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Research article

The driving mechanism and challenges of artificial intelligence innovation to the alternate with industrial upgrading from multiple perspectives

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Abstract: Based on the provincial panel data of China from 2000 to 2023, we systematically examined the impact effect and internal mechanism of artificial intelligence (AI) innovation on the alternate with industrial upgrading. The empirical results showed that AI innovation has a significant promoting effect on the alternate with industrial upgrading, and this conclusion remains valid after a series of robustness tests and endogeneity treatments. This study advances the literature in three major ways: First, we integrated a nonlinear threshold framework with a multi-dimensional moderation analysis, enabling a more nuanced understanding of how AI innovation affects industrial chain modernization under heterogeneous institutional and factor conditions. Second, we empirically identified the industrialization level as a partial mediating mechanism, thereby clarifying the internal transmission path from AI innovation to structural upgrading. Third, by uncovering a negative moderating role of enterprise productivity, the study revealed an 'efficiency trap' that challenges the conventional assumption that higher productivity always enhances technological returns.

Keywords: artificial intelligence innovation; industrial chain modernization; new quality productivity; industrialization level; human capital level; enterprise production efficiency; regional disparities

JEL Codes: O33, L63, D24

1. Research background

The alternate with industrial upgrading is a fundamental requirement for achieving high-quality development and building a modernized industrial system, and an inherent choice for a country to participate in international competition and respond to exogenous shocks. In recent years, affected by external shocks, such as the reorganization of global supply chains and the intensification of geopolitical risks, the uncertainties facing the security of China's industrial chains have significantly increased, and promoting the alternate with industrial upgrading has become a core concern of government departments (Research Group & Zhang, 2021). China is facing a double challenge in the process of building its industrial chain: On the one hand, the fading demographic dividend has led to the replacement of the labor cost advantage of traditional labor-intensive industries by emerging countries; on the other hand, structural problems, such as weak industrial foundation, shortcomings in core technologies, and low industrial added value, persist. In this context, artificial intelligence (AI), as a general-purpose technology of the fourth industrial revolution, empowers industrial chain upgrading through multiple paths, such as automated production, intelligent management, and big data analysis, and is positioned as a key engine to break through development bottlenecks in the "14th Five-Year Plan for Intelligent Manufacturing Development": The plan explicitly proposes to drive innovation with innovation. By promoting technological innovations such as AI, the manufacturing industry will climb to the medium and high ends of the global value chain. However, there is a significant gap in academic research: Discussions on the alternate with industrial upgrading mostly focus on connotative definitions, such as technical and economic linkages among industrial sectors and global value chain value-added capabilities, and realization paths, such as demand-supply linkage, new quality productivity cultivation, "chain leader" enterprise leadership, and other theoretical mechanisms. Empirical research on AI has mostly been confined to a single dimension, such as the employment substitution effect, changes in income distribution, and macroeconomic growth, and has not systematically examined the multi-dimensional mechanisms and nonlinear threshold laws that drive the alternate with industrial upgrading.

Based on panel data from 31 provinces in Chinese mainland from 2000 to 2023, we constructed a multi-dimensional analytical framework integrating technology penetration, institutional synergy, and factor allocation to empirically examine the impact effect and mechanism of AI technological innovation on industrial chain modernization. We found that AI significantly enhances the modernization level of industrial chains through the core path of industrial upgrading and shows a gradient diffusion characteristic from the east to the central and western regions. Moreover, the positive moderating effect of human capital advancement and new quality productivity and the negative inhibitory effect of enterprise productivity form a tension, revealing the nonlinear threshold law of technology adaptation. The research results provide theoretical support and practical guidance for cracking the "efficiency trap", optimizing regional policy design and implementing the innovation-driven strategy.

2. Theoretical analysis and research hypotheses

2.1. Literature review and research ideas

In recent years, the deep reconfiguration of global industrial chains and the upgrading of economic security demands have driven industrial chain research to become a focus area of the academic community.

At present, researchers focus mainly on the measurement of industrial chain modernization and industrial chain resilience. For example, in terms of modernization level assessment, the three-dimensional index system of industrial foundation sophistication, industrial chain synergy, sustainability constructed by Li et al. (2024)complements the innovation-green two-dimensional model focused on manufacturing by Chen et al. (2025), Cai & Xu (2021) quantitatively presented the gradient distribution characteristics of the modernization level of China's manufacturing industry for the first time, jointly addressing the problem of dimension fragmentation in traditional assessment. Research on industrial chain security resilience shows a significant trend of empirical deepening. For example, Lyu & Zhang, (2024), based on the different-in-differences model of the automotive industrial chain empirically, revealed import dependence (34.7% in 2021) and structural risks caused by regional concentration. Feng (2024) found that digital technology-driven manufacturing service transformation can increase the added value of the industrial chain by 12%–15%, providing new ideas for resilience building.

