



Research on the Innovative Development of the Artificial Intelligence Industry from the Perspective of a Modernized Industrial System

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SUMMARY: *This article carries out investigation on the creative development of the artificial intelligence industry from the angle of a modernized industrial system. Utilizing panel data of 30 provinces in China during 2013 to 2024, this paper constructs a dual-system framework which is composed by the modernized industrial system index (MISI) and the artificial intelligence industry innovative development index (AIIDI), and it evaluates the relationship between them through the methods of coupling-coordination analysis, fixed-effects estimation, mechanism testing, threshold analysis, spatial spillover estimation, and super-efficiency SBM comparison. The outcome demonstrates that MISI had an increase from 0.312 to 0.587, thus AIIDI also had a rise from 0.184 to 0.511. The benchmark regression makes it clear that MISI has an obviously positive influence on AIIDI and that the result keeps stable after lag replacement, weight replacement, and municipality exclusion. Mechanism examinations indicate that digital infrastructure is the most powerful transmission path, followed by talent gathering and industrial financing, with indirect effect proportions being 24.5%, 20.3%, and 18.0%, separately. Threshold and heterogeneity outcomes further give indication that, after local manufacturing support attains critical levels, the effect becomes stronger, hence it is more obvious in the eastern region and in provinces with urban agglomeration. The outcome of efficiency indicates that the national average SBM efficiency has promoted from 0.684 to 0.923, although the superfluity in innovation inputs and the deficiencies in technology transfer still can be seen clearly.*

KEYWORDS: *modernized industrial system; artificial intelligence industry; industrial innovation; spatial spillover; threshold effect*

1 Introduction

Artificial intelligence has moved from laboratory experimentation into the operating core of manufacturing scheduling, visual inspection, pharmaceutical discovery, logistics routing, financial risk control, and public service delivery. Once AI is embedded in these application environments, the binding constraint is no longer the availability of a single algorithm. What matters is whether the surrounding industrial system can supply computing infrastructure, data circulation capacity, specialized talent, financing channels, compatible equipment, and scalable downstream scenarios at the same time. In this sense, the development of the AI industry is increasingly shaped by the quality of the industrial system in which it is located. Recent evidence also points in this direction: global private AI investment has continued to expand,

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<https://doi.org/10.65102/is2026748>

China remains highly visible in AI patenting and publications, generative AI patenting has rapidly broadened across application fields, and AI capability is still concentrated in a relatively small number of countries and organizations [1-3].

China gives a especially exposible background for people to look into this problem. The ascending of China's AI trade has close connection with global knowledge flowing, internal market size, and regionally different industry abilities, hence, this means AI industry growth can not be explained only by model development alone [4]. The researches that have relation already show that the common evolution of artificial intelligence, big data, algorithms, and Industry 4.0 is again making the structure of enterprises and clusters have a new shape, hence, the study circle of innovation management more and more regards AI as a technology framework that alters searching, testing, and knowledge reorganization, hence does not regard it as a narrow automatic tool [5, 6]. These researches make clear why AI ought to be researched as an industrial transformation question, yet they still leave open the problem of how a broader modernized industrial system influences the innovative growth of the AI industry itself.

The same direction can be found in studies about industrial policy, infrastructure build, and innovation distribution arrangement. Existing researches show that financial subsidy policies and tax encouragement measures can stimulate technology innovation activities in strategic industries, that broadband infrastructure constructions can promote regional innovation abilities through promoting connection and knowledge spread, and that selective industrial policies can also aggravate innovation resource wrong allocation when system support is distributed not evenly [7-10]. To the AI industry, this academic literature has extremely high connection, because upstream research work, model building work, intelligent hardware device, industrial application software, and scenario arrangement work all rely on institution coordination and infrastructure level quality. But, these research works normally put their focus on a single policy instrument or a single enabling condition each time. They are not able to directly give answer to whether a more modernized industrial system can in a systematic way strengthen the innovation of AI industry.

A second thread of investigation has moved the debate from policy inputs to technical configuration and output efficiency results. Macro economic research has sent out reminding that the advantages brought by AI depend on complementary characters, work re-adjustment, and diffusion conditions, not merely on automatic substitution effects [11]. In the same time, current experience-based research puts forward the argument that AI is more and more showing the features of a newly appeared technical mode which brings broader economic results [12]. The firm level proof which comes from China further points out that AI is able to promote new quality productive forces and the innovation of enterprises, especially when data elements and the nearby digital economy have enough development [13, 14]. These existing works push forward the discussion, but their result variables still stay mostly limited to enterprises, patents, or productivity proxy indicators. Up to the present time, they still cannot give a direct measurement about whether the AI industry, when regarded as an industrial system, is moving in the direction of a development stage that has more innovation, stronger resilience and better coordination.

The investigation regarding clusters, networks and the integration of digital and real domains makes the related argument much closer to this present research. Research about artificial intelligence groupings indicates that policy effect is restricted by network position and cross-region cooperation modes, while researches about manufacturing clusters stress the combined significance of local resources, cooperation networks and supporting surroundings for AI innovation [15, 16]. In the meanwhile, the existing documents about digital-physical combination and high-grade manufacturing growth point out that flexible value chains, area cooperation, and space diffusion are core to industrial promotion under digital change [17, 18].

These results have very high connection with the concept of an updated industrial system, because this kind of system is required to put together advanced producing ability, digital support, firm supply chains, and effective innovation-resource arrangement. Even so, the currently existing articles seldom put these dimensions together into one empirical frame which is specially made for the AI industry's creative development.

Hence, three gaps still exist. Firstly, the object which we carry out analysis with is still broken into pieces. Some research works inspect AI as a general-purpose technology, some pay attention to enterprise adoption, and some make analysis of cluster evolution or single policy impacts. This division brings difficulty to the judgment of whether the AI industry is able to achieve sustainable development, hence when scientific research, industrialization, application deployment and supporting services all must work together to operate. Second, the measurement work of innovation development is frequently conducted in an excessively narrow scope. Patent output, financing affairs, or text-based adoption indexes show one aspect of AI development, but they cannot reflect whether industrial bases, digital basic facilities, talent provision, green-resilient production ability, and regional cooperation are moving forward in a coordinated manner. Thirdly, the discussion of causation often ceases at the level of direct effects. The existing academic documents have not yet sufficiently made clear whether a more modernized industrial system can push forward AI industrial innovation by means of stronger digital infrastructures, thicker talent gathering, and more effective industrial financial support, nor whether these influences have spatial overflow effects and nonlinear threshold values.

These gaps have determined the core question of this research: under which conditions can a modernized industrial system change AI-connected scientific and technological activity into continuous industrial innovation? For answering this question, the present paper utilizes provincial panel data of China during 2013 to 2024 and builds an integrated analysis framework which connects industrial foundation, digital enablement, innovation resources, green resilience, industrial coordination to the innovative development of AI industry. This research has three points of contribution. Firstly, it moves the analysis unit from separate technology or enterprise index to the perspective of industrial system, and constructs a comprehensive framework to assess the innovative development of AI industry under the condition of modern industry. Second, it finds the main transmission paths through testing the intermediary functions of digital base construction, talent gathering, and industrial financing, therefore it makes clear how industrial-system modernization is changed into AI innovation ability. Third, this work carries out examination on spatial spillovers, threshold characteristics, and regional heterogeneity, which therefore helps to give explanation on why the development of AI industry deepens quickly in some regions but keeps shallow or discontinuous in other regions. By doing this, the paper gives an experimental foundation for policies that are targeted at making AI transform from a boundary science and technology into an industry that can be scaled, has strong resistance, and is pushed forward by innovation.

2 Methods

2.1 Construction of the Evaluation Index System and Data Sources

For changing the research question into measurable observations at the provincial level, this research takes the modernized industrial system and the creative development of the AI industry as two connected but not same combined systems. This sample includes 30 provinces which belong to China's mainland, covering the time from 2013 to 2024. Tibet is got rid of because a number of core sequences that are used for measuring software service, industrial robot, and technology-market business are not continuously existing during the whole time period. The

time interval is aligned to the official yearly yearbook order and the newest yearly-data publish timetable [19-21]. The size design of the updated industry system follows the now policy stress on advanced production, deeper combination between the real economy and the digital economy, and stronger industry-chain anti-impairment ability.

Province-level statistics are pooled from the National Bureau of Statistics annual yearbook system and thematic science-and-technology data, sectoral statistics released through the industrial-information system, CNIPA patent records, the CNRDS research database, and the IFR World Robotics dataset. Monetary indicators are converted to 2013 constant prices. Short missing gaps are completed by adjacent-year interpolation and local-trend calibration, while variables with long structural breaks are removed. To reduce distortion from extreme observations, all continuous variables are winsorized at the 1st and 99th percentiles. To clarify how the two composite systems are organized before indicator weighting, the overall evaluation architecture is presented first, as shown in Figure 1.

