To provide a more intuitive illustration of the spatial agglomeration patterns, we plotted Moran's I scatterplots and spatiotemporal distribution maps for the AI development index and population mobility for 2019, 2021, and 2023 (Figures 3 and 4), with the numbers in the figures corresponding to city codes.

Figures 3 and 4 show that AI development and population mobility across Chinese cities exhibit clear spatial heterogeneity and uneven distribution patterns. Further examination of Moran scatterplots and spatiotemporal distribution maps of these two variables yielded several key findings. First, the scatterplot of AI development versus population mobility confirms a significant spatial correlation between the two indicators.

Second, from 2019 to 2023, the spatiotemporal evolution of AI development exhibited minor overall changes. Specifically, cities characterised by 'H-H' (high-high) and 'H-L' (high-low) clustering patterns are predominately located in eastern and central China, while those displaying 'L-L' (low-low) and 'L-H' (low-high) clustering patterns are concentrated in northeastern and western regions. A few central cities exhibit 'L-H' clustering, suggesting diffusion of AI development from core to peripheral areas. Additionally, H-H clusters are predominantly found in economically developed and closely connected urban agglomerations such as the Beijing-Tianjin-Hebei and the Yangtze River Delta regions, whereas H-L clusters tend to be located on their peripheries.

Third, population mobility displayed a more scattered spatial distribution. The spatiotemporal evolution maps indicate that between 2019 and 2023, the clustering patterns of cities in terms of population mobility closely resemble those of the AI development index; however, cities with H-H clustering are more numerous and spatially widespread. This aligns with the observation that the Moran's I value for population mobility was higher than that for AI development.

Fourth, overall, the clustering patterns of both the AI development index and population mobility demonstrated a notable degree of similarity and remained relatively stable throughout the study period. Moran's I statistics, together with the findings illustrated in Figures 3 and 4, provide strong evidence of significant spatial autocorrelation in both AI development and population mobility, indicating that spatial econometric analysis of the linkage between the two variables is appropriate.

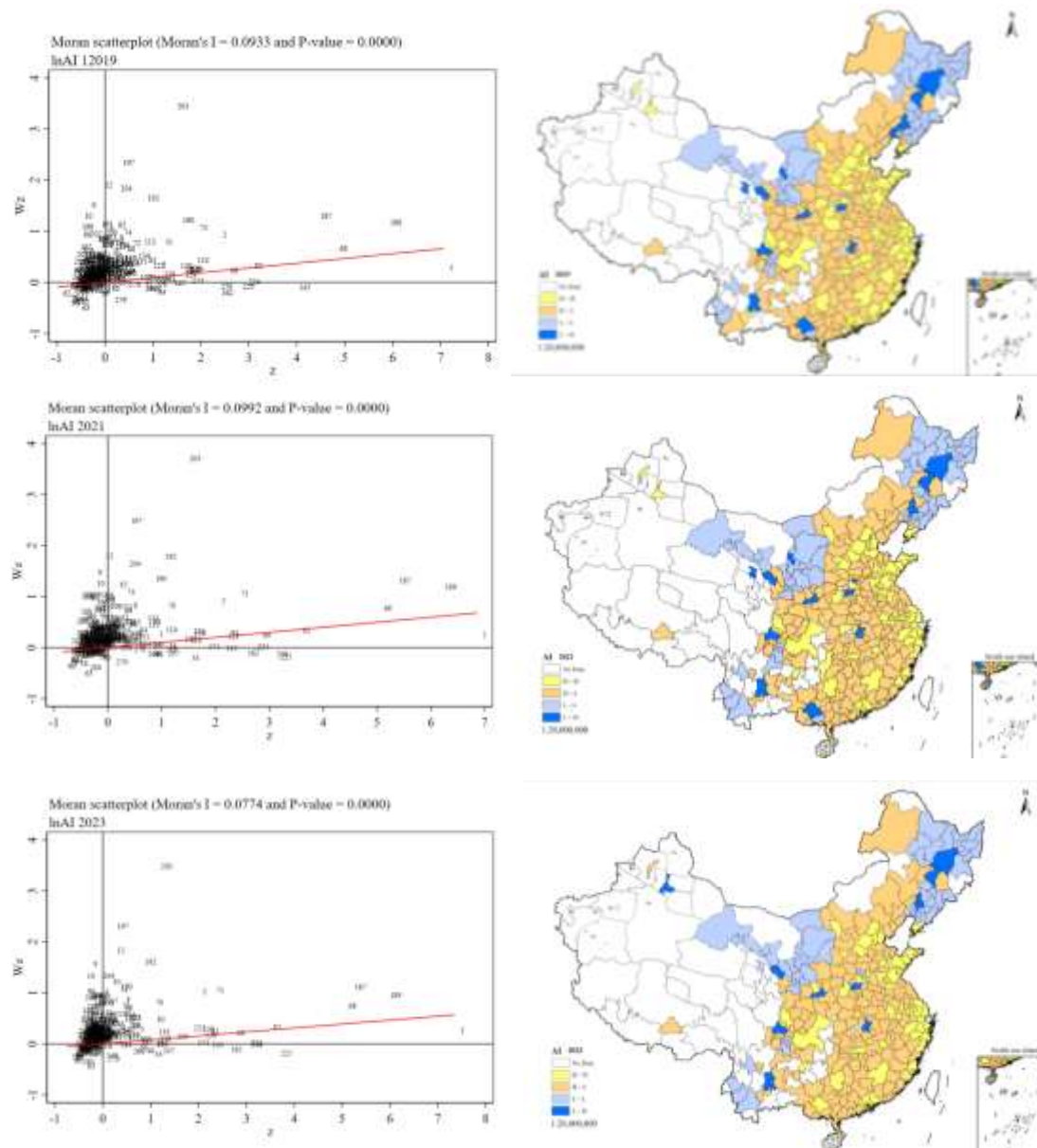


Figure 3. Artificial intelligence development index, local Moran's I scatter plot, and spatiotemporal evolution trend chart.

Note: AI is the dependent variable in this study, namely the Artificial Intelligence Development Index.