AI, as a key technology of the present, has attracted the attention of many scholars. Zou and Ren (2025) explored how the new generation of AI drives new industrialization. The application in the industrial field brings increased demand for computing power, which poses challenges to the low-carbon transformation of industry and should be advanced in a coordinated manner from multiple aspects such as technological innovation and production organization. Wu and Wu (2025) conducted a comparative analysis of the competitiveness of the AI industry in China and the United States from the perspective of the integration of the industrial chain and the value chain, and proposes China's policy options. Chen and Lian (2025) conducted an empirical study on the impact of AI development on the resilience of the logistics industry chain and found that it promotes the resilience of the industry chain by directly enhancing capabilities such as early warning and response and indirectly enhancing total factor productivity; the effects vary between regions. Song (2025) analyzed the mechanisms and challenges of AI-driven economic growth quality improvement, pointing out that it transforms economic activities while causing problems such as market monopolies; and institutional guarantees need to be improved. Ren et al. (2025) proposed that AI is a new trend driving the development of the world economy and has a "head goose" effect, empowering high-quality development at the industrial, enterprise, and technological levels. Zhao and Liu (2025) proposed the concept of an AI penetration rate and found that it significantly enhances the innovation efficiency of enterprises, shows a U-shaped curve feature, and works through mechanisms such as improving enterprise performance. Guo et al. (2025) studied how AI can enhance enterprise competitiveness and found that it is achieved by optimizing the human capital structure and increasing the skill premium. Chen et al. (2025) explored how AI applications drive the emergence of new quality productivity in enterprises and found that it has promoting and inhibitory effects, activating new quality productivity through substantive innovation and industrial chain integration effects; the effects are heterogeneous. Dimitriadis et al. (2025b) explored the key applications of AI in the digital economy, which is deeply reshaping the underlying logic and organizational form of the industrial chain. Taking the cryptocurrency field as an example, AI technology not only drives automated transactions (Dimitriadis et al., 2024a), risk prediction, and blockchain network optimization, but also promotes the evolution of the industrial chain toward greater transparency, decentralization, and intelligent collaboration by reconfiguring trust mechanisms and resource allocation efficiency, thereby exerting a structural impact on the traditional industrial structure (Dimitriadis et al., 2025a). Furthermore, the global value chains embedded within AI now play a critical role in the world economy, underscoring its strategic importance. Moreover, the rapid advancement of AI has outpaced society’s capacity to fully comprehend and adapt to its impacts (Jugravu & Dumitrășconiu, 2025), with its scale and speed of adoption significantly exceeding those of previous technological transformations .

Although researchers have explored the correlation between AI and industrial chain modernization from multiple perspectives, covering areas such as application effects, mechanisms of action, and challenges, empirical research focusing on the intrinsic relationship between the two is scarce, with insufficient depth of exploration of the mechanism of action and a relatively single research perspective. The subsequent research of this paper follows the logical chain of “hypothesis and mechanism of action → data source and processing → variable definition → model construction → empirical test → further analysis → conclusion and recommendation”.

2.2. Innovation in AI technology and modernization of the industrial chain

As a highly pervasive general-purpose technology, AI reconfigures production functions and optimizes industrial ecosystems, thereby driving the alternate with industrial upgrading. These impacts manifest in the following ways: At the production stage, deep learning-based machine vision improves quality inspection accuracy and increases product qualification rates; at the organizational stage, intelligent scheduling algorithms enhance the allocation efficiency of supply chain resources; and at the innovation stage, knowledge graphs and patent analytics accelerate research and development cycles and facilitate upward movement along the value chain.

AI further advances industrial chain upgrading through two complementary pathways: End-to-end empowerment and systemic optimization. At the process level, AI spans the industrial workflow, from research and design, manufacturing, to service delivery, achieving performance gains through big data analytics, automated equipment, and intelligent systems. At the systemic level, AI not only deepens industrial specialization and transforms operational models but also strengthens the industrial chain’s capacity for resilience forecasting and collaborative governance. Moreover, cross-sector applications have demonstrated tangible benefits: Manufacturing leverages intelligent inspection to overcome capacity bottlenecks, agriculture enhances decision-making through environmental monitoring, and the service sector improves operational quality via intelligent risk management.