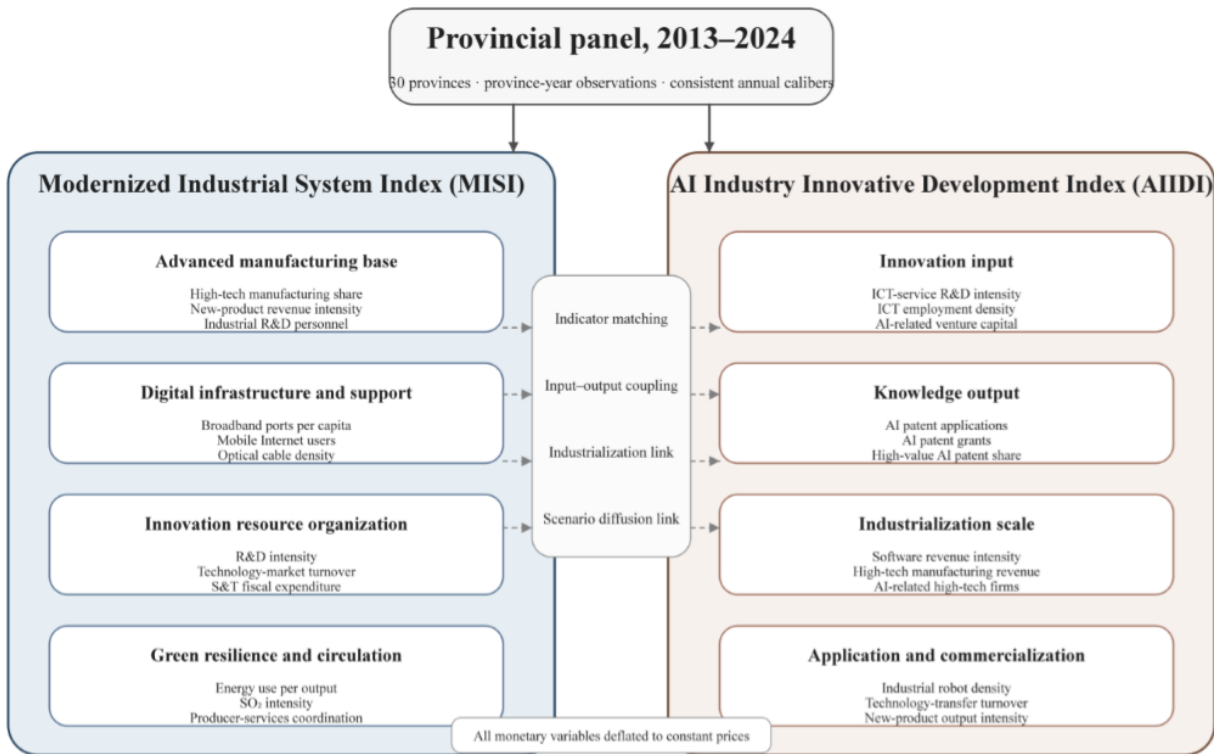


Figure 1: Evaluation Architecture of MISI and AIIDI.

Figure 1 shows that the measurement framework is organized around two parallel but related systems. MISI puts key point on industrial base, digital support, innovation-resource arrangement, and resistible circulation, while AIIDI holds innovation input, knowledge output, industrialization size, and application-commercialization ability. This set-up lets the follow-up connection and economic measurement analyses possess consistency on structure. According to the system structural framework, Table 1 gives the detailed index design, variable definitions, directions and source calibers which are used in the empirical measurement.

Table 1: Indicator System, Variable Definitions, and Data Sources.

System	Dimension	Indicator	Symbol	Unit	Direction	Source
MISI	Advanced manufacturing base	High-tech manufacturing value added/industrial value added	(m_1)	%	+	NBS annual data
MISI	Advanced manufacturing base	New-product sales revenue of industrial enterprises above designated size/industrial operating revenue	(m_2)	%	+	NBS science and technology data
MISI	Advanced manufacturing base	R&D personnel in industrial enterprises above designated size per 10,000 employees	(m_3)	person-years	+	NBS science and technology data
MISI	Digital infrastructure and support	Broadband Internet access ports per 100 persons	(m_4)	number	+	NBS annual data
MISI	Digital infrastructure and support	Mobile Internet users per 100 persons	(m_5)	number	+	NBS annual data
MISI	Digital infrastructure and support	Optical cable density	(m_6)	km/km(^2)	+	NBS annual data
MISI	Innovation resource organization	R&D expenditure/GDP	(m_7)	%	+	NBS science and technology data
MISI	Innovation resource organization	Technology-market turnover/GDP	(m_8)	%	+	NBS science and technology data
MISI	Innovation resource organization	Science and technology expenditure/fiscal expenditure	(m_9)	%	+	NBS annual data
MISI	Innovation resource organization	Higher-education and research R&D personnel per 10,000 persons	(m_{10})	person-years	+	NBS science and technology data
MISI	Green resilience and circulation	Energy consumption per unit industrial value added	(m_{11})	tons of standard coal/10,000 yuan	-	NBS energy statistics
MISI	Green resilience and circulation	Industrial SO ₂ emissions per unit industrial value added	(m_{12})	tons/100 million yuan	-	NBS environmental statistics
MISI	Green resilience and circulation	Producer-services value added/manufacturing value added	(m_{13})	%	+	NBS annual data
MISI	Green resilience and circulation	Freight turnover/GDP	(m_{14})	ton-km/10,000 yuan	+	NBS annual data
AIIDI	Innovation input	R&D expenditure of information transmission, software, and IT services/GDP	(a_1)	%	+	NBS science and technology data; sectoral statistics
AIIDI	Innovation input	Employment in information transmission, software, and IT services per 10,000 persons	(a_2)	persons	+	NBS annual data
AIIDI	Innovation input	AI-related venture capital investment/GDP	(a_3)	%	+	CNRDS
AIIDI	Knowledge output	AI invention patent applications per 10,000 persons	(a_4)	Item/10000 persons	+	CNIPA patent database
AIIDI	Knowledge output	AI invention patent grants per 10,000 persons	(a_5)	Item/10000 persons	+	CNIPA patent database
AIIDI	Knowledge output	High-value AI invention patents/AI patent stock	(a_6)	%	+	CNIPA patent database
AIIDI	Industrialization scale	Software business revenue/GDP	(a_7)	%	+	Sectoral statistics; NBS annual data
AIIDI	Industrialization scale	High-tech manufacturing operating revenue/GDP	(a_8)	%	+	NBS science and technology data
AIIDI	Industrialization scale	AI-related high-tech firms per 10,000 market entities	(a_9)	firms	+	Torch statistics
AIIDI	Application and commercialization	Industrial robot density	(a_{10})	units/10,000 workers	+	IFR World Robotics
AIIDI	Application and commercialization	Technology-transfer turnover in electronic information and intelligent manufacturing/GDP	(a_{11})	%	+	NBS science and technology data; CNRDS
AIIDI	Application and commercialization	New-product output of high-tech industries/GDP	(a_{12})	%	+	NBS science and technology data

Note: AI patents are screened from CNIPA patent records by combining AI-related IPC/CPC classes with keyword matching and are then assigned to provinces by the first applicant's registered address. High-value AI patents refer to valid invention patents with stronger legal status and commercialization potential.

Table 1 indicates that the measurement of AI industry innovation is not limited to patents or software output alone. It is instead linked with industrial support, resource organization, and commercialization conditions, which helps avoid a one-sided interpretation of AI industrial development. The two composite systems are estimated by min-max standardization followed by entropy weighting. Positive and negative indicators are treated separately so that all transformed variables point in the same direction.

$$z_{ijt} = \begin{cases} \frac{x_{ijt} - \min(x_j)}{\max(x_j) - \min(x_j)}, & \text{if indicator } j \text{ is positive,} \\ \frac{\max(x_j) - x_{ijt}}{\max(x_j) - \min(x_j)}, & \text{if indicator } j \text{ is negative.} \end{cases} \quad (1)$$

$$p_{ijt} = \frac{z_{ijt}}{\sum_{i=1}^N \sum_{t=1}^T z_{ijt}} \quad (2a)$$

$$e_j = -\frac{1}{\ln(NT)} \sum_{i=1}^N \sum_{t=1}^T p_{ijt} \ln(p_{ijt}) \quad (2b)$$

$$d_j = 1 - e_j \quad (3a)$$

$$w_j = \frac{d_j}{\sum_{j=1}^K d_j} \quad (3b)$$

$$S_{it} = \sum_{j \in J_S} w_j z_{ijt} \quad (3c)$$

$$S \in \{MISI, AIIDI\} \quad (3d)$$

In these expressions, x_{ijt} denotes the original value of indicator j for province i in year t ; z_{ijt} is the standardized value; p_{ijt} is the proportional share used to calculate information entropy; e_j is the entropy of indicator j ; d_j is the information utility; w_j is the objective weight; and S_{it} is the composite index score for either the modernized industrial system or the AI industry innovative development. A small constant is added when $z_{ijt}=0$ to avoid undefined logarithms.