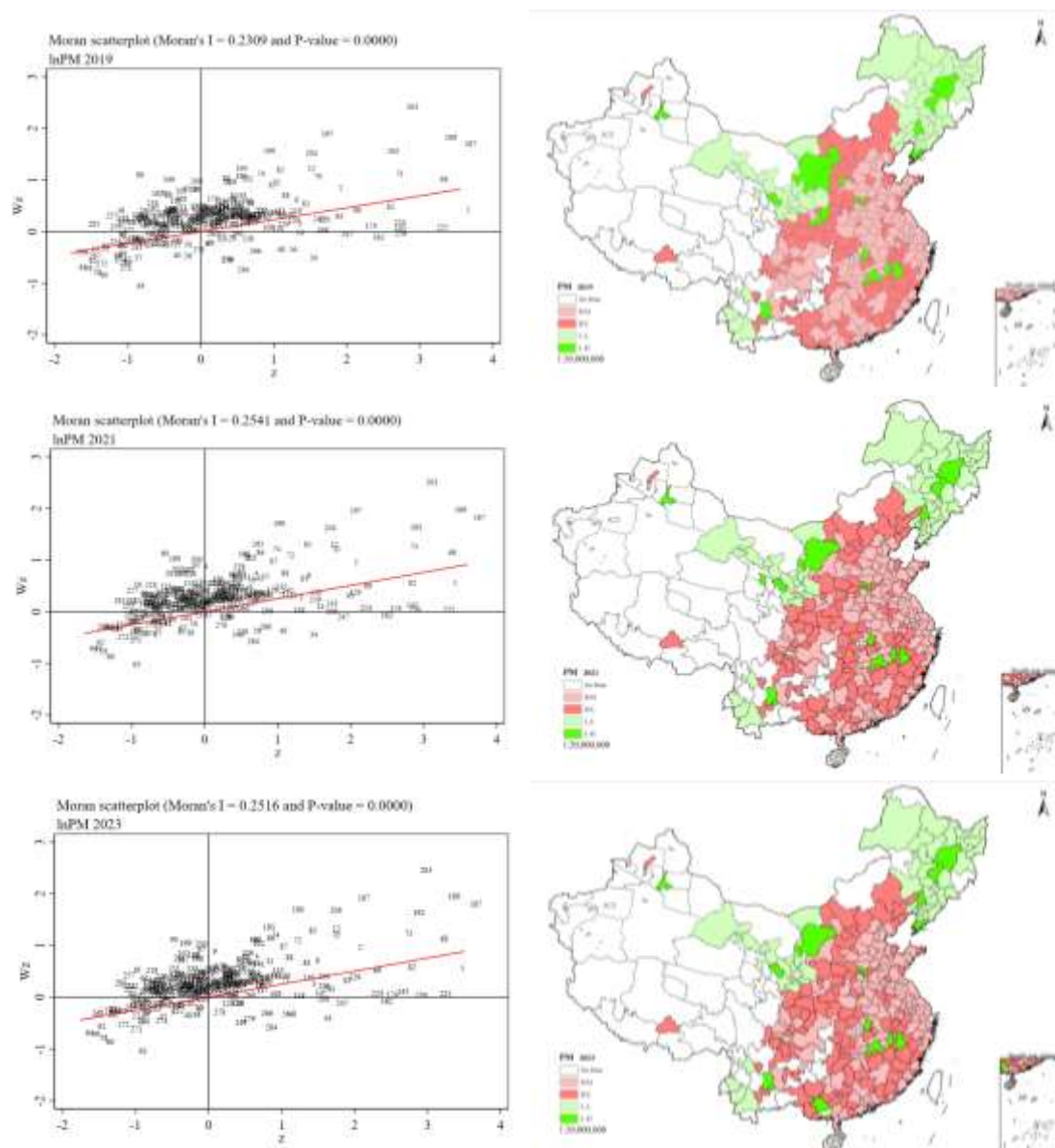


Figure 4. Population mobility, local Moran I scatter plot and spatiotemporal evolution trend map

Note: PM is the explanatory variable in this paper, population migration

Analysis of Spatial Regression Results

Model Selection

This study employed a spatial econometric model with both temporal and spatial fixed-effects. The Lagrange multiplier (LM), likelihood ratio (LR), and Wald tests were used to assess model robustness and determine the optimal specification. As shown in Table 3, both the LR test and Wald test yielded p-values of 0.000. In contrast, the LM test revealed all p-values (except for the Lagrange multiplier term at 0.039) to be 0.000, indicating the need for a more comprehensive SDM model. The Hausman test further confirmed that the fixed-effects model was preferable to the random-effects model.

Table 3. Spatial metrology model selection test.

	Test	Result
LR Test	Spatial error	80.27***
	Spatial lag	62.52***

Wald Test	Spatial error	80.95***
	Spatial lag	57.90***
LM Test	Moran's I	3.640***
	LM-error	13.397***
	Robust-LM-error	24.907***
	LM-lag	4.280**
	Robust-LM-lag	15.791***
Hausman Test		65.93***

Note: ***, **, and * indicate that the variables are significant at the 1 %, 5 %, and 10% levels, respectively; standard deviations are in parentheses.

Analysis of Spatial Spillover Effects

The regression results of SDM are presented in Table 4, indicating that the p-values for the main regression results and lagged terms of population mobility are 0.000 and 0.004, respectively. The spatial lag coefficient (ρ) is 0.273 with a p-value of 0.000, consistent with the sign and direction of the previously reported global Moran's I index. The baseline regression results indicated that local population mobility promotes the development of the local AI industry while inhibiting the development of the AI industry in neighbouring regions. Thus, H1 was supported.

To further disentangle the spatial mechanisms through which population mobility affects AI development, the SDM was decomposed into direct, indirect, and total effects using Equation (3), as listed in Table 4.

Table 4. Spatial Durbin model benchmark regression results.

Variables	Main	Wx
lnPM	0.031*** (0.007)	-0.022*** (0.008)
lnELC	-0.006*** (0.002)	0.048*** (0.009)
lnIND	0.043*** (0.009)	-0.037** (0.018)
lnROD	0.002 (0.002)	0.002 (0.008)
lnDIG	0.006*** (0.001)	-0.003 (0.003)
lnCAP	-0.001 (0.001)	0.009*** (0.003)
lnGOV	0.006 (0.006)	0.015 (0.013)
ρ	0.273***	(0.057)
sigma2_e	0.000***	(0.000)
Observations	1,425	1,425
R-squared	0.450	0.450
Number of id	285	285

Note: ***, **, and * indicate that the variables are significant at the 1 %, 5 %, and 10% levels, respectively; standard deviations are in parentheses. AI stands for AI Development Index, PM for Population Mobility, and ELC, IND, ROD, DIG, CAP, GOV

are the selected control variables in this study, which are respectively total annual electricity consumption (ELC), industrial structure (IND), road area (ROD), digital infrastructure level (DIG), fixed asset investment in municipal public facilities (CAP), government fiscal debt (GOV).

As shown in Table 5, the direct, indirect, and total effect coefficients of population mobility on AI development are 0.031, -0.019, and 0.011 respectively, with corresponding p-values of 0.000, 0.022, and 0.014. Specifically, a one standard-deviation increase in population mobility was associated with an 8.85% increase (0.031×2.858) in local AI industry development, while AI industry development in other regions declined by 5.43% (-0.019×2.858). A comparison of the direct effect coefficient of lnPM with the main regression coefficient in Table 4 revealed no significant feedback effect on population mobility in the local region. The results in Table 4 indicate that increased local population mobility promotes the development of the regional AI industry, but it may reduce the level of such development in neighbouring regions, potentially because of siphon effects, innovation network transmission, and related mechanisms operating at the government, firm, and societal levels. These findings further support Hypothesis H1.

Regarding the control variables, an increase in lnELC hindered local AI industry development, while promoting AI industry growth in adjacent regions. A plausible explanation is that when local electricity consumption rises, tightening power supply and shifting supply-demand dynamics drive up local electricity prices. As the AI industry is highly energy-intensive and sensitive to electricity costs, higher prices increase operational expenses and erode the competitiveness of local AI firms. If neighbouring regions enjoy relatively abundant and stable power supplies, local AI enterprises may consider relocating data centres, computing nodes, and other infrastructure to these areas. Consequently, the AI industry in adjacent regions may benefit from electricity constraints in the local region. Moreover, a sharp increase in local electricity consumption may strain grid capacity, undermining the stable operation of high-density data centres and further constraining AI enterprise development. The finding that industrial structure and digital infrastructure significantly enhance local AI industry development is consistent with Javaid et al. (2024), Fan and Liu (2021), and Wang et al. (2024a).

Table 5. Decomposition results of spatial spillover effect.

