International Journal of Computer Information Systems and Industrial Management Applications
ISSN 2150-7988 Volume 18 (2026) pp. 1-13

https://doi.org/10.70917/ijcisim-2026-3355
Article

A Study on the Determinants of Artificial Intelligence Economy Development Based on Spatial Statistical Analysis

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Abstract: As a key manifestation of the new round of technological and industrial revolution, the artificial intelligence economy has become a major force reshaping the global economic landscape. Based on panel data from 30 Chinese provinces covering the period 2015–2024, this paper employs the entropy-weighted TOPSIS method to measure the level of China's Artificial intelligence (AI) economy development and uses the Dagum Gini coefficient to analyze regional disparities in this development. Additionally, drawing on knowledge of spatial statistical analysis, the study systematically reveals the spatiotemporal evolution characteristics of AI economy development across China's regions and explores its development mechanisms and influencing factors. The results indicate that the overall level of AI economy development increased from 0.2722 in 2015 to 0.4276 in 2024, representing a growth rate of 57.09%; however, the overall trend remains modest. The level of AI economy development across different provinces exhibits strong stability, demonstrating a "club convergence" pattern, and a significant "Matthew effect" is observed in the development levels among provinces. Factor analysis indicates that the improvement in the foundational conditions for AI economy development has shifted from hardware deficiencies to institutional and structural constraints. Among these, the level of social digitization, the institutional and policy environment, the level of technology adoption, and the talent structure have become the primary bottlenecks. AI economy development is transitioning from a technology-driven phase to a stage of synergistic optimization between institutions and talent.

Keywords: AI economic; spatial statistical analysis; Dagum Gini coefficient; spatiotemporal evolution; Matthew effect

1. Introduction

Against the backdrop of increasingly fierce global technological competition, the artificial intelligence industry is experiencing rapid growth [1–2]. As the world's second-largest economy, China is currently in a transitional phase from a model of high-speed growth to one of high-quality development, and the AI economy plays a crucial role in this process [3–4]. The AI economy encompasses all economic activities centered on intelligent technologies that enable the intelligent processing, transmission, and storage of information. It represents the primary focus of the new round of technological and industrial revolutions and further enhances a nation's standing in global competition [5–8]. However, significant disparities exist across China's regions in terms of the level of AI economic development, industrial structure, and resource endowments. These disparities may lead to spatial imbalances in AI economic development, which in turn could affect the balanced development of the national economy [9–11]. Therefore, studying the factors influencing its development holds significant practical importance, and spatial statistical analysis provides methodological support for this research topic.

Spatial statistical analysis is a technique that combines statistical methods with geographic information systems (GIS) to study the distribution and correlations of geospatial data [12–13]. It primarily employs methods such as spatial statistical indicators, spatial patterns, and spatial regression to explore the spatial distribution patterns of geographic phenomena and reveal the interactive relationships among them [14–16]. In the study of factors influencing the development of the AI economy, spatial statistical analysis can provide a detailed examination of these factors from the perspectives of spatial distribution, population, economy, and policy. This facilitates the adoption of targeted measures to promote balanced regional development of the AI economy [17–19].

This paper constructs an evaluation index system for the level of AI economy development based on three dimensions: the foundation of smart resources, the integration of smart factors, and the support of the smart environment. It then calculates the level of AI economy development using the Entropy-weighted TOPSIS method. Furthermore, the Dagum Gini index is employed to conduct an in-depth analysis of regional disparities in the level of AI economy development, providing a reference for understanding the status of regional AI economy development. Subsequently, using Geoda software, a spatial correlation analysis is conducted on the levels of China's AI economy development across provinces from 2015 to 2024. This analysis identifies the spatial interactions among regional AI economy development and the spatial structural characteristics within each region, and a Moran's I plot is generated. Finally, the barrier index model is applied to thoroughly examine the development mechanisms and constraining factors.

2. Research Design

2.1. Development of an Indicator System

The AI economy is a new economic model that has emerged through the application of AI technology. Characterized by data-driven operations, human-machine collaboration, co-creation and sharing, and cross-sectoral integration, it is built on the foundation of AI infrastructure, driven by the industrialization of smart technologies, and supported by the intelligent transformation of industries, thereby empowering high-quality socio-economic development. The AI economy primarily consists of two major components: intelligent industrialization and industrial intelligence. In general, intelligent industrialization refers to the creation of a cluster of similar enterprises or organizations that leverage new-generation information technologies—such as big data, cloud computing, the Internet of Things (IoT), and mobile internet—with the core objective of enhancing economic efficiency.

Industrial intelligence refers to the promotion of the application and penetration of core intelligent technologies—such as virtual reality (VR), artificial intelligence (AI), and blockchain—across various industries, based on new technologies like cloud computing, the Internet of Things (IoT), big data, and mobile internet. Smart industrialization represents the development and commercialization of artificial intelligence (AI) technology as an independent industry, while industrial intelligence involves applying AI technology to traditional industries. This provides the data and scenarios necessary for the development of smart industrialization, facilitates the effective integration of AI technology with the real economy, and enhances the level of industrial intelligence. Therefore, evaluating the level of high-quality development of the AI economy from the dual dimensions of smart industrialization and industrial intelligence can reflect the comprehensive development level of a region's AI economy.