2.2 Analytical Framework, Coupling Coordination, and Econometric Specification

A composite score alone cannot distinguish parallel growth from effective coordination. This section therefore evaluates the interaction between the two systems first and then estimates the net contribution of the modernized industrial system to AI industry innovation under a fixed-effects framework. To explain why the modernized industrial system is expected to affect AI industry innovation through more than one route, the transmission logic is summarized in Figure 2.

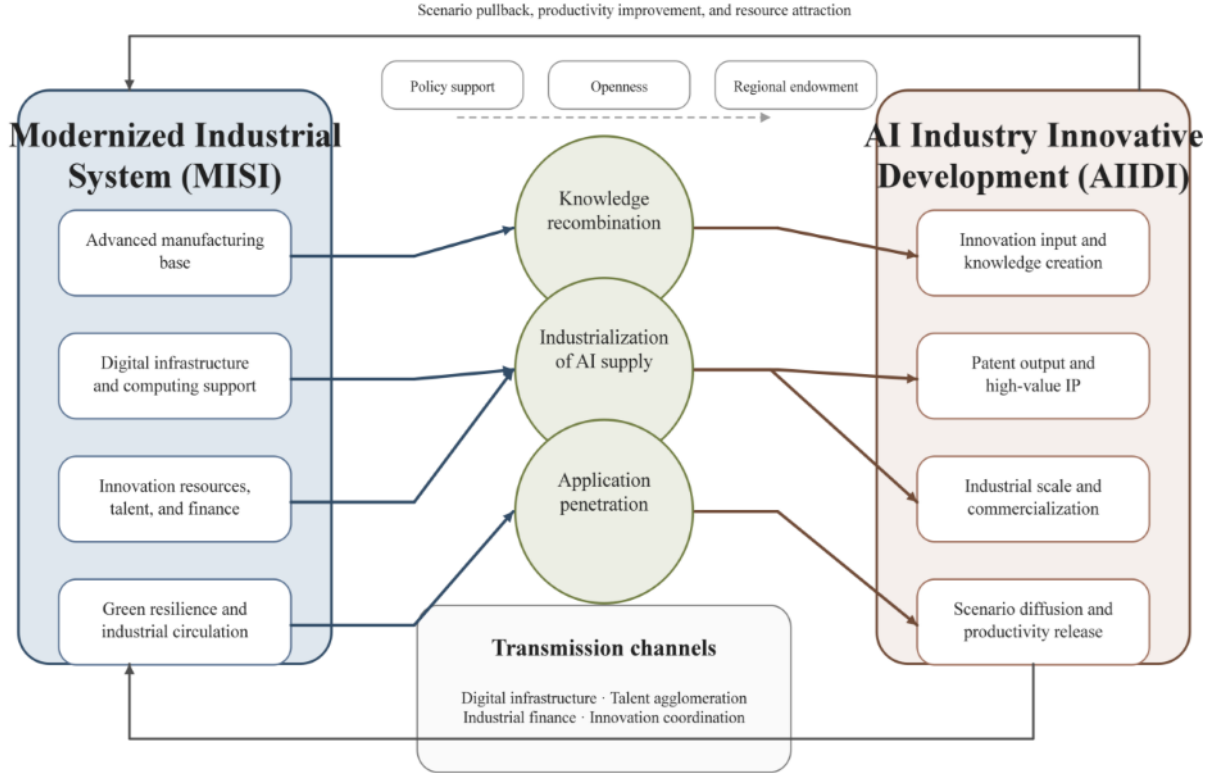


Figure 2: Mechanism linking MISI to AIIDI under transmission channels

Figure 2 shows that the effect of industrial-system modernization is transmitted through production support, digital infrastructure, innovation resources, and resilient circulation, and then enters knowledge recombination, AI supply formation, and application penetration. The final feedback appears in productivity improvement, scenario expansion, and renewed factor attraction.

The coupling-coordination degree is used to capture whether system upgrading and AI industrial innovation evolve in a synchronized manner.

$$C_{it} = \frac{2\sqrt{MISI_{it} \cdot AIIDI_{it}}}{MISI_{it} + AIIDI_{it}} \quad (4a)$$

$$T_{it} = 0.5 MISI_{it} + 0.5 AIIDI_{it} \quad (4b)$$

$$D_{it} = \sqrt{C_{it} \cdot T_{it}} \quad (4c)$$

Here, C_{it} measures the coupling intensity between the two systems, T_{it} is the comprehensive development level, and D_{it} is the coupling-coordination degree. A higher D_{it} indicates that industrial-system modernization and AI innovation development are moving with greater internal consistency rather than drifting apart.

To identify the independent effect of industrial-system modernization, the benchmark model is specified as a two-way fixed-effects panel equation.

$$AIIDI_{it} = \beta_0 + \beta_1 MISI_{it} + \gamma' \mathbf{X}_{it} + \mu_i + \lambda_t + \varepsilon_{it}. \quad (5)$$

In this equation, $AIIDI_{it}$ is the dependent variable, $MISI_{it}$ is the core explanatory variable, \mathbf{X}_{it} is the control-variable vector, μ_i captures province fixed effects, λ_t captures

year fixed effects, and ε_{it} is the error term[22-25] The coefficient of interest is β_1 . Standard errors are clustered at the provincial level to account for serial correlation and heteroskedasticity.

The control vector includes five variables. Real GDP per capita is used to capture the local economic foundation. Human capital is measured by higher-education enrollment or equivalent college-level population per 10,000 persons. Urbanization is proxied by the share of urban permanent residents. Openness is measured by actual utilized FDI relative to GDP. Environmental regulation is proxied by industrial pollution-control investment relative to industrial value added. These controls are retained because they shape local market size, labor quality, policy intensity, and adjustment costs, all of which are relevant to AI industrial development.

2.3 Identification Strategy, Robustness Tests, and Heterogeneity Protocol

After the benchmark setting is specified, the empirical protocol needs to be extended to mechanism testing, robustness, nonlinear analysis, and regional validation. The overall identification and extension path is summarized in Figure 3.

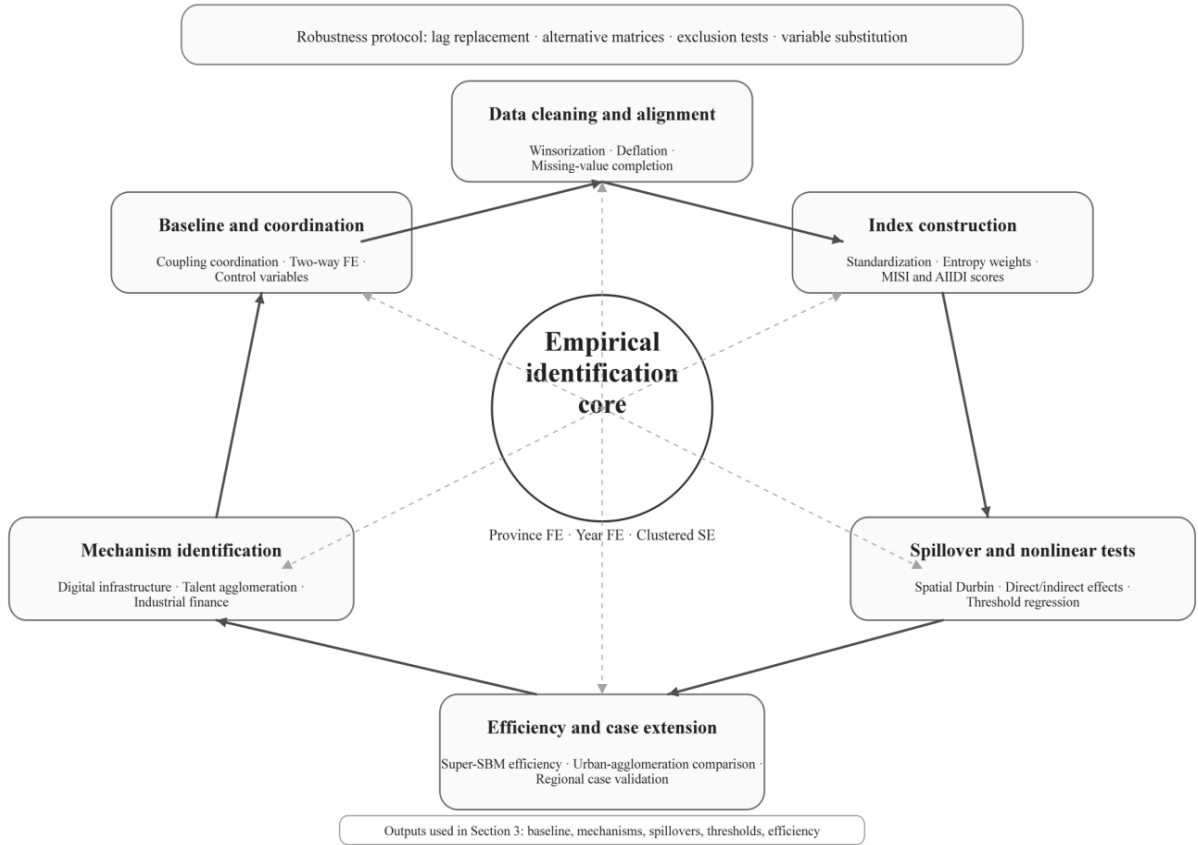


Figure 3: Identification, validation, and extension protocol

Figure 3 shows that the empirical design proceeds from data cleaning and indicator construction to baseline estimation, mechanism decomposition, threshold and spatial testing, and then to efficiency comparison and regional case validation. This arrangement helps keep the main result, the extended tests, and the regional interpretation within one coherent analytical structure. The mediation framework is written as follows:

$$M_{it} = a_0 + a_1 MISI_{it} + \mathbf{a}'\mathbf{X}_{it} + \mu_i + \lambda_t + u_{it} \quad (6)$$

$$AIIDI_{it} = c_0 + c_1MISI_{it} + c_2M_{it} + \mathbf{c}'\mathbf{X}_{it} + \mu_i + \lambda_t + v_{it} \quad (7)$$

Here, M_{it} represents one of three channel variables. The first is digital infrastructure, measured from broadband ports, optical cable density, and mobile-Internet penetration. The second is talent agglomeration, measured by the location quotient of ICT and R&D personnel. The third is industrial finance, measured by a composite of AI-related venture-capital intensity, science-and-technology fiscal expenditure, and credit support for high-tech manufacturing and software-related activities. The frequently used Peking University Digital Financial Inclusion Index is not taken as the main provincial finance measure here because its publicly released provincial series currently ends in 2021 and does not match the 2013-2024 main sample. The talent-agglomeration measure is defined as:

$$TA_{it} = \frac{(Emp_{it}^{ICT+RD}/Emp_{it})}{(\sum_{i=1}^N Emp_{it}^{ICT+RD}/\sum_{i=1}^N Emp_{it})} \quad (8)$$

In this formulation, TA_{it} is the location quotient of technology-intensive labor in province i and year t ; Emp_{it}^{ICT+RD} is employment in ICT and R&D-related activities; and Emp_{it} is total employment. Values above 1 indicate a concentration of relevant talent above the national average in the same year.

Because AI innovation diffuses through supply chains, capital flows, and interregional knowledge exchange, the spatial Durbin model is adopted to separate direct and indirect effects.

$$AIIDI_{it} = \rho \sum_{j=1}^N w_{ij} AIIDI_{jt} + \beta MISI_{it} + \theta \sum_{j=1}^N w_{ij} MISI_{jt} + \gamma' \mathbf{X}_{it} + \phi' \sum_{j=1}^N w_{ij} \mathbf{X}_{jt} + \mu_i + \lambda_t + \epsilon_{it} \quad (9a)$$

$$w_{ij} = \begin{cases} \frac{d_{ij}^{-1}}{\sum_{j \neq i} d_{ij}^{-1}}, & i \neq j, \\ 0, & i = j. \end{cases} \quad (9b)$$

In these equations, w_{ij} is the benchmark inverse-distance spatial weight, d_{ij} is the great-circle distance between provincial capitals, ρ captures dependence in the dependent variable, and θ captures spillovers transmitted through the modernized industrial system. The benchmark matrix is later replaced by contiguity and economic-distance matrices in robustness tests.

To examine whether the effect of the modernized industrial system varies across different stages of local development, this study further applies a panel threshold test. The benchmark threshold variable is the advanced-manufacturing-base subindex, and the replacement test uses the digital-infrastructure subindex. If the estimated coefficients differ significantly across regimes, the effect of industrial-system modernization is treated as nonlinear and stage-dependent.

The efficiency comparison in Section 3.3 is conducted with a super-efficiency SBM framework. Inputs include R&D personnel, R&D expenditure, and industrial finance; desirable outputs include AI patent output, software-business revenue, and new-product output; undesirable outputs include energy intensity and carbon-related pressure associated with industrial digitalization. A score above 1 indicates that the corresponding province-year unit remains on the efficiency frontier and can still be ranked.

To stabilize identification, five robustness checks are built into the protocol. The first replaces the contemporaneous core explanatory variable with a one-period lag. The second replaces entropy weights with principal-component weights. The third replaces the dependent

variable with a patent-oriented AI innovation index. The fourth excludes the four municipalities to reduce leverage from extreme innovation concentration. The fifth replaces the inverse-distance spatial matrix with contiguity and economic-distance matrices. Heterogeneity is examined by eastern, central, and western regions; urban-agglomeration membership; manufacturing-base intensity; and human-capital intensity. The case comparison in Section 3.3 focuses on the Yangtze River Delta, the Pearl River Delta, and the Chengdu-Chongqing region because they represent three distinct combinations of industrial depth, digital support, and AI commercialization conditions.

3 Results and Discussion

3.1 Spatiotemporal Evolution and Baseline Estimation

This sub-section first makes examination on whether the modernized industrial system and the innovative development of the AI industry have evolution of coordinated situation across time and space, and then carries out test on whether the former still holds explanation power after province heterogeneity and year effects are absorbed by us. To identify whether the two systems moved upward together over time, the temporal evolution of MISI and AIIDI is reported first, as shown in Figure 4.

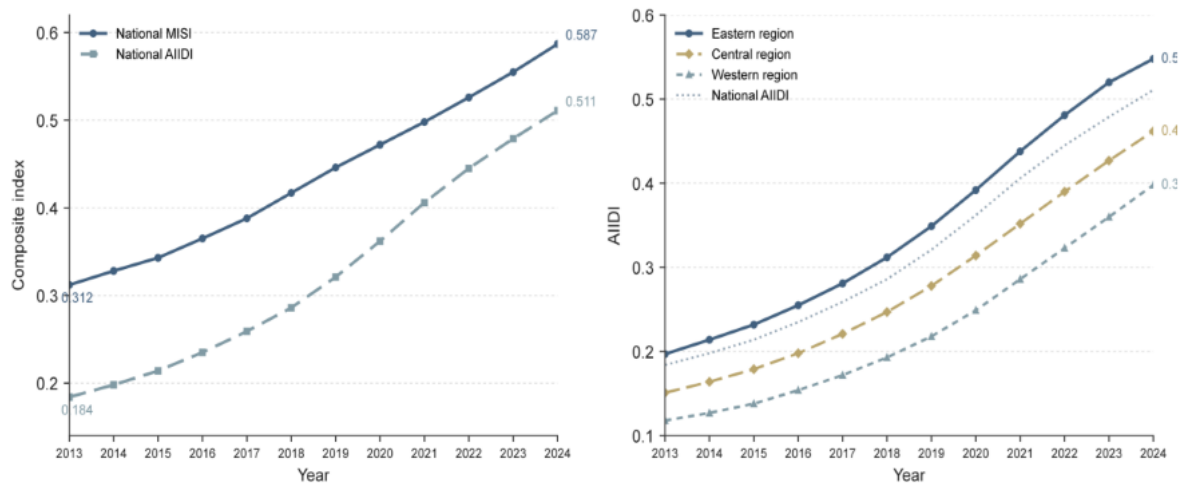


Figure 4: Temporal evolution of MISI and AIIDI.

Figure 4 has built the time foundation of our analysis. The following question is whether this ascending movement was also accompanied by a visible spatial reorganization among all provinces. As what Figure 4(a) shows, the national average MISI had a growth from 0.312 in 2013 to 0.587 in 2024, while the national average AIIDI went up from 0.184 to 0.511 in the same time period. The difference between the two groups decreased from 0.128 to 0.076, hence this shows that the subsequent enlargement of the AI domain was increasingly sustained by industrial-system promotion instead of by separated innovation achievements. The moving path also has alteration in its form. MISI presented a continuous ascending trend over the whole sample period, while AIIDI had a more obvious speedup starting from 2018, hence especially in the time section after 2020. This shows that after digital infrastructure, industrial software, and engineering support have accumulated to a certain degree, the transformation from industrial scenes to AI-linked knowledge making and commercialization has become faster.