In conclusion, by harnessing its core strengths in data processing, intelligent decision-making, and automation, AI continuously drives progress across industrial chains. It reinforces foundational capabilities, enhances operational efficiency, and enables leaps along the value chain, positioning itself as a pivotal engine for modernization and transformation.

Based on the above analysis, the underlying logic and implementation pathways for AI empowering the industrial chain upgrade can be summarized as shown in Figure 1 below.

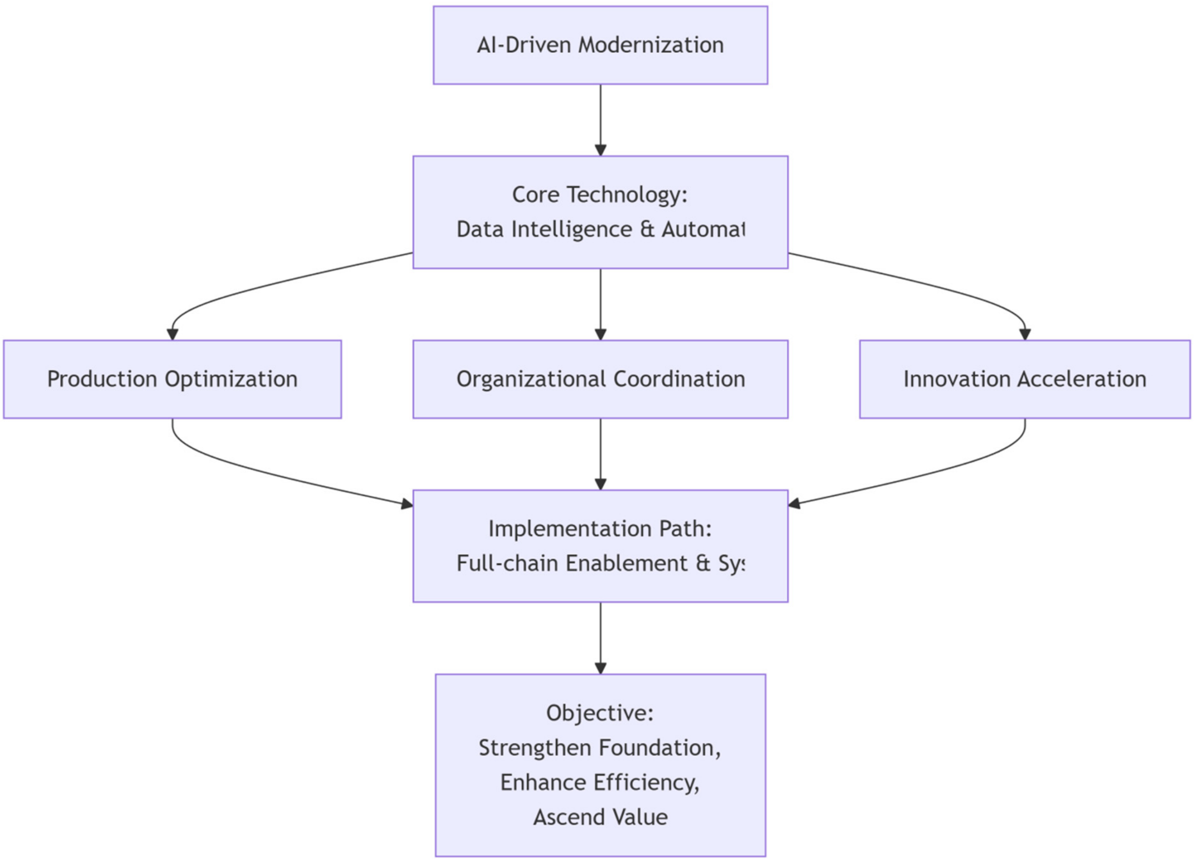

Figure 1. The impact of AI on the modernization of the industrial chain.

In conclusion, Hypothesis 1 is proposed: AI technological innovation can significantly enhance the modernization level of industrial chains.

2.3. *AI technology innovation, industrialization level, and industrial chain modernization*

As a general-purpose technology, AI is advancing industrial upgrading and industrial chain modernization through the reconfiguration of production factors and the transformation of production paradigms. Its core capability lies in integrating perception, decision-making, and execution, thereby fundamentally reshaping the operational logic of industrial systems.