Variables	Direct	Indirect	Total
lnPM	0.031*** (0.007)	-0.019** (0.008)	0.011** (0.005)
lnELC	-0.005*** (0.002)	0.064*** (0.011)	0.059*** (0.011)
lnIND	0.043*** (0.008)	-0.035 (0.023)	0.008 (0.020)
lnROD	0.002 (0.002)	0.003 (0.011)	0.005 (0.011)
lnDIG	0.006*** (0.001)	-0.002 (0.005)	0.004 (0.005)
lnCAP	-0.001 (0.001)	0.012*** (0.004)	0.011*** (0.004)
lnGOV	0.006 (0.006)	0.023 (0.017)	0.029* (0.015)

Note: ***, **, and * indicate that the variables are significant at the 1 %, 5 %, and 10% levels, respectively; standard deviations are in parentheses. AI stands for AI Development Index, PM for Population Mobility, and ELC, IND, ROD, DIG, CAP, GOV are the selected control variables in this study, which are respectively total annual electricity consumption (ELC), industrial

structure (IND), road area (ROD), digital infrastructure level (DIG), fixed asset investment in municipal public facilities (CAP), government fiscal debt (GOV).

Robustness Tests

To assess the robustness of the local and spatial spillover effects of population mobility on AI development identified in the previous analysis, three approaches were employed: (1) substituting the dependent variable, (2) replacing the spatial weighting matrix, and (3) excluding data for specific years. The results are summarised in Table 6.

Column (1) of Table 6 presents results when the dependent variable was replaced by an AI development index constructed using the entropy method. This index included five core indicators: the frequency of AI-related terms in government work reports, stock of AI enterprises, robot installation density, total number of authorised AI patents, and level of public attention to AI. After substituting the dependent variable, the sign and significance of the spatial lag term for lnPM on lnAI, the significance of the rho value, and the magnitude of the R-squared remained largely consistent with the baseline regression results. In Column (2), the economic-geographic gravity matrix was replaced by an inverse-squared geographic distance matrix. The main regression results and spatial lag effects for lnPM exhibited no substantive changes in either sign or significance compared to the baseline model. Similarly, the direction and significance of the rho coefficient and R-squared values were almost identical to those in the benchmark regression. In Column (3), the data from 2019 were excluded to test the sensitivity of the results to temporal variations. The signs and significance levels of the key variables remained consistent with the baseline estimates.

Table 6. Robustness test results.

Variables	(1)		(2)		(3)	
	Main	Wx	Main	Wx	Main	Wx
lnPM	0.037*** (0.009)	-0.024** (0.010)	0.033*** (0.007)	-0.025*** (0.008)	0.078*** (0.007)	-0.047*** (0.009)
lnELC	-0.007*** (0.002)	0.063*** (0.011)	-0.006*** (0.002)	0.055*** (0.009)	-0.009 (0.005)	0.039*** (0.015)
lnIND	0.052*** (0.011)	-0.041* (0.023)	0.042*** (0.009)	-0.039** (0.018)	0.048*** (0.009)	-0.104*** (0.022)
lnROD	0.003 (0.003)	-0.001 (0.010)	0.002 (0.002)	-0.001 (0.008)	0.004 (0.003)	-0.013 (0.010)
lnDIG	0.008*** (0.001)	-0.002 (0.004)	0.006*** (0.001)	-0.002 (0.003)	0.005*** (0.001)	-0.002 (0.003)
lnCAP	-0.001 (0.001)	0.013*** (0.003)	-0.001 (0.001)	0.007*** (0.003)	0.000 (0.001)	0.004 (0.003)
lnGOV	0.007 (0.007)	0.021 (0.017)	0.007 (0.006)	0.014 (0.012)	0.006 (0.006)	0.015 (0.012)
rho	0.241***	(0.057)	0.339***	(0.070)	0.092**	(0.069)
sigma2_e	0.000***	(0.000)	0.000***	(0.000)	0.000***	(0.000)
Observations	1,425	1,425	1,425	1,425	1,140	1,140
R-squared	0.409	0.409	0.458	0.458	0.689	0.689
Number of id	285	285	285	285	285	285

Note: ***, **, and * indicate that the variables are significant at the 1 %, 5 %, and 10% levels, respectively; standard deviations are in parentheses. AI stands for AI Development Index, PM for Population Mobility, and ELC, IND, ROD, DIG, CAP, GOV

are the selected control variables in this study, which are respectively total annual electricity consumption (ELC), industrial structure (IND), road area (ROD), digital infrastructure level (DIG), fixed asset investment in municipal public facilities (CAP), government fiscal debt (GOV).

To mitigate potential endogeneity issues arising from the effect of population mobility on AI development, an instrumental variable approach was adopted based on spatial econometrics, following the basic logic of two-stage least squares (2SLS). The procedure was as follows: (1) Drawing on Miao and Li (2025), Zhao et al. (2023), Chen et al. (2022a), and Li (2023), we constructed two instrumental variables: the interaction between the U.S. industrial robot stock and city-level characteristics and the interaction between prefecture-level city household registration population in 1990 and a time trend. From one perspective, growth in U.S. industrial robotics stock reflects a technological development trajectory that satisfies the relevance condition with respect to China's AI development level, while exhibiting no direct correlation with China's AI-related variables, thus meeting the exogeneity requirement for instrumental variables. By contrast, the 1990 city household registration population size could only indirectly affect the dependent variable through historical industrial and economic structures, yet it likely influenced the post-2019 population mobility index, thereby satisfying the exclusion restriction or exogeneity requirement for instrumental variables. (2) Given the current lack of mature testing methods specifically designed for instrumental variables in spatial econometric models, applied instrumental variable testing procedures were first applied within the fixed-effects model framework to assess the validity of the selected instruments. (3) Following the two-stage least-squares estimation approach, we first examined the impact of instrumental variables on population mobility through an economic-geographic gravity model (first-stage regression) and computed the fitted value $\ln PM^*$, which was then regressed on $\ln AI$ (second-stage regression). For brevity, only the second-stage regression results are reported in the main text.

Column (1) of Table 7 reports the instrumental variable regression results based on the fixed-effects model, together with the corresponding statistical tests. The coefficient of $\ln PM^*$ on $\ln AI$ was significantly positive and consistent in both sign and significance with the main regression results of the baseline model. The outcomes of the LM, Wald F, and Hansen J statistics confirmed that the selected instruments adequately identified the endogenous explanatory variables, exhibited no evidence of weak instruments, and satisfied the assumption of exogeneity. Column (2) presents the spatial model results using the fitted $\ln PM^*$, demonstrating that the chosen instruments were valid and suitable for further estimation. The signs and significance levels of the main regression coefficient, spatial lag term, and rho parameter, as well as the magnitude of R-squared, closely resembled those in the benchmark regression. This consistency further supported the robustness of the estimation results and indicated that endogeneity issues were addressed adequately.

Table 7. Results of the instrumental variable test.