Regional differentiation remains visible, but Figure 4(b) shows that the lagging regions were not static. The eastern-region AIIDI increased from 0.197 to 0.548, the central region from

0.151 to 0.462, and the western region from 0.118 to 0.398. The eastern region remained in the lead over the whole period, yet the central region displayed the clearest catch-up after 2018, while the western region improved more slowly but still maintained an upward trajectory without interruption. The national AIIDI series stayed between the eastern and central paths in the first half of the sample and moved closer to the eastern path after 2020, which is consistent with the broader diffusion of intelligent manufacturing, industrial software application, and AI-enabled platform services. The time-series result does not reveal where the growth poles were located or how far the diffusion frontier had moved. For that reason, the provincial spatial distribution of AIIDI in three benchmark years is further reported in Figure 5.

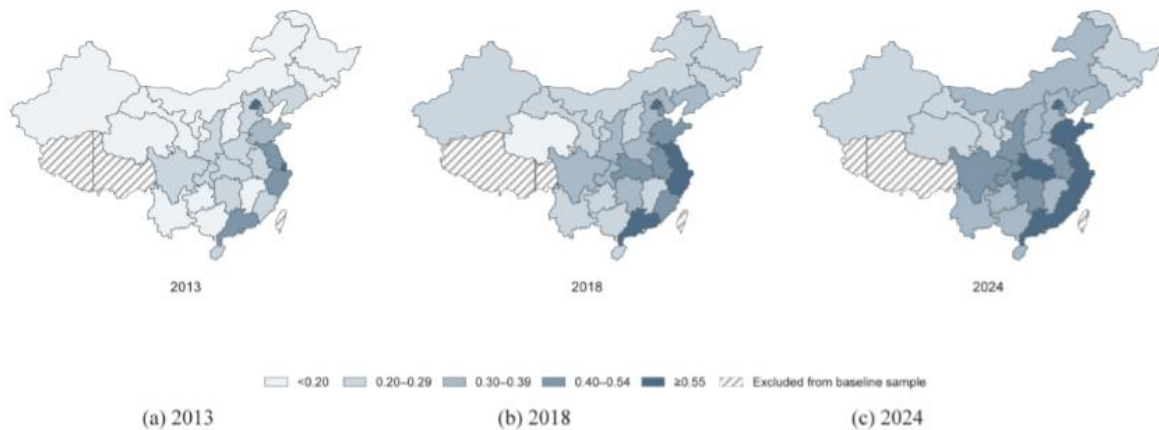


Figure 5: Spatial distribution of AIIDI across provinces.

Figure 5 adds the spatial dimension to the temporal result. Once the geographic clustering pattern is identified, the remaining issue is whether the two systems also became more coordinated internally during the same period. In 2013, the highest-value provinces were concentrated in Beijing, Shanghai, Guangdong, Jiangsu, and Zhejiang, while most inland provinces were still distributed in the low or lower-middle intervals. By 2018, the higher-value area had extended inward, with Anhui, Fujian, Hubei, and Chongqing entering more advanced intervals and forming clearer linkages with the coastal poles. In 2024, the Yangtze River Delta and the Pearl River Delta had become the most stable high-value clusters, and the Chengdu-Chongqing axis, together with the Hubei-Shaanxi belt, had become the most visible inland growth corridor. Several western and northeastern provinces still remained in the 0.20-0.39 interval, and some provinces such as Jilin, Heilongjiang, Gansu, Ningxia, and Qinghai were still below 0.30. The figure therefore indicates that AI industrial innovation has moved from single-core concentration toward corridor-based diffusion, but the frontier of diffusion is still constrained by the local thickness of manufacturing support and digital connectivity. To move from spatial differentiation to internal system matching, Figure 6 reports both the coupling-coordination structure and the fitted marginal effect of MISI on AIIDI.

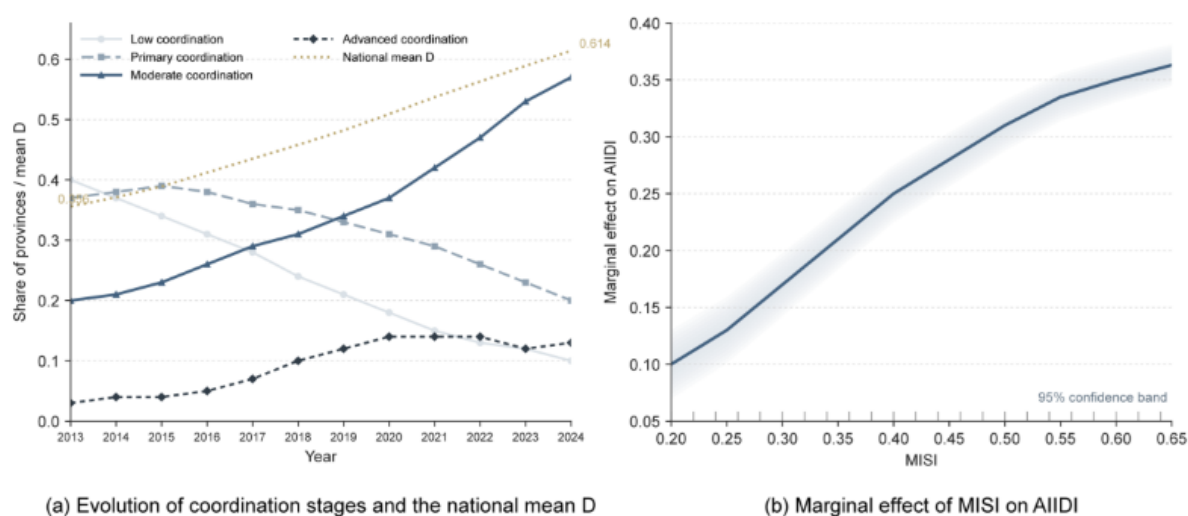


Figure 6: Coupling coordination and marginal effect.

Figure 6(a) further shows that the internal coordination between the two systems improved steadily. The share of provinces in the low-coordination state declined from 0.40 in 2013 to 0.10 in 2024, while the share in the moderate-coordination state increased from 0.20 to 0.57. The advanced-coordination share rose from 0.03 to 0.13, and the national mean coupling-coordination degree increased from 0.356 to 0.614. Measured in province counts, the number of provinces in the moderate-or-above group increased from 7 to 21 over the sample period. This indicates that the growth of AI-connected output was more and more accompanied by more balanced promotion of industrial support, hence not by a simple enlargement of patents or software income in a structurally unbalanced situation.

The same direction appears in the fitted-effect panel. Figure 6(b) shows that, as MSI rises from 0.20 to 0.65, the fitted marginal effect on AIIDI increases from about 0.10 to 0.364. The slope is steepest in the middle interval, roughly between 0.35 and 0.55, and the rug marks at the bottom show that most observations are concentrated in this range. The 95% confidence band remains stable and does not alter the positive direction of the estimated relationship. This matters for interpretation. The main explanatory effect is not generated by a few extreme provinces at the boundary of the sample. It is identified in the range where most provinces were actually moving during the period of accelerated AI industrial expansion. Figure 6 suggests that the relationship is positive not only in descriptive terms but also in its fitted pattern. Table 2 then provides the formal benchmark, robustness, and spatial-spillover estimates.

Table 2: Baseline, Robustness, and Spatial Spillover Estimation Results.

Variables	(1) Baseline FE	(2) FE + Controls	(3) Lagged MISI	(4) PCA-Weighted Index	(5) Excluding Municipalities	(6) SDM Direct Effect	(7) SDM Indirect Effect
MISI	0.284***	0.261***	—	0.269***	0.221***	0.217***	0.082**
L.MISI	—	—	0.247***	—	—	—	—
GDP per capita	—	0.036***	0.034***	0.038***	0.029**	0.031**	0.012
Human capital	—	0.041***	0.039***	0.043***	0.035***	0.037***	0.015
Urbanization	—	0.012	0.011	0.013	0.010	0.009	0.004
Openness	—	0.018*	0.017*	0.019*	0.014	0.015	0.006
Environmental regulation	—	0.015*	0.014*	0.016*	0.012	0.013	0.005
Spatial lag of dependent variable (ρ)	—	—	—	—	—	0.146**	0.146**
Spatial lag of MISI	—	—	—	—	—	0.091**	0.091**
Province fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls included	No	Yes	Yes	Yes	Yes	Yes	Yes
Spatial weight matrix	No	No	No	No	No	Inverse-distance	Inverse-distance
Observations	360	360	330	360	312	360	360
Within R^2	0.61	0.68	0.67	0.69	0.63	0.70	0.70
Wald test for spatial effects	—	—	—	—	—	24.36***	24.36***
LR test for SDM vs. SAR/SEM	—	—	—	—	—	18.92***	18.92***

Note: Clustered standard errors at the provincial level are reported in parentheses in the final typeset version. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. Column (1) reports the benchmark two-way fixed-effects model. Column (2) adds the full control set. Column (3) replaces the contemporaneous core explanatory variable with its one-period lag. Column (4) replaces the entropy-weighted MISI with a principal-component-based composite index. Column (5) excludes Beijing, Shanghai, Tianjin, and Chongqing. Columns (6) and (7) report the decomposed direct and indirect effects under the spatial Durbin model. Control variables include GDP per capita, human capital, urbanization, openness, and environmental regulation.