Furthermore, as a crucial foundational condition for fostering the AI economy and driving high-quality economic development, AI infrastructure serves as a vital practical platform for the development of the AI economy and is an indispensable component of its growth. Consequently, this paper constructs an evaluation index system for the level of AI economy development based on three dimensions: the foundation of smart resources, the integration of smart factors, and the support of the smart environment, as detailed in Table 1. A multicollinearity test of the indicators revealed that the variance inflation factor (VIF) for each indicator was less than 3, which is below the critical value of 10. This indicates that there is no significant multicollinearity among the indicators.

Table 1. Evaluation Index System for the Development Level of AI Economy

Logic layer	Element layer	Observation layer	Attribute	VIF
AI resource foundation	Information infrastructure	Digital Access Capability (X1)	+	1.402
		Network organization level (X2)	+	1.135
		Density of Communication Facilities (X3)	+	2.029
	Data resource capability	Data service capability (X4)	+	1.225
		Data innovation output (X5)	+	2.010
		Computing power resource investment (X6)	+	2.810
Integration of AI elements	Technological innovation ability	Structure of scientific research talents (X7)	+	1.315
		Intensity of technological input (X8)	+	2.759
		Quality of innovation achievements (X9)	+	1.268
	Human capital structure	Scale of innovative talents (X10)	+	2.561
		Education supply level (X11)	+	2.622
		Skill structure optimization (X12)	+	1.686
AI environment support	Institutional and policy environment	Governance execution capacity (X13)	+	2.911
		Policy guidance intensity (X14)	+	1.519
		Degree of system openness (X15)	+	1.543
	The level of social intelligence	Terminal usage popularization (X16)	+	2.711
		Technology adoption level (X17)	+	2.298
		Enterprise intelligence level (X18)	+	1.843

The specific descriptions of each indicator are as follows:

X1: The number of Internet access users per 100 people (per 100 people), an important indicator for measuring the ability of urban residents to integrate into the digital economy system, provides a basis for population participation in the operation of the AI economy. X2: Websites per 100 enterprises (%), used to measure the basic conditions for the integration of industrialization and informatization of the AI economy. X3: The number of 4G and 5G base stations per 10,000 people (in units per 10,000 people), reflecting the physical carrying capacity of the urban wireless communication network and the completeness of the infrastructure. X4: The number of employees in the information transmission, computer services and software industry (person), which represents the scale of human capital in the data service field of a city, is an important condition for promoting a data-driven AI economy. X5: Number of AI patent applications (pieces), reflecting the number of innovative AI patent application achievements of a city in the fields of AI and data technology, is a measure of the marketization and innovation capabilities of data elements. X6: The book value of AI enterprise machines (in ten thousand yuan) measures the degree of capital investment by enterprises in a city in AI computing power and hardware facilities, and it serves as the material basis for data processing and AI algorithm training capabilities.

X7: Number of scientific research practitioners/total number of practitioners (%), an important human resource indicator for measuring the core competitiveness of a city's AI economy. X8: Expenditure on science and Technology/general public budget Expenditure (%), which measures the government's financial support for AI technological innovation and reflects the allocation efficiency of policy resources in scientific and technological development. X9: The number of AI invention patent applications/the number of patent applications (%) is a core indicator for measuring the contribution of technological progress to the AI economy. X10: The number of scientific research practitioners (in person), a fundamental condition for measuring the accumulation of AI capital and the development of a talent-driven economy. X11: The number of students in regular institutions of higher learning/total population (%) reflects a city's continuous capacity in knowledge production and technology supply, providing a guarantee for the innovative supply of the AI economy. X12: The number of employees in the information transmission, computer services and software industry/total number of employees (%) reflects the degree of intelligent and high-tech transformation of the economic structure and serves as the structural foundation for promoting the efficient operation of the AI economy.

X13: The number of employees in public administration and social organizations (person), reflecting the coordination and implementation level of the government and social organizations in promoting the implementation of the AI economic policy. X14: Artificial Intelligence Policy Attention, measuring the degree of emphasis placed by local policy systems on the AI economy and AI development. X15: The fiscal transparency of the municipal government reflects the degree of financial information disclosure and institutional transparency of the municipal government, which is conducive to promoting enterprise innovation and the formation of a trust mechanism for the AI economy. X16: The number of mobile phone users per 10,000 people (households/per 10,000 people) reflects the penetration rate of mobile communication terminals among urban residents and demonstrates their information consumption capacity and digital living standards. X17: The degree of AI adoption measures the breadth of acceptance and application of AI technology by social organizations, enterprises and the public, and is an important reflection of the penetration of the intelligent economy and the atmosphere of social innovation. X18: The development level of AI in listed companies reflects the technological integration level of urban enterprises in intelligent production, management and decision-making, and is a key indicator for measuring the intelligent and high-quality transformation capabilities of urban industrial systems.