Variables	(1)	(2)	
		Main	Wx
$\ln PM^*$	0.198*** (0.035)	0.125*** (0.048)	-0.165*** (0.049)
$\ln ELC$	-0.014*** (0.005)	-0.009*** (0.002)	0.029*** (0.010)
$\ln IND$	-0.024 (0.018)	0.046*** (0.009)	-0.055*** (0.020)
$\ln ROD$	0.020*** (0.006)	0.001 (0.002)	-0.021* (0.011)

lnDIG	0.016*** (0.003)	0.006*** (0.001)	-0.009*** (0.003)
lnCAP	0.004** (0.002)	-0.001 (0.001)	0.008*** (0.003)
lnGOV	0.030** (0.012)	0.005 (0.006)	0.040*** (0.015)
LM statistic	35.125***		
Wald F statistic	24.981	19.93	
Hansen J statistic	0.013		
rho		0.248***	(0.058)
sigma2_e		0.000***	(0.000)
Observations	1,425	1,425	1,425
R-squared	0.204	0.454	0.454
Number of id	285	285	285

Note: ***, **, and * indicate that the variables are significant at the 1 %, 5 %, and 10% levels, respectively; standard deviations are in parentheses. AI stands for AI Development Index, PM for Population Mobility, and ELC, IND, ROD, DIG, CAP, GOV are the selected control variables in this study, which are respectively total annual electricity consumption (ELC), industrial structure (IND), road area (ROD), digital infrastructure level (DIG), fixed asset investment in municipal public facilities (CAP), government fiscal debt (GOV).

Spatial Spillover Effect Fluctuation

Hagerstrand (1968) proposed that the diffusion of spatial spillover effects follows the distance-decay law, exhibiting a general tendency to weaken as distance increases. However, traditional SDMs typically analyse cities within an integrated geographic or economic framework, making it difficult to capture structural variations in spillover effects across different distance intervals. Given China's vast territory and pronounced regional heterogeneity, with municipal administrative areas ranging from approximately 30 km² to more than 430,000 km², defining too narrow a geographic distance band could have constrained the analysis within localised characteristics, limiting the generalisability of the findings to broader spatial scales. Furthermore, China exhibits clear regional differences in climatic conditions, economic structures, and population distribution. Many macro-level factors exhibit significant spatial regularities or gradient patterns only when examined at larger geographic scales. Empirical evidence (Qian et al., 2023) confirms that the spatial spillover effects of AI vary with intercity geographic distance. Similarly, studies such as Wang et al. (2024b), Liu et al. (2022b), Chai et al. (2023), Chai et al. (2025), and Liu et al. (2022a) adopted geographic thresholds exceeding 1,000 km, with some extending up to 1,600 km, to capture the diffusion mechanisms of spatial spillovers. Building on these existing studies and considering the specific characteristics of the present research, the geographic threshold for the spatial weight matrix was set between 100 km and 1,500 km. Following the methodological framework proposed by Rao et al. (2025), a series of stepwise economic-geographic gravity matrices were constructed using 100 km as the incremental distance interval, as follows:

$$W_{ij}^d = \begin{cases} pgdp_i \times pgdp_j / d_{ij}^2, & d_{ij}^2 \geq d, d=200, 300, \dots, 1500 \\ 0, & \text{other} \end{cases} \quad (5)$$

Based on Equations (2) and (5), Figure 5 presents the estimated results of the spatial distance spillover effects, together with the 95% confidence intervals. The figure also reports the spillover effects generated by the new energy demonstration city policy, illustrating how the spatial influence of the policy varied across geographic distance ranges.

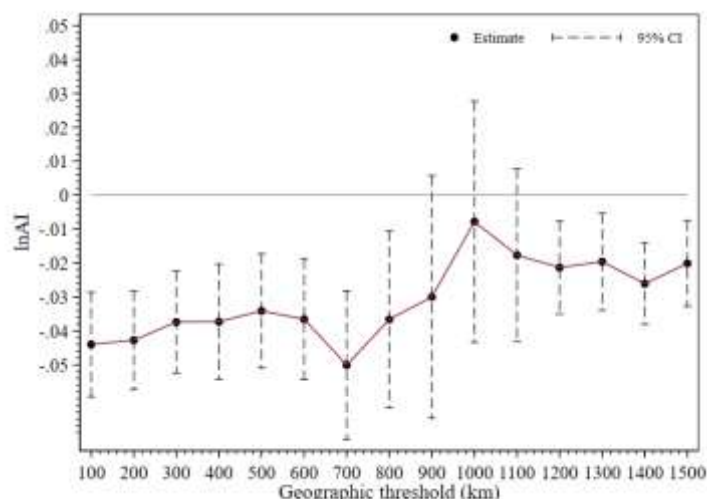


Figure 5. Spatial spillover effect fluctuation.

Figure 5 shows that the spatial spillover effects of population mobility can be approximately divided into three distinct phases, exhibiting a ‘significant–nonsignificant–significant’ pattern. Specifically, within the range of 100–800 km, population mobility exerted a significant negative spatial spillover effect on the development of AI in neighbouring cities. When the distance increased to 900–1,100 km, this negative spillover effect became statistically nonsignificant. However, once the distance exceeded 1,200 km, the negative spillover effect became significant, suggesting that geographic distance shapes a nonlinear spatial evolution of spillover effects by altering intercity economic interaction costs and strategic response mechanisms. These results empirically support H2, confirming that the impact of population mobility on AI development varied with distance in a complex and non-monotonic manner.

Further Discussion: Spatial Interaction Patterns of the AI Industry Across Cities with Varying Levels of Population Mobility

The previous analyses systematically examined the impact of population mobility on AI development, confirming that population mobility exhibited a negative spatial spillover effect with a nonlinear pattern of diffusion due to factors such as urban siphoning effects, regional innovation networks, and intergovernmental competition. The traditional spatial econometric models employed in this study primarily estimate the average spatial spillover effect, which makes it difficult to capture asymmetric spillovers that may arise among cities with different scales of population mobility. Even when conventional grouped regression techniques are used, the estimated spillover effects across different regimes lack strict comparability, making it challenging to precisely measure differences in spatial interactions and spillover intensity (Elhorst & Fréret, 2009). Such grouped regressions still focus on how varying population scales affect the relationship between mobility and AI development, which does not fully meet our analytical goal. To further explore the heterogeneous spatial interaction patterns within the AI industry across cities characterised by different levels of population mobility—namely, the varying spatial sensitivity of each city’s AI industry to others within its group—it was necessary to adopt a two-regime SDM. This approach enabled differentiated estimation of spatial effects under distinct population mobility regimes, providing deeper insights into the heterogeneity of intercity AI development dynamics.

Drawing on Elhorst and Fréret (2009) and Peng et al. (2022), a two-regime spatial econometric model was developed to examine whether the response coefficients of the AI industry differed significantly between cities with high and low levels of population mobility. Thus, Model (1) was extended to a two-regime SDM.

$$AI_{it} = \alpha_1 + \rho_1 d_{it} \sum_{j=1}^N W_{ij} AI_{it} + \rho_2 (1 - d_{it}) \sum_{j=1}^N W_{ij} AI_{it} + \beta_1 PM_{it} + \beta_2 \sum_{j=1}^N W_{ij} PM_{it} + \beta_3 X_{it} + \omega_t + \mu_t + \varepsilon_{it};$$

$$\varepsilon_{it} = \lambda \sum_{j=1}^N W_{ij} \varepsilon_{it} + v_{it} \quad (6)$$

In Equation (6), d_{it} is a dummy variable that takes the value of 1 if region i is classified as a high-mobility city in year t and 0 otherwise. The classification of cities by population mobility scale was based on the population mobility indices calculated earlier. Specifically, the mean population mobility index across 285 prefecture-level cities was computed for each year from 2019 to 2023. Cities with an index above the annual mean were designated as high-mobility cities (assigned a value of 1), whereas those below the mean were designated as low-mobility cities (assigned a value of 0). This yielded annual groupings of cities by population mobility scale over the five-year period. The parameters ρ_1 and ρ_2 represent the response coefficients of the AI development index for high-mobility and low-mobility cities, respectively. If high-mobility cities were less sensitive to changes in AI industry development in surrounding regions, the response coefficient for high-mobility cities should be significantly smaller than that for low-mobility cities ($\rho_1 < \rho_2$). The definitions of the remaining variables and parameters are consistent with those in Equation (1). As Stata 18.0 does not currently support the relevant estimation methods for this analysis, MATLAB 2025b was used.