In column (1), the coefficient on MISI is 0.284***. After controls and two-way fixed effects are introduced in column (2), the coefficient remains 0.261***, which means that a 0.1-point increase in MISI is associated with a 0.0261-point increase in AIIDI. Real GDP per capita and human capital are significantly positive, while openness is positive but more moderate in magnitude. Urbanization loses part of its explanatory power after the industrial-system

variables are absorbed, suggesting that population concentration alone is less decisive than the quality of infrastructure, innovation-resource organization, and industrial-service matching.

The result is stable across alternative specifications. When MISI is lagged by one period, the coefficient remains 0.247^{***}. Replacing entropy weights with principal-component weights yields 0.269^{***}, and excluding the four municipalities gives 0.221^{***}. Taken together, Figure 4 through Figure 6 and Table 2 support the first empirical conclusion of the paper: provinces with a more modernized industrial system tend to achieve higher levels of innovative development in the AI industry, and this relationship is not sensitive to standard robustness adjustments.

3.2 Mechanism Decomposition and Nonlinear Heterogeneity

After the baseline relationship is established, the next issue is why the effect is positive and why its magnitude differs across provinces. Figure 7 and Table 3 are used first to identify the roles of digital infrastructure, talent agglomeration, and industrial finance. Figure 8 and Table 3 are then used to test whether the coefficient changes across threshold regimes and regional structures. The purpose of this subsection is therefore to move from whether the effect exists to how it is transmitted and under what local conditions it becomes stronger. Once the benchmark effect is established, the next step is to determine through which channels it is transmitted. The mediation results are therefore reported in Figure 7.

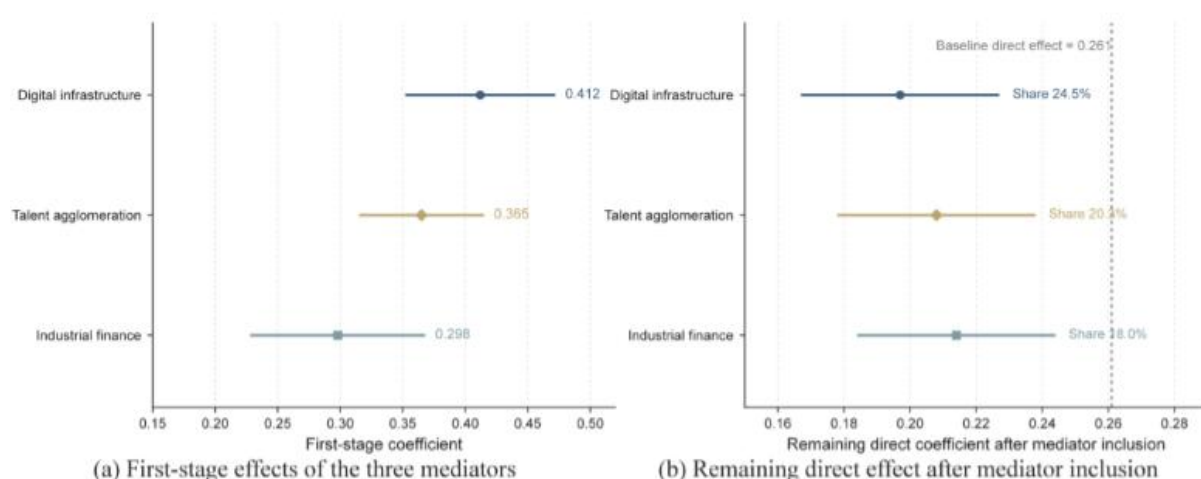


Figure 7: Mechanism decomposition of mediator channels.

Figure 7 identifies the ordering of the three transmission channels. The remaining issue is whether the same effect changes in magnitude across development stages and regional structures. In Figure 7(a), MISI significantly improves all three channel variables, with first-stage coefficients of 0.412 for digital infrastructure, 0.365 for talent agglomeration, and 0.298 for industrial finance. The ranking already indicates that infrastructure and factor concentration respond more strongly to industrial-system modernization than finance alone. Figure 7(b) shows the same mechanism from the attenuation side. The baseline direct coefficient of MISI is 0.261. After introducing digital infrastructure, the remaining direct coefficient falls to 0.197, corresponding to an indirect-effect share of 24.5%. After introducing talent agglomeration, the remaining direct coefficient is 0.208, with an indirect share of 20.3%. After introducing industrial finance, the remaining direct coefficient is 0.214, with an indirect share of 18.0%. The two panels therefore point to the same conclusion: digital infrastructure is the strongest transmission channel, talent agglomeration is second, and industrial finance is significant but somewhat weaker.

This ranking is consistent with the operating logic of the AI industry. AI deployment depends on data transmission, industrial-Internet access, software-equipment compatibility, and the ability to connect model capability with actual industrial scenarios. These conditions are most directly reflected in digital infrastructure. Talent agglomeration matters next because applied algorithm development, engineering integration, and product deployment require compound labor that remains regionally concentrated. Industrial finance still matters, but its effect is stronger when the infrastructure and talent conditions are already in place. Table 3 confirms the same ordering in the block-exclusion test. Removing the digital-infrastructure block lowers the core coefficient to 0.183*** and produces the largest decline in explanatory power. Removing innovation-resource organization yields 0.201***, while excluding green resilience and circulation leaves the coefficient at 0.229***. The current stage of AI industrial development in China therefore still relies most heavily on infrastructure depth and resource-organization quality.

The spillover results further indicate that industrial-system modernization is not confined to local effects. In the spatial Durbin estimates reported in Table 2, the direct effect of MISI is 0.217*** and the indirect effect is 0.082***. The spatial autoregressive coefficient is also significantly positive, which indicates that provincial AI industry innovation is spatially interdependent rather than locally isolated. This suggests that improvements in one province's industrial system raise AI industrial innovation not only locally but also in neighboring provinces through supply-chain matching, interprovincial service linkages, talent movement, and demonstration effects. The spillover magnitude is smaller than the direct effect, but large enough to show that provincial optimization remains incomplete when regional industrial networks are weak. To examine whether the effect of MISI remains constant across local development stages and regional settings, the threshold and heterogeneity results are reported in Figure 8.

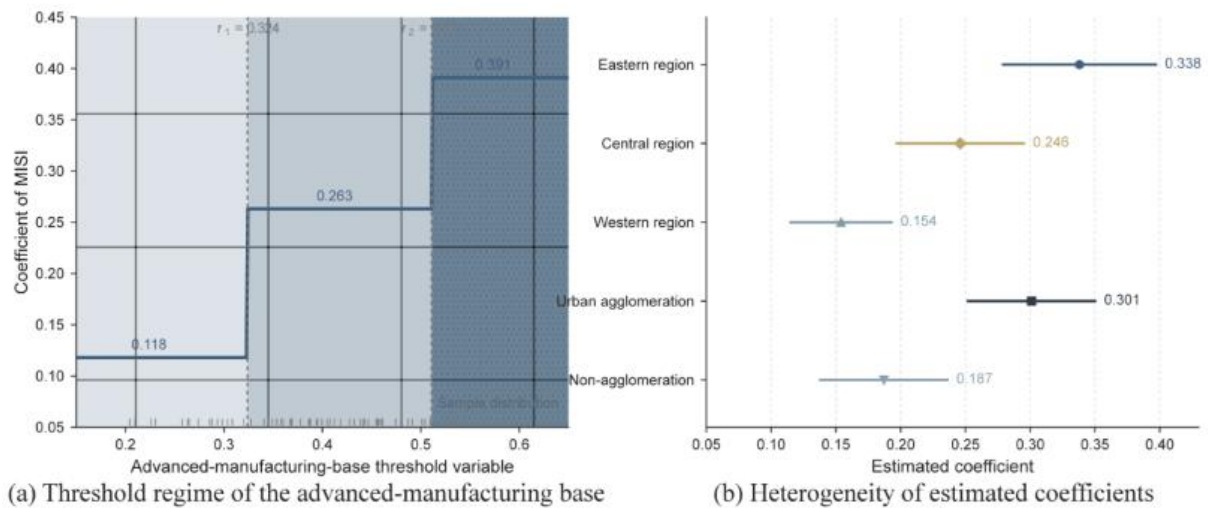


Figure 8: Threshold and heterogeneity results.

Figure 8 shows that the effect of industrial-system modernization is both nonlinear and structurally differentiated. The analysis can therefore move from transmission logic to input-output performance and regional comparison. Figure 8(a) reports the threshold test in a way that makes the regime change directly visible. The threshold variable is the advanced-manufacturing-base subindex, and the two estimated breakpoints are $(\tau_1=0.324)$ and $(\tau_2=0.511)$. Below the first threshold, the coefficient of MISI is 0.118**. Between the two thresholds, it rises to 0.263***. Above the second threshold, it increases further to 0.391***.