2.2. Data Source

This paper analyzes the level of high-quality development in the AI economy using panel data from 30 Chinese provinces (excluding Tibet, Hong Kong, Macao, and Taiwan) for the period 2015–2024. The relevant data is primarily sourced from the *China Statistical Yearbook*, the *China Science and Technology Statistical Yearbook*, corresponding research reports from the China Academy of Information and Communications Technology (CAICT), the Wind database, and publicly available data from third-party platforms. Among these, third-party platforms primarily include Tianyancha, cloud computing service providers, artificial intelligence enterprise databases, the China Research Data Service Platform (CNRDS), and the CSMAR database. The artificial intelligence industry is primarily classified according to the sub-sectors related to artificial intelligence in the *Classification of Strategic Emerging Industries (2018)*, specifically covering basic software development and application software development within artificial intelligence software development; the manufacturing of wearable smart devices, smart unmanned aerial vehicles, other smart consumer devices, and other electronic devices within the manufacturing of smart consumer-related equipment; and information system integration services within artificial intelligence system services. Additionally, individual missing data points were imputed using linear interpolation.

2.3. Empirical methods

2.3.1. Entropy-Weighted TOPSIS Method

This paper uses the entropy-weighted TOPSIS method to measure the level of AI economy development in China. First, the entropy-weighted method is used to objectively assign weights to the information content provided by each evaluation indicator of AI economy development. Next, the TOPSIS method is employed to compare the relative distances between the evaluation objects and the optimal and worst-case scenarios, thereby determining the ranking of the evaluation objects. Finally, the comprehensive scores and rankings of AI economy development across China's various provinces are calculated.

2.3.2. Dagum Gini coefficient

The Dagum Gini coefficient and its decomposition method can break down spatial disparities into intra-regional, inter-regional, and super-density variations. The specific calculation model is shown below:

$$G = \frac{\sum_{j=1}^{k}\sum_{h=1}^{k}\sum_{i=1}^{n_j}\sum_{r=1}^{n_h}\left|PC_{ji} - PC_{hr}\right|}{2n^2\overline{PC}} \tag{1}$$

Here, n represents the total number of provinces, k represents the total number of regions, and n_j and n_h represent the number of provinces in the j th and h th regions, respectively, PC_{ji} and PC_{hr} represent the level of AI economy development in the h th province within the j th region and the $i(r)$ th region, respectively, $\overline{PC}$ represents the average level of AI economy development. The overall Gini coefficient G is decomposed into intra-regional disparities G_w, inter-regional disparities G_{nb}, and cross-regional interactions G_t. Specifically, G_w primarily reflects the uneven development of the AI economy across provinces within a region; G_{nb} primarily reflects the degree of disparity in the level of AI economy development between regions; and G_t focuses on the extent of cross-regional interactions in AI economy development.

Specifically:

$$G = G_w + G_{nb} + G_t \tag{2}$$

2.3.3. Methods of Spatial Statistical Analysis

Spatial statistical analysis is primarily used for the classification and comprehensive evaluation of spatial data. Its core lies in understanding the spatial dependence, spatial associations, or spatial autocorrelation among data related to geographic location, thereby establishing statistical relationships between data points based on their spatial positions. Currently, research on economic growth disparities and agglomeration has mainly focused on describing or statistically analyzing spatial distribution patterns. However, there has been limited research on the spatial similarity (agglomeration) or differences in regional economic growth across different areas, as well as on the causes underlying these spatial patterns. In this paper, using Geoda software, we first conducted a spatial correlation analysis of the AI economy development levels across China's 30 provinces from 2015 to 2024. This analysis identified the spatial interactions among the provinces' AI economy development and the spatial structural characteristics within each region, and we plotted Moran's I plots. Subsequently, we employed a spatial lag regression model to perform regression analysis and determine the relationships between the influencing factors and the AI economy development of each province. This contributes to understanding the current spatial patterns of AI economy development across China's provinces and serves as a supplementary reference for in-depth analysis of influencing factors and the formulation of strategies to address regional disparities.

Below, we will provide a detailed introduction to several methods of spatial statistical analysis:

1) Spatial weighting matrix

Typically, a binary symmetric weight matrix W is defined to represent the neighborhood relationships among n spatial regions, and it takes the following form:

$$W = \begin{bmatrix} w_{11} & w_{12} & \Lambda & w_{1n} \\ w_{21} & w_{22} & \Lambda & w_{2n} \\ \Lambda & \Lambda & \Lambda & \Lambda \\ w_{n1} & w_{n2} & \Lambda & w_{nn} \end{bmatrix} \tag{3}$$

In this context, W_{ij} denotes the proximity between regions i and j, which can be measured using either an adjacency criterion or a distance criterion.

The two most commonly used rules for determining spatial weight matrices:

A simple binary adjacency matrix:

$$w_{ij} = \begin{cases} 1 & \text{When regions } i \text{ and } j \text{ are adjacent} \\ 0 & \text{Other} \end{cases} \tag{4}$$

Distance-based binary spatial weight matrix:

$$w_{ij} = \begin{cases} 1 & \text{When the distance between regions i and j is less than d} \\ 0 & \text{Other} \end{cases} \tag{5}$$

2) Global spatial autocorrelation

The Moran's I index reflects the degree of similarity in attribute values among spatially adjacent or geographically proximate spatial units. For observations at the location (area) level, the global Moran's I index for that variable is calculated using the following formula:

$$I = \frac{n\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}\left(x_i - \bar{x}\right)\left(x_j - \bar{x}\right)}{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}\sum_{i=1}^{n}\left(x_i - \bar{x}\right)^2} = \frac{\sum_{i=1}^{n}\sum_{j\neq i}^{n} w_{ij}\left(x_i - \bar{x}\right)\left(x_j - \bar{x}\right)}{S^2\sum_{i=1}^{n}\sum_{j\neq i}^{n} w_{ij}} \tag{6}$$

$$S^2 = \frac{1}{n}\sum_{j}\left(x_i - \bar{x}\right)^2 \tag{7}$$

$$\bar{x} = \frac{1}{n}\sum_{i=1}^{n} x_i \tag{8}$$

In this equation, I represents the Moran's I index; x_i represents the observations in region i; and w_{ij} represents the spatial weight matrix.