At the level of technological integration, AI bridges the physical and digital spaces using data, constructing dynamic knowledge graphs from real-time information to enable the intelligent upgrading of manufacturing equipment. Examples include machine vision for enhanced defect detection, predictive maintenance for optimized equipment performance, and collaborative algorithms for improved production scheduling. These advancements not only increase the precision and reliability of manufacturing processes but also transform production organization, shifting supply chains toward dynamic networks, decision-making toward distributed collaboration, and processes toward flexible systems.

The industrialization process exhibits a systematic evolution along four dimensions:

1. Intelligent production tools, creating closed-loop “perceive–decide–act” systems that reduce operational uncertainty.

2. Collaborative management models, breaking down information silos and enabling global resource optimization.

3. Open innovation systems, fostering cross-domain knowledge integration and accelerating technological iteration.

4. Networked industrial organization, utilizing intelligent platforms to dynamically allocate manufacturing resources.

Together, these shifts transition industrial systems from scale-driven efficiency to systemic resilience, from experience-based to data-driven decision-making, and from linear chains to open ecosystems.

Industrial upgrading further propels industrial chain modernization through three pathways:

1. Enhanced foundational capabilities, as smart factories progressively replace traditional manufacturing, with key equipment incorporating adaptive controls and digital twin technologies to enable breakthroughs in high-end sectors.

2. Reconfigured organizational forms and moving toward networked and flexible structures that enable full-chain real-time coordination and dynamic resource allocation;

3. Elevated position in the global value chain, supported by industrial knowledge graphs and intelligent R&D systems, shifting innovation from isolated breakthroughs to systematic development and refocusing competition toward standards and architecture definition.

This transformation relies on the alignment of technology, institutions, and factor inputs, which are supported by industrial internet infrastructure, data property rights frameworks, and corresponding human capital. AI-driven industrial upgrading thus serves as a pivotal mechanism in industrial chain modernization, consistently steering the industrial system toward greater intelligence, connectivity, and high-value-added development.

How artificial intelligence transmits from industrialization upgrading to industrial chain modernization, along with its underlying mechanisms and implementation pathways, can be summarized as shown in Figure 2 below.

In conclusion, Hypothesis 2 is proposed: AI technological innovation drives industrial chain modernization by elevating industrialization levels.

Figure 2. The mediating role of AI in the modernization of the industrial chain.

2.4. AI technology innovation and human capital, new quality productivity, industrial structure, enterprise productivity, and the modernization level of industrial chains.

The promotion effect of AI innovation on industrial chain modernization is regulated by multi-dimensional factors, and its direction and intensity depend on the complex interaction among factors. Elevated human capital enhances the efficiency of technology absorption and transformation, breaking through cognitive barriers in technology application and elevating AI from a replacement tool to a creative catalyst. Continuous learning capabilities also mitigate the risk of technological discontinuity. Moreover, new-type productive forces amplify AI's effectiveness by restructuring the technological ecosystem foundation, where next-generation infrastructure ensures real-time decision-making, data element circulation eliminates "data silos", and adaptive governance models accelerate large-scale technology implementation. Advanced industrial structures optimize the innovation environment: Technology-intensive industries leverage intelligent algorithms to multiply R&D efficiency, modern services create personalized high-value-added scenarios, and production services strengthen end-to-end collaborative networks.

In contrast, improvements in corporate productivity may exert significant inhibitory effects. An excessive focus on static efficiency can reinforce organizational rigidity, stifling breakthrough exploration of technological paradigms. Path dependence within systems often leads to transformational inertia, making enterprises reluctant to bear the learning costs of adopting AI. The rigidity in resource allocation and bureaucratic barriers further hinder knowledge flow and technology transfer. This efficiency worship tends to create a "capability trap": The more adept an enterprise becomes at its current model, the harder it is to restructure itself to adapt to the intelligent technology revolution, thereby diminishing the marginal contribution of AI as efficiency improves.

The promotional effect of AI innovation on industrial chain modernization is moderated by multiple factors, with both facilitating mechanisms and inhibiting pathways coexisting. The specific logical relationships can be summarized as shown in Figure 3 below.