The rug marks at the bottom show that the sample observations are concentrated mainly between about 0.33 and 0.55, which means that the middle and upper regimes are not driven by a handful of outliers. The stronger coefficient in the higher regimes therefore reflects a substantive change in industrial conditions rather than a mechanical partition of the sample.

The heterogeneity results in Figure 8(b) align with this interpretation. The coefficient of MISI is 0.338*** in the eastern region, 0.246*** in the central region, and 0.154** in the western region. It is 0.301*** for urban-agglomeration provinces and 0.187** for non-agglomeration provinces. Provinces with denser supplier networks, stronger engineering support, and more concentrated human capital thus obtain larger innovation returns from the same increment in industrial-system modernization. The pattern is internally consistent with the threshold result. Once production capacity, supporting services, and scenario demand reach a minimum scale, AI-related innovation diffuses faster and converts more efficiently into industrial output.

This subsection therefore answers the second empirical question of the paper. The positive effect of a modernized industrial system works mainly through digital infrastructure, talent agglomeration, and industrial finance, and the effect becomes substantially stronger after local manufacturing support crosses identifiable threshold values.

3.3 Efficiency Analysis, Regional Cases, and Industrial Implications

A high AIIDI score does not automatically imply efficient factor use. For that reason, the final subsection shifts the focus from level effects to input-output conversion and regional comparison. Table 3 summarizes the super-efficiency SBM results and slack decomposition, while Figure 9 places the Yangtze River Delta, the Pearl River Delta, and the Chengdu-Chongqing region in one comparative frame.

The super-efficiency SBM results show that the national mean efficiency score increased from 0.684 in 2013 to 0.923 in 2024. Beijing, Shanghai, Jiangsu, Guangdong, and Zhejiang maintain annual mean scores above 1.050 and therefore remain the most stable frontier group. Anhui, Hubei, Sichuan, and Chongqing show the fastest improvement, with average efficiency increasing by about 0.2 to 0.3 over the sample period. The national pattern is therefore one of simultaneous expansion and gradual improvement in conversion quality, but the frontier remains relatively concentrated. Because a higher innovation level does not necessarily imply more efficient factor use, Table 3 summarizes the mechanism, threshold, heterogeneity, and efficiency results in one integrated frame before the regional cases are discussed.

Table 3: Mechanism, Threshold, Heterogeneity, and Efficiency Summary.

Module	Indicator	Estimate	Interpretation
Mediation	Digital infrastructure: first-stage coefficient/indirect-effect share	0.412 ^{***} /24.5%	Strongest transmission channel
Mediation	Talent agglomeration: first-stage coefficient/indirect-effect share	0.365 ^{***} /20.3%	Second-largest channel
Mediation	Industrial finance: first-stage coefficient/indirect-effect share	0.298 ^{***} /18.0%	Significant but slightly smaller contribution
One-block exclusion	Drop digital infrastructure: core coefficient/ ΔR^2	0.183 ^{***} /-0.072	Largest explanatory loss
One-block exclusion	Drop innovation-resource organization: core coefficient/ ΔR^2	0.201 ^{***} /-0.054	Second-largest explanatory loss
One-block exclusion	Drop green resilience and circulation: core coefficient/ ΔR^2	0.229 ^{***} /-0.029	Smaller explanatory loss
Threshold test	Manufacturing-base thresholds	$\tau_1 = 0.324, \tau_2 = 0.511$	Increasing returns after threshold crossing
Threshold test	Coefficients below/between/above thresholds	0.118 ^{**} /0.263 ^{***} /0.391 ^{***}	Effect strengthens sharply at higher stages
Heterogeneity	Eastern/central/western region	0.338 ^{***} /0.246 ^{***} /0.154 ^{**}	Eastern region strongest
Heterogeneity	Urban agglomeration/non-agglomeration	0.301 ^{***} /0.187 ^{**}	Agglomeration advantage is clear
Efficiency	Mean SBM efficiency in 2013/2024	0.684/0.923	National efficiency improved steadily
Efficiency	Frontier provinces	Beijing; Shanghai; Jiangsu; Guangdong; Zhejiang	Stable frontier group
Slack decomposition	Main redundancy/shortfall items	R&D personnel 12.4%; fiscal S&T 9.7%; industrial finance 8.9%; technology transfer 13.1%	Input redundancy and output-conversion gap remain the main constraints

Note: *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. ΔR^2 represents the change in within- R^2 relative to the benchmark FE + controls specification after removing the corresponding first-level block from MISI.

Table 3 shows that the main constraint has shifted from simple input shortage to incomplete resource conversion. Slack decomposition clarifies where the inefficiency is located. That the average redundancy rates of R&D personnel, fiscal science-and-technology expenditure, and

AI-related industrial finance are 12.4%, 9.7%, and 8.9%, respectively. On the output side, the shortfalls in high-value AI patents, technology-transfer turnover, and software business revenue are 11.3%, 13.1%, and 10.6%. This means that many provinces are no longer constrained only by input shortage. They also face incomplete conversion from research resources and financing support to marketable AI output, especially in technology transfer and scenario commercialization. To place the efficiency results in a clearer regional context, Figure 9 compares the Yangtze River Delta, the Pearl River Delta, and the Chengdu-Chongqing region in terms of trajectory, coordination, efficiency, and commercialization constraints.

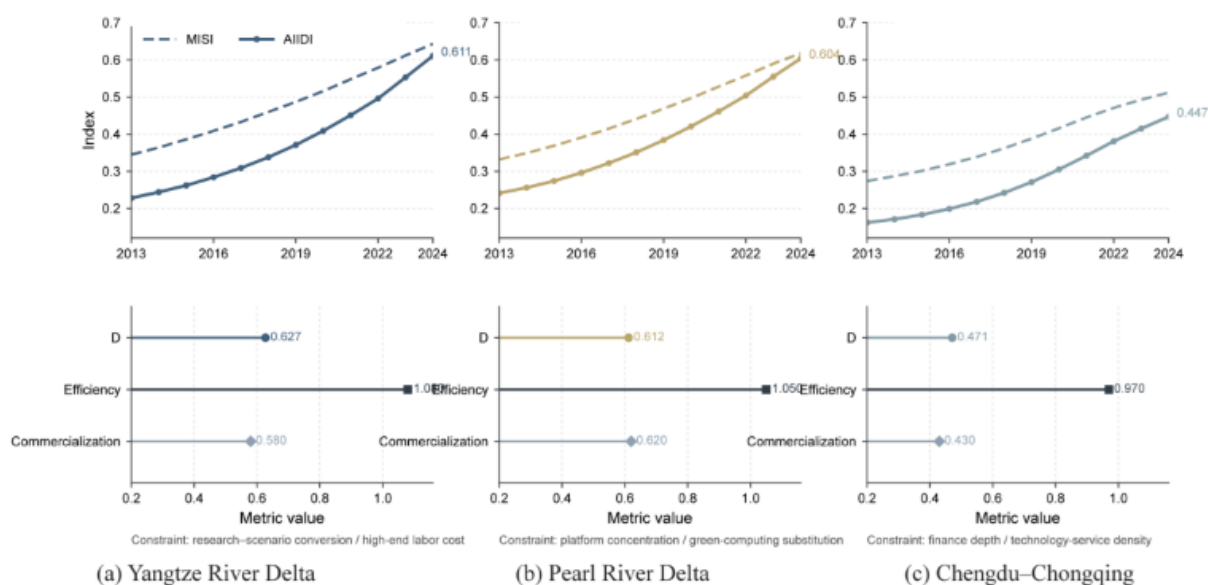


Figure 9: Regional case comparison of trajectories and constraints.

Figure 9 has already provided a more compact comparison regarding these regions. On the most top line, both MISI and AIIDI are going continuously upward in all three regions, but their relative positions are not identical. The Yangtze River Delta holds the tallest system foundation, with MISI reaching 0.643 and AIIDI reaching 0.611 in year 2024. The Pearl River Delta shows a little bit lower MISI with value 0.618, but its AIIDI reaches 0.604 and almost makes up the gap with the Yangtze River Delta when the sample period is concluded. This hence indicates that stronger situation change and commercialization effect are gotten. Chengdu-Chongqing starts its development from a relatively lower starting foundation, with AIIDI rising from 0.162 in 2013 to 0.447 in 2024. This hence causes it to be the most special inland development pole, but therefore its absolute degree still remains lower than the two coastal areas.