The Moran's I index typically ranges from $[-1,1]$; a value less than 0 indicates negative correlation, a value of 0 indicates no correlation, and a value greater than 0 indicates positive correlation.

3) Local Spatial Autocorrelation

Local indicators of spatial association (LISA) satisfy the following two conditions:

(1) The LISA for each spatial unit is a measure of the degree of spatial clustering among spatial units with similar values in the vicinity of that unit;

(2) The sum of the LISA values for all spatial units is proportional to the global spatial association index.

LISA includes the local Moran's I and the local

Geary's I; the following section focuses on and discusses the local Moran's I. The local Moran's I is defined as:

$$I_i = \frac{\left(x_i - \overline{x}\right)}{S^2} \sum_j w_{ij} \left(x_j - \overline{x}\right) \tag{9}$$

Moran's scatter plots are commonly used to study local spatial instability. The four quadrants of a Moran's scatter plot correspond to four types of local spatial relationships between a spatial unit and its neighbors. Compared to the local Moran's index, a key advantage of this approach is its ability to further distinguish which of the four spatial relationship types—high-high, low-low, high-low, or low-high—exists between a spatial unit and its neighbors. Combining the Moran scatter plot with LISA significance levels yields what is known as a "Moran significance level map," which displays significant LISA regions and identifies the areas corresponding to the different quadrants of the Moran scatter plot.

4) Spatial lag regression model

The spatial lag regression model is expressed as follows:

$$y = \rho W y + X\beta + \varepsilon \tag{10}$$

In the equation, y represents the observed vector of the dependent variable; Wy is the spatial lag factor with weight matrix W, which is related to the y values surrounding the observation point; X is the observed matrix of the independent variables; ε is the independent error vector; and ρ and β are parameters.

3. Analysis of Empirical Results

3.1. Analysis of Measurement Results

This paper uses the Entropy-Weighted TOPSIS method to estimate the level of China's AI economy development from 2015 to 2024. The specific results are shown in Table 2 (due to space limitations, only data for representative years are reported). The results indicate that the national level of AI economy development increased from 0.2722 in 2015 to 0.4276 in 2024, showing an overall modest trend.

Table 2. Estimation Results of the Development Level of AI Economy (2015-2024)

Province	2015	2018	2021	2024
Heilongjiang	0.2757	0.2757	0.2915	0.3833
Liaoning	0.2800	0.3072	0.3414	0.3567
Jilin	0.2772	0.2878	0.3082	0.3296
Zhejiang	0.3008	0.3880	0.4035	0.4453
Jiangsu	0.4214	0.4226	0.5110	0.5470
Hebei	0.2718	0.3706	0.4140	0.4665
Tianjin	0.2721	0.3777	0.4745	0.5609
Shandong	0.2777	0.3524	0.4030	0.4797
Fujian	0.2613	0.3135	0.4329	0.4577
Guangdong	0.3674	0.4504	0.6077	0.6846
Shanghai	0.3948	0.5179	0.5758	0.7412
Hainan	0.1914	0.2100	0.2742	0.3152
Anhui	0.2712	0.3050	0.3521	0.3899
Shanxi	0.2381	0.2783	0.2982	0.3593
Beijing	0.3781	0.4555	0.7041	0.7623
Henan	0.2638	0.3257	0.4069	0.4206
Hubei	0.3109	0.3292	0.4358	0.4574
Hunan	0.2882	0.3332	0.3463	0.4068
Jiangxi	0.2309	0.3127	0.3201	0.3503
Chongqing	0.2539	0.3212	0.3994	0.4383
Shaanxi	0.2321	0.3268	0.3675	0.3939
Guangxi	0.3071	0.3205	0.3427	0.3974
Inner Mongolia	0.2266	0.2762	0.2858	0.3547
Sichuan	0.2355	0.2683	0.2809	0.3286
Ningxia	0.2440	0.2669	0.3040	0.3635
Yunnan	0.2511	0.2747	0.3399	0.4122
Xinjiang	0.2557	0.3079	0.3185	0.3627
Qinghai	0.1893	0.2078	0.2458	0.2645
Guizhou	0.2244	0.2599	0.2687	0.2818
Gansu	0.1729	0.2202	0.2525	0.3152
Nationwide	0.2722	0.3221	0.3769	0.4276

3.2. Dagum Gini Coefficient Analysis of Regional Disparities

To further investigate regional disparities in AI economy development, the Dagum Gini coefficient and its decomposition method were employed. The overall Dagum Gini coefficient was decomposed into within-region disparities (Gw), net between-region disparities (Gnb), and transvariation intensity (Gt).

See Table 3, the overall Dagum Gini coefficient increased from 0.1115 in 2015 to 0.1502 in 2021 before declining slightly to 0.1461 in 2024, indicating that regional inequality in AI economy development expanded during the study period and showed a slight convergence in the most recent year.