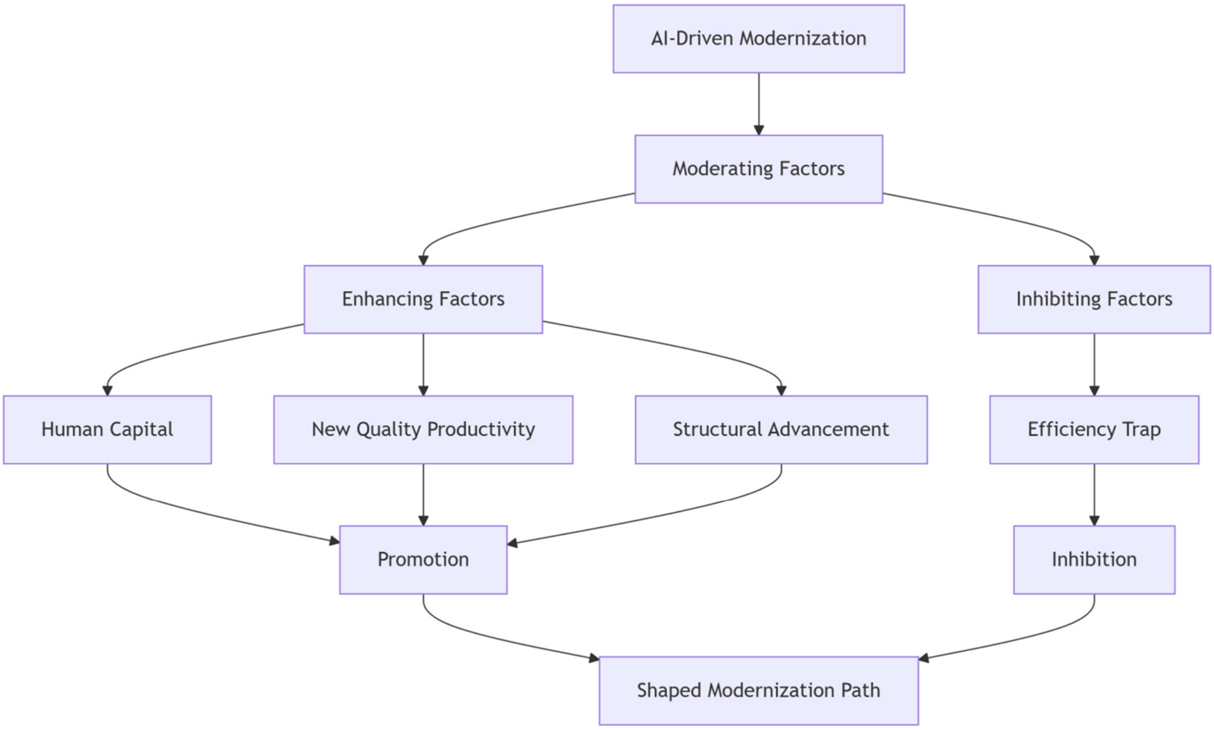

Figure 3. The regulatory effect of AI on the modernization of the industrial chain.

In conclusion, Hypothesis 3 is proposed: The promotion effect of AI innovation on industrial chain modernization is regulated by multiple factors. Human capital, new quality productivity, and industrial structure upgrading exhibit significant positive enhancement effects, while enterprise production efficiency demonstrates a notable inhibitory effect.

Based on the above analysis, the complete logical framework through which AI drives industrial chain modernization via industrialization upgrading, along with its multi-dimensional moderating mechanisms and implementation pathways, can be holistically summarized as shown in Figure 4 below.