The bottom line of Figure 9 lets the regional structure be even more clear. The Yangtze River Delta has recorded that the coupling-coordination degree and the efficiency score are both the highest, which is 1.080. Zhujiang River Delta has a little bit lower coordination degree, which is 0.612, and efficiency is 1.050, therefore it has the highest commercialization strength, which is 0.620. Chengdu-Chongqing has got a lower coordination and efficiency degree than the two coastal areas, its efficiency being 0.970 and commercialization strength being 0.430. When we read these together with the top-row movement paths, such outcomes show three different area characteristics. The Yangtze River Delta has the leading position in the completeness and coordination of systems. The Pearl River Delta changes AI ability into market use in a more radical way. Chengdu-Chongqing region is pursuing rapid advancement, but its financial depth and technological service density still stay lower than those of the two coastal growth poles.

These differences hence therefore help to give explanation for why similar policy information release can lead to different outcomes. In places where production support, industrial software, data infrastructure, and high-level labor already have high density, the innovation of AI industry expands its scale through specialization and cooperation between different enterprises. When one or two core conditions still stay insufficient, policy assistance can still boost activity, but efficiency gets promotion in a more slow way. This is the reason why the bottlenecks which are reported in Figure 9 have differences among regions. In the region of Yangtze River Delta, the main pressures come from the conversion expenses between research and scenario and the high-end labor expenses. In the region of Pearl River Delta, the principal problem is the concentration of platforms together with the pressure for adjustment that is connected with the substitution of green computing. In Chengdu-Chongqing region, the more restrictive binding constraint is still financial depth and technological service density.

Hence, the policy meaning has thus difference. Provinces which are under the first threshold ought to give first priority to broadband and industrial-Internet quality, computing-power access, and the cultivation of engineering and applied-algorithm staff. Provinces that are in the middle stage ought to reinforce technology-transmission organizations, risk-capital matching, and scene opening in intelligent facilities, automobile electronics, industry control, and health-care application items. Border provinces ought pay more attention to data-governance norms, green-calculation replacement, and cross-province creation channels, therefore accumulated benefits can flow outward instead of being kept locked inside a small group of area centers.

Taken together, the level results, mechanism tests, threshold estimates, spillover effects, and efficiency comparison are mutually consistent. The modernization of the industrial system promotes AI industry innovation, the effect works mainly through infrastructure, talent, and finance, and the final quality of that promotion depends on whether local industrial conditions have crossed the scale threshold required for efficient commercialization.

4 Conclusion

This research has inspected the creative development of the artificial intelligence industry from the visual angle of a modernized industrial system through utilizing panel data of 30 provinces in China from 2013 to 2024 and through building a dual-system frame for MISI and AIIDI. The outcome indicates that the expanding of China's AI trade has more and more relied on wider industrial-system circumstances instead of on innovation output that is separated alone. On the whole country scale, MISI elevated from 0.312 in the year 2013 to 0.587 in the year 2024, meanwhile AIIDI got elevated from 0.184 to 0.511, and the benchmark regression has the confirmation that MISI produces a significantly positive influence on AIIDI under multiple robust establishment conditions.

First, the paper shows that AI industry upgrading is closely tied to improvements in industrial support, digital connectivity, and innovation-resource organization. Second, the mechanism results indicate that digital infrastructure is the strongest transmission channel, followed by talent agglomeration and industrial finance; the effect also becomes markedly stronger after local manufacturing support crosses identifiable thresholds, with higher returns in the eastern region and in urban-agglomeration provinces. Third, the efficiency comparison suggests that a high development level does not automatically imply efficient resource conversion. Although national SBM efficiency improved from 0.684 to 0.923, input redundancy and output-conversion shortfalls remain visible, especially in R&D staffing, fiscal science-and-technology support, industrial finance, and technology transfer.

The main limitation of this study lies in the provincial level of aggregation and in the use of several proxy indicators for AI-related activity. Further work can combine provincial

evidence with firm-level adoption, patent-quality tracing, and industrial-chain network data to examine the micro-level conversion path from AI capability to industrial productivity.

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References

- [1] Maslej, N., Fattorini, L., Perrault, R., et al. (2025). Artificial intelligence index report 2025. Stanford: AI Index Steering Committee, Institute for Human-Centered AI, Stanford University.
- [2] World Intellectual Property Organization. (2024). Generative artificial intelligence: Patent landscape report. Geneva: WIPO.
- [3] United Nations Conference on Trade and Development. (2025). Technology and innovation report 2025: Inclusive artificial intelligence for development (Report No. UNCTAD/TIR/2025). Geneva: UNCTAD.
- [4] Yu, Z., Liang, Z., & Xue, L. (2022). A data-driven global innovation system approach and the rise of China's artificial intelligence industry. *Regional Studies*, 56(4), 619-629.
- [5] Lazzeretti, L., Boix Domenech, R., Hervás-Oliver, J. L., et al. (2023). Artificial intelligence, big data, algorithms and Industry 4.0 in firms and clusters. *European Planning Studies*, 31(7), 1297-1303.
- [6] Brem, A., Giones, F., & Werle, M. (2023). The AI digital revolution in innovation: A conceptual framework of artificial intelligence technologies for the management of innovation. *IEEE Transactions on Engineering Management*, 70(2), 770-776.
- [7] Song, L., & Wen, Y. (2023). Financial subsidies, tax incentives and technological innovation in China's integrated circuit industry. *Journal of Innovation & Knowledge*, 8(3), 100406.

- [8] Li, C., Xu, Y., Zheng, H., et al. (2023). Artificial intelligence, resource reallocation, and corporate innovation efficiency: Evidence from China's listed companies. *Resources Policy*, 81, 103324.
- [9] Wang, C., & Wang, L. (2024). Does broadband infrastructure promote urban innovation? Evidence from "Broadband China" demonstration policy. *Structural Change and Economic Dynamics*, 69, 349-362.
- [10] Huang, X., Wang, X., & Ge, P. (2024). Selective industrial policy and innovation resource misallocation. *Economic Analysis and Policy*, 82, 124-146.
- [11] Acemoglu, D. (2025). The simple macroeconomics of AI. *Economic Policy*, 40(121), 13-58.
- [12] Damioli, G., Van Roy, V., Vertesy, D., et al. (2025). Is artificial intelligence leading to a new technological paradigm? *Structural Change and Economic Dynamics*, 72, 347-359.
- [13] Chen, X., Liu, L., Li, D., et al. (2025). The impact of artificial intelligence on the new quality productive forces of enterprises. *Journal of Digital Management*, 1, 3.
- [14] Ma, Y., Zhang, W., Ma, C., et al. (2025). Artificial intelligence, data elements, digital economy, and corporate innovation performance. *International Review of Economics & Finance*, 103, 104560.
- [15] Wang, T., Yu, N., Zhou, W., et al. (2025). Industry policies and technological innovation in artificial intelligence clusters: Are central positions superior? *Humanities and Social Sciences Communications*, 12, 1262.
- [16] Yu, J., Xie, W., Zhao, X., et al. (2025). Drivers of artificial intelligence innovation in manufacturing clusters: Insights from cellular automata simulations. *Humanities and Social Sciences Communications*, 12, 1024.
- [17] Huo, C., Bian, S., He, D., et al. (2025). Research on the impact of the integration of digital economy and real economy on China's domestic value chain resilience. *Digital Economy and Sustainable Development*, 3, 13.
- [18] Xie, J., Xue, C., Zhou, J., et al. (2025). Digital economy on high-quality manufacturing development: A spatial spillover and regional coordination perspective. *Finance Research Letters*, 85(Part B), 107928.
- [19] Shi, J., & Jiang, S. (2025). Toward open-source foundation model ecosystem: Impact evaluation framework and promotion mechanism. *Technological Forecasting and Social Change*, 221, 124328.
- [20] Fatemi, M., Nasri, S., & Ghazinoory, S. (2025). Anatomy of innovation biosphere in global AI landscape: Actors, interactions, and evolution. *Journal of Engineering and Technology Management*, 78, 101923.
- [21] Ma, L., Luo, X., & Xi, M. (2025). The impact of regional artificial intelligence development on the resilience of enterprise supply chains. *International Review of Economics & Finance*, 102, 104305.

- [22] Zhu, Y., Zhao, X., & Liu, Y. (2025). Artificial intelligence, digital financial development, and corporate innovation performance. *Finance Research Letters*, 86(Part E), 108640.
- [23] Guo, L., Pei, H., & Liu, Y. (2025). Artificial intelligence and corporate green innovation: Evidence from China. *Research in International Business and Finance*, 79, 103039.
- [24] Ștefan, S. C., Popa, I., & Breazu, A. (2025). A new framework for the artificial intelligence entrepreneurship ecosystem. *Journal of Innovation & Knowledge*, 10(6), 100850.
- [25] Mane, K., Park, G., & Shen, A. (2025). High-tech clusters, labor demand, and inequality: Evidence from “Made in China 2025”. *Regional Science and Urban Economics*, 115, 104142.