Table 3. Overall Dagum Gini Decomposition Results

Year	Overall Gini (G)	Within-region (Gw)	Between-region (Gnb)	Transvariation (Gt)
2015	0.1115	0.0269	0.0657	0.0189
2018	0.1187	0.0255	0.0773	0.0160
2021	0.1502	0.0317	0.1039	0.0146
2024	0.1461	0.0311	0.1015	0.0135

As shown in Table 4, the overall regional disparity was mainly attributable to net between-region differences, while within-region disparities remained relatively stable.

Table 4. Contribution Rates of Dagum Gini Components

Year	Within-region Share	Between-region Share	Transvariation Share
2015	24.10%	58.95%	16.94%
2018	21.45%	65.06%	13.49%
2021	21.11%	69.18%	9.71%
2024	21.30%	69.47%	9.23%

Table 4 demonstrates that net between-region disparities consistently represented the largest source of inequality, with their contribution increasing from 58.95% in 2015 to 69.47% in 2024. In contrast, the contribution of within-region disparities remained between approximately 21% and 24%, whereas the contribution of transvariation intensity declined steadily from 16.94% to 9.23%, suggesting that the overlap in AI economy development across regions gradually weakened.

3.3. Analysis of Spacetime Jumps

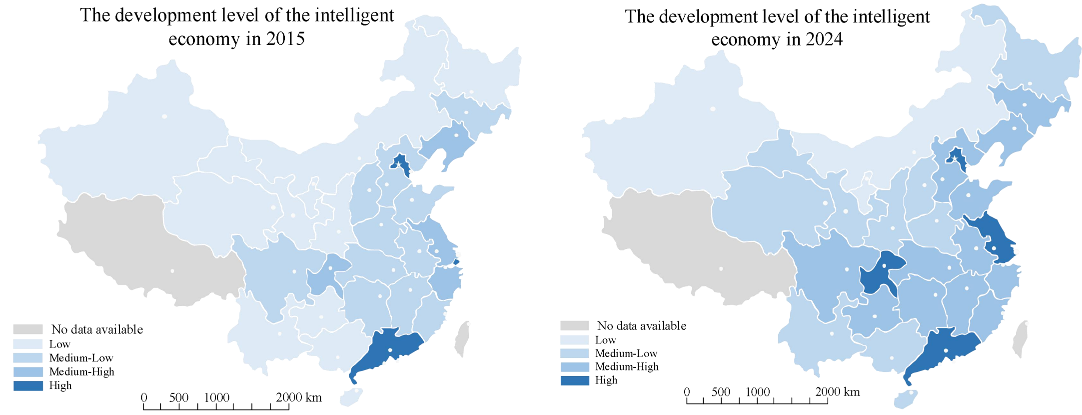
The Dagum Gini coefficient was used to analyze the dynamic evolution of the AI economy's development level, and high-quality development of the AI economy was categorized into four tiers—low, lower-middle, upper-middle, and high—based on quartile points (see Table 5 for details). The results indicate that the stability of China's AI economy in maintaining its initial state is relatively strong. Under the transition probability matrix, the probabilities on the main diagonal are significantly higher than those on the off-diagonal. This suggests that the distribution of AI economy development levels is relatively fixed, exhibiting a trend of limited internal mobility and reflecting the "Matthew effect."

Table 5. National Spatial Markov Chain Transition Probability Matrix

Spatial lag type		Low	Medium-Low	Medium-High	High
No lag	Low	0.7077	0.1577	0.0802	0.0544
	Medium-Low	0.0394	0.6308	0.2740	0.0558
	Medium-High	0.0490	0.1579	0.5765	0.2166
	High	0.0215	0.0497	0.1043	0.8245
Low	Low	0.8833	0.1063	0.0091	0.0013
	Medium-Low	0.1521	0.7579	0.0757	0.0143
	Medium-High	0.0006	0.1658	0.7116	0.1220
	High	0.0047	0.0168	0.0602	0.9183
Medium-Low	Low	0.8585	0.1260	0.0051	0.0104
	Medium-Low	0.0920	0.7687	0.1205	0.0188
	Medium-High	0.0055	0.0868	0.8358	0.0719
	High	0.0002	0.0047	0.0004	0.9947
Medium-High	Low	0.8280	0.1622	0.0082	0.0016
	Medium-Low	0.0691	0.7742	0.1525	0.0042
	Medium-High	0.0178	0.0383	0.8591	0.0848
	High	0.0087	0.0005	0.0468	0.9440
High	Low	0.8253	0.1661	0.0072	0.0014
	Medium-Low	0.0317	0.7469	0.2074	0.0140
	Medium-High	0.0009	0.0005	0.8271	0.1715
	High	0.0003	0.0001	0.0452	0.9544