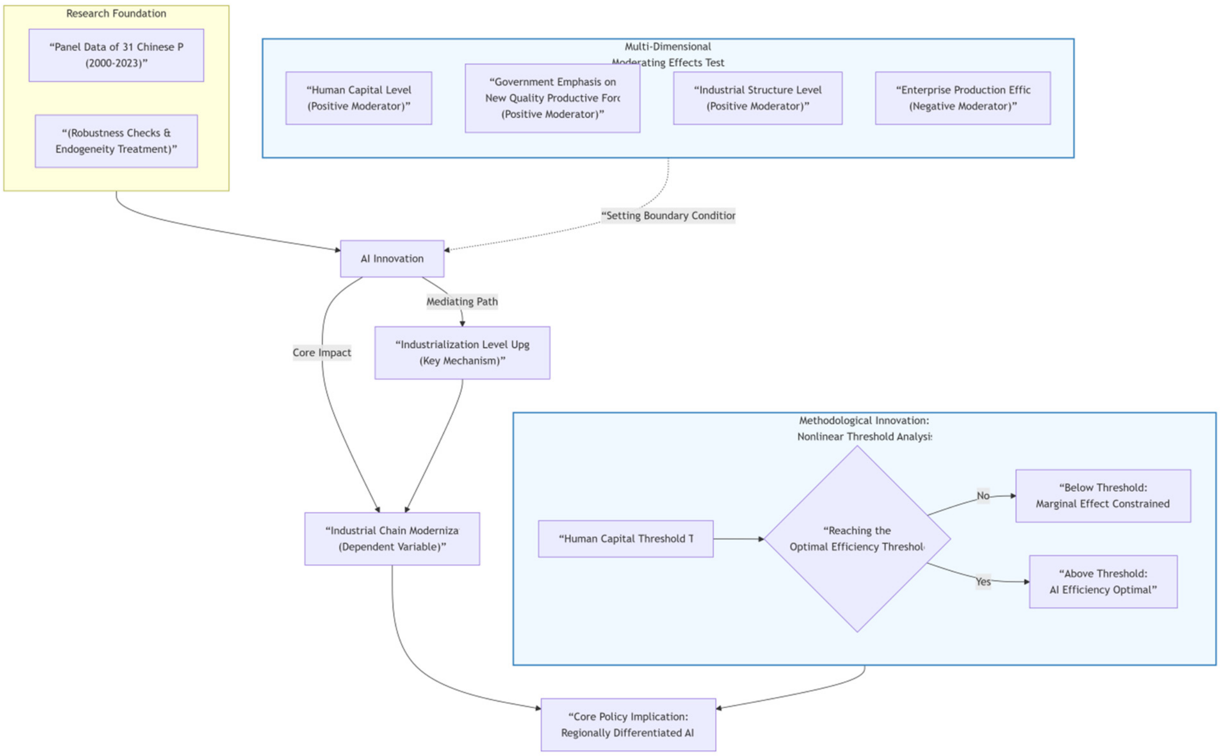

Figure 4. Theoretical framework of AI innovation driving industrial chain modernization

3. Research design

3.1. Data sources and processing

In this study, we built an empirical research framework based on panel data from 31 provincial administrative regions in Chinese mainland from 2000 to 2023. To ensure data quality, for the missing data, the average growth rate or interpolation method was used to fill in the missing data, and logarithmic processing was performed for the data with larger values. The data sources include: National Intellectual Property Administration, National Bureau of Statistics, provincial statistical yearbooks, the EPS Global Statistical Data/Analysis Platform, China Economic and Social Big Data Research Platform, and China Statistical Yearbook, China Industrial Statistical Yearbook, China High-tech Statistical Yearbook, China Energy Statistical Yearbook, China Civil Affairs Statistical Yearbook, and China Regional Economic Statistical Yearbook. The Stata 18.0 software was used to construct fixed-effect models for parameter estimation and robustness testing.

This study was based on the publicly available macro statistical data of 31 provinces in China from 2000 to 2023 (sourced from authoritative platforms such as the National Bureau of Statistics, various statistical yearbook and EPS). The data did not involve human participants, strictly adhering to academic ethics and having no conflicts of interest. Although we made every effort to ensure data quality through cross-validation and robustness tests, it was necessary to recognize the possible non-systematic measurement errors based on statistical yearbooks and interpolated data, especially the differences in historical statistical scales and interpolation smoothing, which may have affected the accuracy of variable measurement. However, the core conclusion demonstrated strong robustness: The instrumental variable method effectively alleviated endogenous bias, and through substitution variable measures, tailing processing, and sub-sample testing, the positive effects of AI innovation remained consistent in direction and statistically significant. The processed dataset can be obtained from us upon reasonable request.

3.2. Variable definitions

3.2.1. Explained variable: Industrial Chain Modernization Level (ICM)

Based on the definition of the connotation of industrial chain modernization, we drew on and integrated the research ideas of scholars, such as Zhang (Zhang et al., 2022), closely adhering to the high-quality requirements of innovation-driven, coordinated optimization, and sustainable development, and based the study on the characteristics of the digital age and the goals of industrial chain resilience and basic capacity building in the complex international environment. The comprehensive evaluation index system was constructed from six dimensions: Industrial chain foundation, innovation, resilience, synergy, digitalization, and sustainability, and the entropy method was used to synthesize the comprehensive measurement index of industrial chain modernization level. The metrics are shown in Table 1.

Table 1. Measure of Industrial Chain Modernization.