The estimation results of the two-regime SDM are presented in Table 8, where ρ_1 and ρ_2 denote the spatial autocorrelation coefficients of the AI development index for high-mobility and low-mobility cities, respectively. The main regression coefficients of $\ln PM$ and the spatial lag term were 0.031 and -0.021 , respectively, both significant at the 1% level. These estimates were highly consistent with the baseline regression results in terms of magnitude, sign, and statistical significance, confirming the robustness of the findings. The core focus of this section is whether the difference in spatial autocorrelation coefficients between the two types of cities was statistically significant. As shown in Table 8, ρ_1 is -0.060 and not statistically significant, whereas ρ_2 is 0.220 and significant at the 5% level. The difference $\rho_1 - \rho_2$ equals -0.279 , and the null hypothesis that ρ_1 equals ρ_2 is rejected at the 5% significance level. This indicates that the response coefficient of the AI development index for high-mobility cities is significantly smaller than that for low-mobility cities, thereby supporting Hypothesis H3. In summary, compared to low-mobility cities, high-mobility cities exhibited greater autonomy in their AI industry development and were therefore less sensitive to changes in the AI industry of neighbouring regions. By contrast, low-mobility cities, constrained by their relatively limited AI development capacity, must rely on regional innovation networks and policy imitation to advance their own AI sectors, resulting in higher external sensitivity.

Table 8. Spatial econometric regression results of the two-district system.

Variables	Main	Wx
$\ln PM$	0.031*** (4.393)	-0.021 *** (-2.633)
$\ln ELC$	-0.005 *** (-3.124)	0.058*** (6.820)
$\ln IND$	0.041*** (4.740)	-0.030 * (-1.643)
$\ln ROD$	0.002 (0.819)	0.013 (1.617)
$\ln DIG$	0.006*** (6.439)	-0.003 (-0.823)
$\ln CAP$	-0.001	0.009***

	(-0.960)	(3.462)
lnGOV	0.005	0.020
	(0.967)	(1.524)
ρ_1	-0.060	
	(-0.739)	
ρ_2	0.220**	
	(2.508)	
$\rho_1 - \rho_2$	-0.279**	
	(-3.422)	
cons	-0.002	
	(-0.8540)	
Observations	1,425	1,425
R-squared	0.955	0.955
Number of id	285	285

Note: ***, **, and * indicate significance at the 1 %, 5 %, and 10% levels, respectively; t-values are in parentheses. AI stands for AI Development Index, PM for Population Mobility, and ELC, IND, ROD, DIG, CAP, GOV are the selected control variables in this study, which are respectively total annual electricity consumption (ELC), industrial structure (IND), road area (ROD), digital infrastructure level (DIG), fixed asset investment in municipal public facilities (CAP), government fiscal debt (GOV).

Discussion and Policy Recommendations

Summary

This study integrated new economic geography, regional innovation system theory, and intergovernmental competition game theory into its analytical framework. Based on panel data from 285 prefecture-level cities in China between 2019 and 2023, a multidimensional AI development index was constructed that encompassed dimensions of government, enterprises, and society. The level of intercity population mobility was measured using Baidu Map big data, enabling systematic examination of the spatial interactions between population flow and AI development. This study first employed a SDM to identify the impact of population mobility on local AI industrial development and depicted the spatial spillover decay pattern using an economic geographic gravity matrix that adjusted with physical distance. Subsequently, a two-regime SDM was estimated by categorising cities according to their population mobility scale to uncover the asymmetric characteristics of spatial interaction among heterogeneous urban groups.

First, population mobility significantly promoted local AI industrial development through a one-way ‘siphoning effect’ and knowledge interaction among regional innovation entities, but generated negative spatial spillovers for neighbouring regions. Robustness checks, including substitution of spatial weighting matrices, alternative dependent variable metrics, and sample year exclusions, alongside a 2SLS approach to address endogeneity, all confirmed the reliability of these results. These findings are consistent with the research on labour flows and other industries of Shi (2021) and Wei and Jian (2024).

Second, to examine distance heterogeneity in the negative spillover effect, we constructed a progressive economic geographic gravity matrix with 100 kilometer intervals and performed stepwise regressions. The results revealed that under the joint influence of cross-regional factor flow costs, siphoning mechanisms, and local government competition strategies, the spatial spillover effect of population mobility on AI development exhibited an inverse U-shaped nonlinear pattern with increasing geographic distance.

Third, estimates from the two-regime SDM demonstrated significant intergroup asymmetry in spillover

effects. Cities with high population mobility that benefited from stronger industrial foundations and mature innovation ecosystems demonstrated greater endogenous growth in AI industries, and lower spatial dependence on surrounding regions. In contrast, low-mobility cities constrained by limited industrial capacity tended to rely more heavily on regional innovation networks and policy imitation strategies, exhibiting pronounced external sensitivity in their AI development dynamics.

Limitations and Prospects

This study had several limitations. First, regarding sample coverage, although the 285 prefecture-level cities selected encompass most Chinese urban areas, data availability constraints prevented the inclusion of certain western cities, leaving room for improvement in spatial completeness. Second, while this study employs a two-stage least squares (2SLS) framework to address endogeneity concerns in the spatial econometric analysis, existing methodological limitations restrict the relevant instrumental variable tests to the fixed-effects 'xtivreg2' command in Stata, which constrains the thoroughness of the testing procedure. Third, regarding temporal scope, because population mobility data have only been systematically collected since 2019, compounded by lags in updating the underlying data for the two core indicator systems, the sample window of this study does not cover the past two years. Given these limitations, several avenues for future research are proposed. First, subsequent studies could expand both the sample of prefecture-level cities and the time horizon, revealing new spatial and temporal phenomena. Second, researchers could develop dedicated commands in Stata 18.0 for spatial econometric endogeneity testing and two-regime spatial Durbin model estimation, enhancing the convenience and completeness of empirical analysis. Third, as population mobility encompasses both inflows and outflows, future research could disaggregate these two dimensions to generate more nuanced insights.

Policy Recommendations

We present policy recommendations from three perspectives: alleviating the siphoning effect, optimising regional collaborative arrangements, and implementing differentiated strategies.

The first recommendation is to establish a differentiated talent mobility guidance mechanism to mitigate the one-way siphoning effect. The analysis confirmed that population mobility, while promoting AI industrial growth in destination cities through a siphoning mechanism, imposes significant negative spillover effects on the surrounding regions, thus widening regional disparities in AI development. To address this imbalance, the following initiatives are recommended. First, develop regional talent-sharing and flexible mobility platforms. National and provincial governments should take the lead in establishing cross-city AI talent-sharing databases and flexible employment platforms, encouraging skilled professionals in core cities to contribute to AI projects in small- and medium-sized cities through collaborative projects, remote mentoring, or joint innovation programs. This approach could reduce the structural imbalance caused by unidirectional talent concentration. The second recommended initiative is to improve differentiated talent attraction and cultivation strategies for small and medium-sized cities. Instead of universally replicating the 'talent war' model, each city should formulate targeted AI talent policies tailored to its own industrial scenarios. Providing integrated support could help smaller cities develop distinct competitive advantages and create complementary dynamics with core innovation hubs.