3.4. Analysis of Spatial Evolution

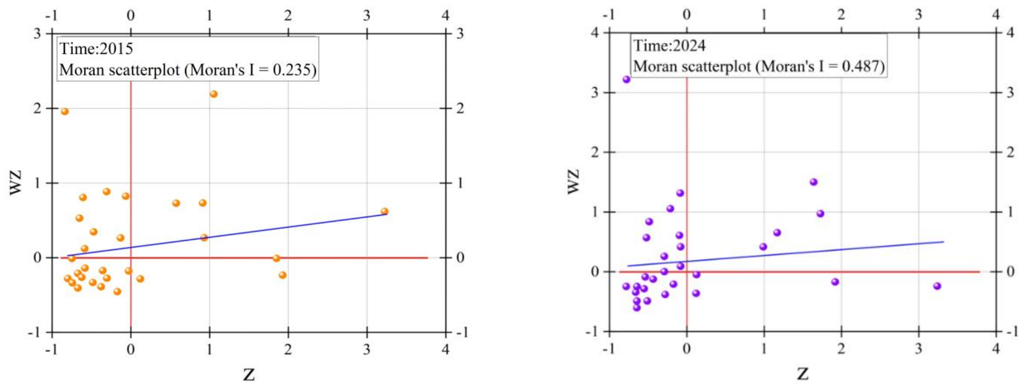
The 30 provinces (autonomous regions and municipalities) were classified into four tiers—low, lower-middle, upper-middle, and high—based on their percentile rankings of AI economy development. The spatial distribution of AI economy development across these 30 provinces (autonomous regions and municipalities) in 2015 and 2024 is shown in Figure 1. Analysis of the spatial distribution maps reveals that, over time, the central and eastern regions have experienced a relatively significant improvement in their development levels. From a spatial perspective, regions with higher levels of AI economy development are concentrated in Jiangsu, Zhejiang, Shanghai, Beijing, Guangzhou, and other areas. Over time, the surrounding regions of these provinces and municipalities have also tended to exhibit growth in digital economic development. Due to their advantageous geographical locations, high concentrations of high-tech talent, and relatively well-developed digital infrastructure, these regions drive economic cooperation, technological exchange, and resource transfer with neighboring areas, thereby positively influencing the development of the AI economy in surrounding regions to a certain extent. As shown in the figure, the level of AI economy development in regions such as Xinjiang, Inner Mongolia, and Gansu has not improved significantly. These provinces are all located in the western region, where infrastructure is relatively weak, and they are situated in China's inland or border areas.



(a) 2015 (b) 2024

Figure 1. Spatial Distribution of Intelligent Economic Development in Various Provinces of China

Based on the above analysis, it is preliminarily concluded that the development of the provincial AI economy exhibits spatial correlations. Therefore, using the adjacency weight matrix as a representative, this study focuses on analyzing the nature of spatial autocorrelation across provinces to identify the locations where clustering or dispersion occurs. Using the local Moran's I, we plotted a Moran's scatter plot for description, focusing on the years 2015 and 2024 for analysis. The results are shown in Figure 2. It displays a scatter plot of provincial AI economy development levels, with the x-axis representing the standardized AI economy development index values and the y-axis representing their spatial lag values; the index in the upper-left corner is the global Moran's I value. As can be seen from the figure, most provinces and cities are located in the first and third quadrants, which represent areas of positive spatial correlation. This indicates that the level of AI economy development exhibits a positive spatial spillover effect. Notably, there are more provinces and cities in the third quadrant, suggesting that those with lower levels of AI economy development share relatively close geographical relationships, resulting in a higher concentration of low-to-low clusters. From the perspective of temporal changes, overall shifts were minimal between 2015 and 2024, with provinces and municipalities remaining relatively stable within their respective quadrants. Most regions continued to cluster in the third quadrant, suggesting that the radiating and driving effects of the AI economy have not yet matured, and regional collaborative development mechanisms require improvement. This has also led to relatively weak AI economy infrastructure and overall underdevelopment in some areas, resulting in a majority of provinces and municipalities exhibiting low-low clustering. Based on this, regional development strategies need to be optimized to promote the "comprehensive penetration" of the AI economy.



(a) 2015 (b) 2024

Figure 2. Local Moran Scatter Plot of the Development Level of the AI economy

3.5. Impact Factor Analysis

1) Measurement of Logical-Level Resistance Contributions

The statistical results for the logical-level resistance factors in the development of the AI economy are shown in Table 6. The foundational conditions for the development of the AI economy across China's provinces and municipalities exhibit distinct structural differences and dynamic evolution characteristics across the three logical-level resistance factors. Support from the smart environment has consistently been the dominant factor, with its resistance level maintaining a range of 75% to 81%, indicating that the institutional and social environment remains the primary bottleneck for the development of the AI economy. Although digital governance, the policy environment, and the level of social intelligence continue to improve, significant disparities persist across regions in terms of policy enforcement, institutional adaptability, and social acceptance. In contrast, the resistance from the smart resource foundation decreased from 16.5320% to 12.5039%, indicating that information infrastructure and data capabilities are continuously improving, underlying conditions are gradually being refined, and the constraining effect is weakening. The resistance from the integration of smart factors rose slightly from 7.4947% to 7.6896%, with minimal fluctuation. This indicates that there are still phased gaps in technological innovation capabilities and the optimization of human capital structure, and that the agglomeration effects of talent and innovation resources have not yet been fully realized. Overall, the structural constraints on the development of the AI economy across China's provinces and cities are shifting from the resource and factor levels to the environmental and institutional levels, reflecting the phased characteristics of the AI economy as it transitions from hardware-driven support to institutional optimization.