Primary indicators	Secondary indicators	Tertiary indicators	Indicator Attributes
Industrial chain foundation	Circulation foundation	Road density (km/100kEP)	+
		Railway density (km/100kEP)	+
		Cargo turnover (billion ton-kilometers)	+
Industrial chain innovation	Communications Infrastructure	Number of Internet broadband access ports per 10,000 people (units)	+
		length of long-distance optical cable lines per 10,000 people (kilometers)	+
	Innovation input	Full-time equivalent of R&D personnel of industrial enterprises above designated size (10,000 people)	+
		proportion of R&D expenditure of industrial enterprises above designated size to GDP (%)	+
	Innovation output	Technology market transaction volume (billion yuan)	+
		proportion of new product sales revenue to main business income of industrial enterprises above designated size (%)	+
Industrial chain resilience	High-end leadership	Proportion of main business income of high-tech industries to GDP (%)	+
	Chain control force	Number of listed companies (in)	+

Continued on next page

Primary indicators	Secondary indicators	Tertiary indicators	Indicator Attributes
Industrial chain synergy	Profitability	Profit rate on total assets of industrial enterprises above designated size (%)	+
	Financial synergy	The proportion of total loan balance of banking financial institutions to GDP (%)	+
	Innovation Synergy	Proportion of R&D external expenditure of industrial enterprises above designated size to GDP (%)	+
Digitalization of industrial chains	Industrial synergy	Manufacturing and production-oriented services co-development EG index	+
	Enterprise digitalization	Number of computers per 100 people (units)	+
		proportion of businesses with e-commerce transactions (%)	+
	Digitalization of industries	Proportion of e-commerce sales to GDP (%)	+
		Proportion of main business income from electronic and communication equipment manufacturing above designated size to main business income of industrial enterprises (%)	+
Sustainable industrial chain	Energy-efficient production	Energy consumption per unit of regional GDP (tons of standard coal/yuan)	-
		Electricity consumption per unit of industrial added value (kilowatt-hours/yuan)	-
	Pollution emissions	Sulfur dioxide emissions per unit of industrial added value (tons/billion yuan)	-
	Green governance	Proportion of investment in industrial pollution control projects completed this year to industrial added value (%)	+

3.2.2. Explanatory variable: Level of AI innovation

Global patent activity in areas such as AI and intelligent robots has seen explosive growth, and AI-based solutions have deeply permeated all scenarios of production and life, systematically reshaping the economic and social structure. Despite the limitations of using patent data to represent AI technology innovation and application, such as companies' potential evasion of patent applications for trade secret protection, or fluctuations in patent quality due to institutional factors, it is widely regarded as a core proxy variable in the economics community. The reason is that, first, patent data can effectively capture the intensity of research and development investment and the depth of technological accumulation of enterprises within a technology cycle, and second, enterprises have a strong incentive to build moats through patents to prevent the competitive replication of technological achievements; More importantly, at the macro level, patent indicators can objectively reflect the trajectory of technological leaps in industries, especially in knowledge-intensive fields, such as AI, where the combined analysis of patent authorizations, citation networks, and technology classification has become the gold standard for measuring innovation dynamics and knowledge stock.

When constructing the provincial AI innovation level index system, we followed the research paradigm of scholars, such as Chen and Cai (2023), and selected four-dimensional patent data at the prefecture-level city as the basic observation unit: The total number of AI patent applications, the number of invention patent authorizations, the number of utility model patent authorizations, and the number of design patent authorizations. In view of the provincial spatial scale characteristics of the research object, by weighted aggregation of four types of patent index data of all prefecture-level cities in the province and logarithmic processing of the results to form a comprehensive measure of the provincial AI innovation level, this method not only continued the refined consideration of the multi-dimensional patent structure in the literature, but also met the analysis requirements of provincial panel data. Moreover, we ensured spatial consistency and data comparability in the measurement of innovation levels.

3.2.3. Adjust the variable: Enterprise productivity

Based on the financial statement data of A-share listed companies in the non-financial sector, excluding special treatment enterprise samples, such as ST/*ST, we used the proportion of current assets to total assets as a proxy indicator of the production efficiency of individual enterprises, and constructed the comprehensive measure value of enterprise production efficiency at the provincial level by calculating the arithmetic mean of this indicator of all eligible enterprises in each province. In the operation, first, financial enterprises were excluded in accordance with the CSRC's "Guidelines for Industry Classification of Listed Companies". Second, listed companies subject to risk warning (ST) were continuously screened out during the observation window period. Finally, microdata were generated based on the accounting formula "enterprise production efficiency = current assets/total assets", and mean aggregation was performed in provinces as spatial units. Additionally, we formed the core indicator reflecting the efficiency of regional enterprise asset allocation.