The second recommendation is to optimise regional collaborative planning based on the distance-decay pattern of spatial spillovers. The empirical results showed that the negative spatial spillover effect of population mobility on AI industrial development followed an inverse U-shaped relationship with geographic distance. This finding provides clear spatial-scale guidance for optimising regional industrial layouts. Accordingly, the following policy measures are proposed. First, the spatial gradient of industrial clusters should be planned scientifically. Regional planning authorities should consider the inverse-U

spillover pattern when designing spatial arrangements. Areas adjacent to core cities should encourage the development of complementary industries that can leverage market demand and technological and knowledge spillovers from the core while avoiding direct homogeneous competition. For medium- and long-distance cities, governments should strengthen cross-regional cooperation networks and cultivate regional ‘secondary hubs’ to form a spatially complementary structure across cities. The second suggested policy measure is to promote industrial co-governance at the urban cluster level. Within major city clusters, such as Beijing-Tianjin-Hebei, the Yangtze River Delta, and the Guangdong-Hong Kong-Macao Greater Bay Area, regional authorities should establish AI–industry coordination mechanisms that integrate research and development agendas, industrial chain specialisation, and data element sharing. The goal would be to transform intergovernmental zero-sum competition into positive-sum cooperation. The third suggested policy measure is to enhance the balanced development of transportation and digital infrastructure. By improving intercity transportation networks, 5G communication systems, and computing power facilities, policymakers could shorten economic geographic distance, reduce the intensity of negative spillover peaks, and create more favourable conditions for large-scale industrial synergy across regions.

The third general recommendation is to implement differentiated and tiered industrial development strategies. The results of the two-regime spatial model revealed fundamental differences in industrial development patterns between high mobility and low mobility cities, highlighting the need for differentiated policy design. For high mobility cities, further classification is required. Among such cities, developed core cities already possess strong industrial autonomy; policy priorities should therefore shift toward basic research and frontier algorithm innovation, strengthening the role of such cities as sources of original innovation. Institutional arrangements, such as technology transfer centres, should be established to promote this transition. Moreover, local governments should encourage positive spillover effects from these industries to help ease the siphoning pressure on surrounding areas. For less-developed high-mobility cities, a targeted assistance mechanism could be established through partnerships with leading cities, enabling precise alignment based on their unique resource endowments and locational advantages. For low-mobility cities, policy efforts should focus on deepening integration into regional innovation networks and enhancing industrial resilience. Forming one-way dependency relationships with a single core city should be avoided. Instead, they should participate in regional industrial alliances and build stable, multi-core cooperative networks. Further, governments should guide the orderly transfer of selected segments of the AI industrial chain from core regions to these cities, strengthening their endogenous development capacity and promoting a more balanced national AI innovation landscape.

In summary, key pathways for promoting balanced and high-quality regional development in China’s AI industry are mitigating the population-siphoning effect, optimising the spatial industrial layout, and implementing differentiated and targeted policies. Integrating population mobility governance with spatial industrial planning will transform population movement from being a zero-sum competition among regions into a driving force for collective progress.

References

- Aghion P, Jones BF, Jones CI (2017). Artificial intelligence and economic growth. NBER Working Papers 23928, National Bureau of Economic Research, Inc.
- Aly H (2022). Digital transformation, development and productivity in developing countries: Is artificial intelligence a curse or a blessing? *Rev Econ Polit Sci* 7:238–256. [10.1108/REPS-11-2019-0145](https://doi.org/10.1108/REPS-11-2019-0145)
- Asheim BT, Smith HL, Oughton C (2011) Regional innovation systems: Theory, empirics and policy. *Reg Stud* 45:875–891. [10.1080/00343404.2011.596701](https://doi.org/10.1080/00343404.2011.596701)

- Bai CE, Du Y, Tao Z et al (2004) Local protectionism and regional specialization: Evidence from China's industries. *J Int Econ* 63:397–417. [10.1016/S0022-1996\(03\)00070-9](https://doi.org/10.1016/S0022-1996(03)00070-9)
- Beduschi A (2021) International migration management in the age of artificial intelligence. *Migr Stud* 9:576–596. [10.1093/migration/mnaa003](https://doi.org/10.1093/migration/mnaa003)
- Bircan T, Korkmaz EE (2021) Big data for whose sake? Governing migration through artificial intelligence. *Humanit Soc Sci Commun* 8:1–11. [10.1057/s41599-021-00910-x](https://doi.org/10.1057/s41599-021-00910-x)
- Braczyk HJ, Cooke P, Heidenreich M (2024) Regional innovation systems: The role of governances in a globalized world Routledge, London.
- Chai J, Tian L, Jia R (2023) New energy demonstration city, spatial spillover and carbon emission efficiency: Evidence from China's quasi-natural experiment. *Energy Policy* 173:113389. [10.1016/j.enpol.2022.113389](https://doi.org/10.1016/j.enpol.2022.113389)
- Chai M, Wu C, Luo Y et al (2025) New energy demonstration city policy and corporate green innovation: From the perspective of industrial and regional spillover effect. *Sustainability* 17:3179. [10.3390/su17073179](https://doi.org/10.3390/su17073179)
- Chen M, Wang S, Wang X (2024) How does artificial intelligence impact green development? Evidence from china. *Sustainability* 16:1260. [10.3390/su16031260](https://doi.org/10.3390/su16031260)
- Chen P, Gao J, Ji Z et al (2022a) Do artificial intelligence applications affect carbon emission performance?—Evidence from panel data analysis of Chinese cities. *Energies* 15:5730. [10.3390/en15155730](https://doi.org/10.3390/en15155730)
- Chen Y, Li K, Zhou Q et al (2022b) Can population mobility make cities more resilient? Evidence from the analysis of Baidu migration big data in China. *Int J Environ Res Public Health* 20:36. [10.3390/ijerph20010036](https://doi.org/10.3390/ijerph20010036), PubMed: [36612356](https://pubmed.ncbi.nlm.nih.gov/36612356/)
- Du Y, Wang Q, Song Y et al (2025) How cross-regional collaborative innovation networks affect regional economic resilience: Evidence from 283 cities in China. *Technol Forecast Soc Change* 215:124057. [10.1016/j.techfore.2025.124057](https://doi.org/10.1016/j.techfore.2025.124057)
- Elhorst JP, Fréret S (2009) Evidence of political yardstick competition in France using a two-regime spatial Durbin model with fixed effects. *J Reg Sci* 49:931–951. [10.1111/j.1467-9787.2009.00613.x](https://doi.org/10.1111/j.1467-9787.2009.00613.x)
- Entezari A, Aslani A, Zahedi R et al (2023) Artificial intelligence and machine learning in energy systems: A bibliographic perspective. *Energy Strategy Rev* 45:101017. [10.1016/j.esr.2022.101017](https://doi.org/10.1016/j.esr.2022.101017)
- Ernst E, Merola R, Samaan D (2019) Economics of artificial intelligence: Implications for the future of work. *IZA J Lab Policy* 9:1–35. [10.2478/izajolp-2019-0004](https://doi.org/10.2478/izajolp-2019-0004)
- Fan D, Liu K (2021) The relationship between artificial intelligence and China's sustainable economic growth: Focused on the mediating effects of industrial structural change. *Sustainability* 13:11542. [10.3390/su132011542](https://doi.org/10.3390/su132011542)
- Fingleton B, Fischer MM (2010) Neoclassical theory versus new economic geography: Competing explanations of cross-regional variation in economic development. *Ann Reg Sci* 44:467–491. [10.1007/s00168-008-0278-z](https://doi.org/10.1007/s00168-008-0278-z)
- Frank MR, Autor D, Bessen JE et al (2019) Toward understanding the impact of artificial intelligence on labor. *Proc Natl Acad Sci U S A* 116:6531–6539. [10.1073/pnas.1900949116](https://doi.org/10.1073/pnas.1900949116), PubMed: [30910965](https://pubmed.ncbi.nlm.nih.gov/30910965/)
- Hagerstrand T (1968) Innovation diffusion as a spatial process. Chicago, University of Chicago Press.
- Hine E, Floridi L (2024) Artificial intelligence with American values and Chinese characteristics: A comparative analysis of American and Chinese governmental AI policies. *AI & Soc* 39:257–278. [10.1007/s00146-022-01499-8](https://doi.org/10.1007/s00146-022-01499-8)