Table 6. Statistics of Logical Resistance Factors for the Development of the AI Economy

Year	**AI resource foundation /%**	**Integration of AI elements /%**	**AI environment support /%**
2015	16.5320	7.4947	75.9733
2016	15.4810	7.1224	77.3966
2017	14.9391	6.8374	78.2235
2018	14.2205	6.6530	79.1265
2019	14.1224	6.6214	79.2562
2020	13.4517	6.7356	79.8127
2021	12.6063	6.8876	80.5061
2022	12.6431	7.3318	80.0251
2023	12.1773	7.3586	80.4641
2024	12.5039	7.6896	79.8065

2) Measurement of Resistance Factors at the Factor Level

The statistical results for resistance factors at the factor level in the development of the AI economy are shown in Table 7. As can be seen from the table, the three resistance factors at the factor level remained generally stable from 2015 to 2024, but there was a marked divergence in their structure. Resistance related to the level of social digitalization and the institutional and policy environment has long been dominant, maintaining at 40–45% and 32–40%, respectively. This indicates that public digital literacy, enterprise adoption of smart technologies, and policy governance remain key bottlenecks to high-quality development. In contrast, resistance related to information infrastructure has declined significantly, from 15.6255% to 11.2961%, demonstrating the notable effectiveness of "new infrastructure" initiatives and the continuous enhancement of network and computing power supply capabilities. Resistance related to human capital structure and technological innovation capacity has generally been low, but has risen slightly since 2019, reflecting that the synergy between the supply of high-end talent and scientific research innovation has not yet been fully established. Resistance related to data resource capacity is the lowest, but is increasing rapidly, indicating that the importance of data as a factor in the AI economy is gradually becoming more prominent.

Table 7. Resistance Factors of the Element Layer for the Development of the AI Economy

Year	**Information infrastructure /%**	**Data resource capability /%**	**Technological innovation ability /%**	**Human capital structure /%**	**Institutional and policy environment /%**	**The level of social intelligence /%**
2015	15.6255	0.9027	1.4016	6.0287	32.0236	44.0179
2016	14.5510	1.0029	1.4058	5.7433	34.4720	42.8250
2017	13.9206	1.0602	1.3687	5.4523	37.0192	41.1790
2018	13.1293	1.0808	1.4100	5.2811	37.7560	41.3428
2019	12.9173	1.1441	1.5523	5.1486	37.0669	42.1708
2020	12.3263	1.0411	1.5331	5.2405	38.2293	41.6297
2021	11.5668	1.1213	1.5000	5.3289	39.6220	40.8610
2022	11.4823	1.1890	1.5815	5.7835	36.4879	43.4758
2023	11.0249	1.1862	1.6622	5.6829	38.1053	42.3385
2024	11.2961	1.2013	1.6696	5.9475	36.5552	43.3303

3) Measurement of Resistance Contributions at the Observational Level

The analysis of resistance factors at the observational level reveals, from a micro perspective, the key issues constraining the development of the AI economy. Based on the statistical results of resistance factors for indicators X1–X18 from 2015 to 2024, as shown in Table 8, the structure of resistance to AI economy development exhibits a trend shifting from hardware constraints toward structural and institutional constraints, indicating that its development is transitioning from the infrastructure stage to a higher-order system optimization stage. From the perspective of human and institutional factors, the resistance of digital access capability (X1) rose from 1.9154% to 3.8242%, indicating that gaps still exist in residents' digital access levels; data service capability (X4) showed little fluctuation, suggesting that the data service system remains a potential constraint. The resistance associated with the structure of scientific research talent (X7) and the scale of innovation talent (X10) has increased, reflecting prominent issues such as insufficient supply of highly skilled talent and an irrational human capital structure. The resistance associated with governance execution capacity (X13) has remained stable, indicating that the intelligent transformation of public governance remains a long-term bottleneck. The resistance associated with the penetration of end-user devices (X16) has decreased slightly, suggesting that barriers to the widespread adoption of smart devices have been somewhat alleviated. Among the institutional factors, the resistance of network organization level (X2) decreased from 13.6502% to 7.2084%, indicating improved collaborative efficiency; however, the resistance of data innovation output (X5) and R&D intensity (X8) increased, suggesting that insufficient innovation and investment continue to constrain the formation of new-quality productive forces. Education supply (X11) and policy orientation (X14) showed little change, indicating limited institutional support. Although the resistance of technology adoption levels (X17) decreased from 24.8787% to 19.0406%, it remains the highest, indicating that the promotion of technology application is still the core bottleneck in the development of the AI economy. Among physical factors, the resistance of communication infrastructure density (X3) and computing power investment (X6) rose slightly, while that of enterprise intelligence (X18) increased from 15.3012% to 21.1248%, indicating that insufficient enterprise intelligence has become a new constraint. The resistance levels for innovation output quality (X9), optimization of skill structures (X12), and institutional transparency (X15) remain high and exhibit significant fluctuations, indicating that improvements are still needed in the development of the innovation system and institutional transparency.