- Huggins R, Thompson P (2015) Entrepreneurship, innovation and regional growth: A network theory. *Small Bus Econ* 45:103–128. [10.1007/s11187-015-9643-3](https://doi.org/10.1007/s11187-015-9643-3)
- Javaid M, Haleem A, Singh RP et al (2024) Digital economy to improve the culture of industry 4.0: A study on features, implementation and challenges. *Green Technol Sustain* 2:100083. [10.1016/j.grets.2024.100083](https://doi.org/10.1016/j.grets.2024.100083)
- Kalai M, Becha H, Helali K (2024) Effect of artificial intelligence on economic growth in European countries: A symmetric and asymmetric cointegration based on linear and non-linear ARDL approach. *J Econ Struct* 13:22. [10.1186/s40008-024-00345-y](https://doi.org/10.1186/s40008-024-00345-y)
- Khursanaliev B (2023) The impact of population growth on the country's economic development. *KU* 6:8–11. [10.54613/ku.v6i6.236](https://doi.org/10.54613/ku.v6i6.236)
- Korinek A, Stiglitz JE (2021) Artificial intelligence, globalization, and strategies for economic development. [10.36687/inetwp146](https://doi.org/10.36687/inetwp146)
- Lam A, Rui H (2023) Global human mobility and knowledge transfer: Highly skilled return migrants as agents of transnational learning. *Glob Netw* 23:311–331. [10.1111/glob.12384](https://doi.org/10.1111/glob.12384)
- LeSage JP, Pace RK (2009) Spatial econometric models. in Fischer MM, Getis A (ed), *Handbook of applied spatial analysis: Software tools, methods and applications* Springer, (p. 355–376). [10.1007/978-3-642-03647-7_18](https://doi.org/10.1007/978-3-642-03647-7_18)
- Li J, Yan Y, Pan L (2023) Artificial intelligence, types of labor tasks, and urban scale wage premium. *J Finance Econ* 49:62–76. [10.16538/j.cnki.jfe.20230917.401](https://doi.org/10.16538/j.cnki.jfe.20230917.401)
- Liu J, Chang H, Forrest JYL et al (2020) Influence of artificial intelligence on technological innovation: Evidence from the panel data of china's manufacturing sectors. *Technol Forecast Soc Change* 158:120142. [10.1016/j.techfore.2020.120142](https://doi.org/10.1016/j.techfore.2020.120142)
- Liu J, Liu L, Qian Y et al (2022a) The effect of artificial intelligence on carbon intensity: Evidence from China's industrial sector. *Socioecon Plan Sci* 83:101002. [10.1016/j.seps.2020.101002](https://doi.org/10.1016/j.seps.2020.101002)
- Liu J, Yu Q, Chen Y et al (2022b) The impact of digital technology development on carbon emissions: A spatial effect analysis for China. *Resour Conserv Recycl* 185:106445. [10.1016/j.resconrec.2022.106445](https://doi.org/10.1016/j.resconrec.2022.106445)
- Luo S, Yimamu N, Li Y et al (2023) Digitalization and sustainable development: How could digital economy development improve green innovation in China? *Bus Strategy Environ* 32:1847–1871. [10.1002/bse.3223](https://doi.org/10.1002/bse.3223)
- Lv K, Pan J, Lin Z et al (2024) Construction of innovative provinces, regional digital intelligence, and competitiveness of regional innovation ecosystems: Influence mechanism and quasi-natural experiment. *Res Dev Manag* 36:137–150. [10.13581/j.cnki.rdm.20231424](https://doi.org/10.13581/j.cnki.rdm.20231424)
- Mahтта R, Fragkias M, Güneralp B et al (2022) Urban land expansion: The role of population and economic growth for 300+ cities. *npj Urban Sustain* 2:5. [10.1038/s42949-022-00048-y](https://doi.org/10.1038/s42949-022-00048-y)
- Malecki E (2004) Jockeying for position: What it means and why it matters to regional development policy when places compete. *Reg Stud* 38:1101–1120. [10.1080/0034340042000292665](https://doi.org/10.1080/0034340042000292665)
- Martin R, Sunley P (1996) Paul Krugman's geographical economics and its implications for regional development theory: A critical assessment. *Econ Geogr* 72:259–292. [10.2307/144401](https://doi.org/10.2307/144401)
- McAuliffe M, Blower J, Beduschi A (2021) Digitalization and artificial intelligence in migration and mobility: Transnational implications of the COVID-19 pandemic. *Societies* 11:135. [10.3390/soc11040135](https://doi.org/10.3390/soc11040135)
- Miao S, Li S (2025) Urban-rural population mobility, government governance and regional coordinated development. *Int Rev Econ Finance* 101:104229. [10.1016/j.iref.2025.104229](https://doi.org/10.1016/j.iref.2025.104229)