Table 8. Resistance Elements in the Observation Layer of Intelligent Economic Development

Year	**X1/%**	**X2/%**	**X3/%**	**X4/%**	**X5/%**	**X6/%**	**X7/%**	**X8/%**	**X9/%**
2015	1.9154	13.6502	0.0471	0.3900	0.5107	0.0790	0.9689	0.0117	0.3957
2016	1.9750	12.5873	0.0129	0.3607	0.5473	0.0767	0.9061	0.0317	0.3706
2017	2.2118	11.5730	0.0772	0.2803	0.6871	0.0660	1.0874	0.0308	0.3004
2018	2.5686	10.4863	0.1051	0.3175	0.6811	0.0756	0.9881	0.0816	0.2907
2019	2.9317	9.8813	0.1032	0.3261	0.6640	0.0862	1.0219	0.1148	0.2699
2020	3.0243	9.0899	0.0806	0.3422	0.6208	0.0823	1.0920	0.2056	0.2383
2021	3.1519	8.2310	0.1069	0.3613	0.6224	0.1217	1.0696	0.1903	0.2481
2022	3.4528	7.7282	0.2046	0.3027	0.6708	0.1486	1.0926	0.1999	0.2460
2023	3.5356	7.3262	0.1729	0.2923	0.6345	0.1939	1.0801	0.2333	0.2485
2024	3.8242	7.2084	0.3177	0.3844	0.7293	0.1311	1.0873	0.2150	0.2795
	X10/%	X11/%	X12/%	X13/%	X14/%	X15/%	X16/%	X17/%	X18/%
2015	0.0437	3.6192	2.3058	3.7796	14.5111	14.1557	3.4363	24.8787	15.3012
2016	0.0376	3.6463	2.0978	3.6417	14.6577	16.6376	3.1548	23.6017	15.6565
2017	0.1048	3.4706	1.9038	3.4616	15.7013	18.2423	3.0797	22.0936	15.6283
2018	0.1502	3.3510	1.7658	3.5043	15.2677	19.7678	3.2615	21.7484	15.5887
2019	0.1661	3.3580	1.6077	3.6118	14.5465	18.3856	3.3555	21.6175	17.9522
2020	0.1975	3.5335	1.6028	3.7400	13.9906	20.5829	3.2309	21.2014	17.1444
2021	0.1897	3.5874	1.5582	3.6973	13.5849	22.6306	3.2676	19.6238	17.7573
2022	0.2791	3.8383	1.6429	3.7415	14.9054	16.9233	3.1255	20.4669	21.0309
2023	0.2407	3.9248	1.6060	3.6530	14.2713	20.8795	3.0372	19.7493	18.9209
2024	0.3164	4.0172	1.6806	3.8149	13.3226	19.3388	3.1672	19.0406	21.1248

In summary, the primary obstacles to the development of the AI economy are shifting from hardware and infrastructure to talent, institutional frameworks, and the capacity to adopt technology. Moving forward, efforts should focus on enhancing technological application capabilities, optimizing the structure of human capital, and strengthening investment in innovation and institutional transparency, in order to effectively reduce resistance and promote the high-quality and sustainable development of the AI economy.

4. Conclusion

This paper uses the Entropy-Weighted TOPSIS method to assess the level of AI economy development across China's 30 provinces and employs multiple methods to conduct an in-depth analysis of regional disparities and constraining factors in AI economy development. The following conclusions are drawn: First, while the overall level of AI economy development in China is not high, it exhibits a steady upward trend, demonstrating characteristics of "club convergence," and a significant "Matthew effect" is evident in the levels of AI economy development among provinces. Second, the development of the AI economy is a gradual process of improvement, with little possibility of leapfrog development; high-quality development of the AI economy tends to maintain the stability of its initial state. Third, the primary obstacles to AI economy development are shifting from hardware shortcomings to institutional and structural constraints. At the logical level, the lack of a supportive smart environment remains the greatest source of resistance; at the factor level, resistance from the level of social intelligence and the institutional and policy environment is prominent, while constraints from information infrastructure are weakening; At the observational level, technology adoption, enterprise digitalization, institutional transparency, and human capital structure have become key bottlenecks, signaling that the AI economy is moving toward a phase of synergistic optimization between institutions and talent.

Based on the above conclusions, this paper offers the following recommendations:

1) Improve policy mechanisms for the high-quality development of the AI economy. Specifically, relevant departments should establish a national-level special R&D fund for smart technologies targeting "bottleneck" technologies in the AI economy, with a focus on supporting breakthroughs in industrial software, large-scale models, and core components of smart hardware. Relevant departments should strengthen top-level design and strategic guidance, establish cross-departmental coordination mechanisms, and integrate policies, standards, data, and regulatory oversight to facilitate the construction of a high-quality development system for the AI economy, thereby achieving the goals of high-quality development in the AI economy.

2) Establish a platform for the coordinated high-quality development of the AI economy. Create a "data interconnection–intelligent collaboration–value co-creation" system, develop a replicable model for the coordinated development of the AI economy, and accelerate the establishment of a platform for the coordinated high-quality development of the AI economy to support its high-quality development.

3) Strengthen the capacity for high-quality development of the AI economy across all regions. Leading regions should fully leverage their technological advantages in big data, artificial intelligence, and the Internet of Things to establish demonstration zones for high-quality development of the AI economy. They should encourage leading enterprises to spearhead the formation of cross-industry innovation alliances, share proven solutions for industrial digital transformation and operational models, and thereby enhance the capacity for high-quality development of the AI economy across all regions, thereby driving the high-quality development of the AI economy.

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