- Murugesan U, Subramanian P, Srivastava S et al (2023) A study of artificial intelligence impacts on human resource digitalization in industry 4.0. *Decis Anal* 7:100249. [10.1016/j.dajour.2023.100249](https://doi.org/10.1016/j.dajour.2023.100249)
- Peng S, Qi Z, Huimin Z (2022) Implementation interaction of environmental regulations and pollution control in urban agglomerations. *China Popul Resour Environ* 32. [10.12062/cpre.20210601](https://doi.org/10.12062/cpre.20210601)
- Polenske KR (2012) Competition, collaboration and cooperation: An uneasy triangle in networks of firms and regions. *Reg Stud* 38:1029–1043. [10.1080/0034340042000292629](https://doi.org/10.1080/0034340042000292629)
- Qian Y, Liu J, Shi L et al (2023) Can artificial intelligence improve green economic growth? Evidence from china. *Environ Sci Pollut Res Int* 30:16418–16437. [10.1007/s11356-022-23320-1](https://doi.org/10.1007/s11356-022-23320-1), PubMed: [36184706](https://pubmed.ncbi.nlm.nih.gov/36184706/)
- Rao M, Chen G, Yang Z et al (2025) Does climate risk impacts government environmental concern in china? Insights from the volatility of spatial spillover effects. *Sage Open* 15. [10.1177/21582440251388710](https://doi.org/10.1177/21582440251388710)
- Rehman A, Ma H, Ozturk I et al (2022) Sustainable development and pollution: The effects of CO2 emission on population growth, food production, economic development, and energy consumption in Pakistan. *Environ Sci Pollut Res Int* 29:17319–17330. [10.1007/s11356-021-16998-2](https://doi.org/10.1007/s11356-021-16998-2), PubMed: [34661835](https://pubmed.ncbi.nlm.nih.gov/34661835/)
- Rizvi AT, Haleem A, Bahl S et al (2021) Artificial intelligence (AI) and its applications in Indian manufacturing: A review. In: Acharya SK, Mishra DP (eds) *Current Advances in Mechanical Engineering*. Lecture Notes in Mechanical Engineering. Springer, Singapore. [10.1007/978-981-33-4795-3_76](https://doi.org/10.1007/978-981-33-4795-3_76)
- Shen Y, Zhang X (2024) The impact of artificial intelligence on employment: The role of virtual agglomeration. *Humanit Soc Sci Commun* 11. [10.1057/s41599-024-02647-9](https://doi.org/10.1057/s41599-024-02647-9)
- Shi L (2021). Labor industry allocation, industrial structure optimization, and economic growth. *Discrete Dyn Nat Soc* 2021:1–8. [10.1155/2021/5167422](https://doi.org/10.1155/2021/5167422)
- Siyao L, Ya W, Yingfeng L (2024) How can industrial intelligence change the employment structure of the floating population? *PLOS One* 19:e0297266. [10.1371/journal.pone.0297266](https://doi.org/10.1371/journal.pone.0297266), PubMed: [38709814](https://pubmed.ncbi.nlm.nih.gov/38709814/)
- Wang KL, Sun TT, Xu RY (2023) The impact of artificial intelligence on total factor productivity: Empirical evidence from China's manufacturing enterprises. *Econ Change Restruct* 56:1113–1146. [10.1007/s10644-022-09467-4](https://doi.org/10.1007/s10644-022-09467-4)
- Wang Q, Sun T, Li R (2025) Does artificial intelligence promote green innovation? An assessment based on direct, indirect, spillover, and heterogeneity effects. *Energy Environ* 36:1005–1037. [10.1177/0958305X231220520](https://doi.org/10.1177/0958305X231220520)
- Wang X, Chen M, Chen N (2024a) How artificial intelligence affects the labour force employment structure from the perspective of industrial structure optimisation. *Heliyon* 10:e26686. [10.1016/j.heliyon.2024.e26686](https://doi.org/10.1016/j.heliyon.2024.e26686), PubMed: [38434398](https://pubmed.ncbi.nlm.nih.gov/38434398/)
- Wang X, Long R, Sun Q et al (2024b) Spatial spillover effects and driving mechanisms of carbon emission reduction in new energy demonstration cities. *Appl Energy* 357:122457. [10.1016/j.apenergy.2023.122457](https://doi.org/10.1016/j.apenergy.2023.122457)
- Wei Q, Jian C (2024) Impact of non-agricultural employment on industrial structural upgrading -Based on the household consumption perspective. *PLOS One* 19:e0294333. [10.1371/journal.pone.0294333](https://doi.org/10.1371/journal.pone.0294333), PubMed: [38381749](https://pubmed.ncbi.nlm.nih.gov/38381749/)
- Wei S, Wang L (2020) Examining the population flow network in China and its implications for epidemic control based on Baidu migration data. *Humanit Soc Sci Commun* 7. [10.1057/s41599-020-00633-5](https://doi.org/10.1057/s41599-020-00633-5)
- Wei YD, Wu Y, Liao FH et al (2020) Regional inequality, spatial polarization and place mobility in provincial China: A case study of Jiangsu Province. *Appl Geogr* 124:102296. [10.1016/j.apgeog.2020.102296](https://doi.org/10.1016/j.apgeog.2020.102296)

- 830 Yang S, Liu F (2024) Impact of industrial intelligence on green total factor productivity: The indispensability
831 of the environmental system. *Ecol Econ* 216:108021. [10.1016/j.ecolecon.2023.108021](https://doi.org/10.1016/j.ecolecon.2023.108021)
- 832 Yangtianzheng Z, Ying G (2024) Spatial patterns and trends of inter-city population mobility in China—
833 Based on Baidu migration big data. *Cities* 151:105124. [10.1016/j.cities.2024.105124](https://doi.org/10.1016/j.cities.2024.105124)
- 834 You D, Zhang Y, Yuan B (2019) Environmental regulation and firm eco-innovation: Evidence of moderating
835 effects of fiscal decentralization and political competition from listed Chinese industrial companies.
836 *J Clean Prod* 207:1072–1083. [10.1016/j.jclepro.2018.10.106](https://doi.org/10.1016/j.jclepro.2018.10.106)
- 837 Zeng P, Zong C (2023) Research on the relationship between population distribution pattern and urban
838 industrial facility agglomeration in China. *Sci Rep* 13:16225. [10.1038/s41598-023-43376-4](https://doi.org/10.1038/s41598-023-43376-4),
839 PubMed: [37758815](https://pubmed.ncbi.nlm.nih.gov/37758815/)
- 840 Zhang H, Liu H, Chen R (2026) Multilayer innovation network resilience: A framework for digital economy
841 vulnerability assessment. *iScience* 29:114295. [10.1016/j.isci.2025.114295](https://doi.org/10.1016/j.isci.2025.114295), PubMed: [41492467](https://pubmed.ncbi.nlm.nih.gov/41492467/)
- 842 Zhang Z (2023) The impact of the artificial intelligence industry on the number and structure of employments
843 in the digital economy environment. *Technol Forecast Soc Chang* 197:122881.
844 [10.1016/j.techfore.2023.122881](https://doi.org/10.1016/j.techfore.2023.122881)
- 845 Zhao P, Gao Y, Sun X (2023) The impact of artificial intelligence on pollution emission intensity—Evidence
846 from China. *Environ Sci Pollut Res Int* 30:91173–91188. [10.1007/s11356-023-28866-2](https://doi.org/10.1007/s11356-023-28866-2), PubMed:
847 [37470975](https://pubmed.ncbi.nlm.nih.gov/37470975/)
- 848 Zhou B, Li Y, Lu X et al (2019) Effects of officials’ cross-regional redeployment on regional environmental
849 quality in China. *Environ Manage* 64:757–771. [10.1007/s00267-019-01216-0](https://doi.org/10.1007/s00267-019-01216-0), PubMed: [31732773](https://pubmed.ncbi.nlm.nih.gov/31732773/)
- 850 Zhou G, Chu G, Li L et al (2020) The effect of artificial intelligence on China’s labor market. *China Econ J*
851 13:24–41. [10.1080/17538963.2019.1681201](https://doi.org/10.1080/17538963.2019.1681201)
- 852 Zhou H, Wang L, Cao Y et al (2025) The impact of artificial intelligence on labor market: A study based on
853 bibliometric analysis. *J Asian Econ* 98:101926. [10.1016/j.asieco.2025.101926](https://doi.org/10.1016/j.asieco.2025.101926)
- 854 Zhou W, Zhang Y, Li X (2024) Artificial intelligence, green technological progress, energy conservation,
855 and carbon emission reduction in China: An examination based on dynamic spatial Durbin modeling.
856 *J Clean Prod* 446:141142. [10.1016/j.jclepro.2024.141142](https://doi.org/10.1016/j.jclepro.2024.141142)