3.2.4. Instrumental variable IV: Number of fixed-line telephones in 1984

To overcome potential endogeneity issues (such as bidirectional causality and omitted variables) between the level of AI innovation and the modernization of the industrial chain, we followed the identification strategy of the instrumental variable method and introduced the number of fixed-line phones in each province in 1984 as the instrumental variable and the core explanatory variable. Its validity was based on theoretical logic and empirical evidence in the dual dimensions of correlation and exogeneity. In terms of correlation, the spatial distribution differences of fixed-line telephones, as pre-industrial infrastructure for information transmission, profoundly reflected the initial accumulation state of regional technological endowments during the planned economy period. This historical accumulation continuously shaped the spatial pattern of contemporary AI innovation activities through the technical talent reserve mechanism, the path of information sensitivity cultivation, and the process of institutional adaptability evolution. This satisfied the strong correlation condition between instrumental variables and endogenous variables.

At the exogeneity level, the core guaranteed that the instrumental variable satisfied the exclusivity constraint from dual mechanisms: First, historical isolation. The scale of fixed-line telephone deployment was rigidly determined by the national telecommunications investment plan in the 1980s. Its value remained unchanged over the sample period and predated the AI technology revolution (the sample began in 2000) and the industrial chain modernization policy intervention cycle, fundamentally avoiding reverse causality with current economic variables. Second, technological generational break. There was an essential generational gap between the wired transmission technology paradigm of the analog communication era and contemporary digital technologies (such as cloud computing and deep learning), and instrumental variables could indirectly influence only current industrial chain modernization through long-term paths that shape regional technological cognitive endowments. This transmission channel was captured by the provincial fixed effect (absorbing genetic factors that do not change over time) and the time fixed effect (controlling the national trend of technological progress), ensuring to some extent that the residual term was orthogonal to the instrumental variable.

The number of fixed-line telephones was the sum of local and rural telephones in each province. This data was missing for Chongqing, and it was calculated using the data for 1985, 1986, and 1987. The data for Sichuan Province was obtained by subtracting the data of Chongqing from the data of Sichuan Province in the China Statistical Yearbook.

3.2.5. Control variables and mechanism variables

Table 2. Indicator measurements.

Metric Names	Measurement methods
Control variables	
FS (Financial support)	Local fiscal general budget expenditure (billion yuan)/ regional GDP (billion yuan)
CF (Levels of capital flows)	Internal expenditure on research and development (R&D) (ten thousand yuan) / 10,000 / regional GDP (billion yuan)*100
SC (Level of social consumption)	Total retail sales of consumer goods/regional GDP
IPP (Intellectual property protection strength)	Technology market transaction volume /GDP
OPEN (Intensity of openness to the outside world)	(Total volume of goods imports and exports * USD/CNY exchange rate)/ regional GDP
ED (Economic development level)	Take the logarithm of per capita GDP for processing
Mediating variables	
IND (Industrialization level)	Industrial value added/Gross regional product
Moderating variables	
HC (Human capital level)	Number of students enrolled in higher education institutions/total population
EP (Enterprise productivity)	Current assets/total assets
IS (Industrial structure level)	Tertiary industry value added/secondary industry value added
NOP (New Quality Productivity Government Attention)	In the government report, 61 high-frequency words related to new quality productivity were identified, including but not limited to the sum of word frequencies such as “quantum”, “data”, “high efficiency”, “technological innovation”, “low loss”, etc. The final data was logarithmic plus 1

3.3. Model settings

① Benchmark regression model:

$$ICM_{it} = \alpha + \beta_0 AI_{it} + \beta_1 Controls_{it} + \gamma_i + \delta_t + \varepsilon_{it}$$

② Intermediary mechanism test model:

$$IND_{it} = \alpha + \beta_0 AI_{it} + \beta_1 Controls_{it} + \gamma_i + \delta_t + \varepsilon_{it}$$

$$ICM_{it} = \alpha + \beta_0 AI_{it} + \beta_2 IND_{it} + \beta_1 Controls_{it} + \gamma_i + \delta_t + \varepsilon_{it}$$

In the methodological selection of the mediation mechanism test in this study, the classical three-step test procedure was strictly followed to identify the conduction path of the mediating variable through a progressive regression equation system, aiming to enhance the rigor and structural transparency of causal chain inference. The method requires sequential validation: The total effect of the core explanatory variable on the dependent variable, the significant effect on the mediating variable, and the direct effect of the explanatory variable on the dependent variable after controlling the mediating variable. The partial/complete mediating effect is determined based on the product term and the total effect decomposition results. The programmatic framework can effectively avoid the mechanism ambiguity that may result from the modern minimalist method. It is particularly suitable for fine-tuning potential transmission paths in theory-led studies.

③ Moderating effect test model:

$$ICM_{it} = \alpha + \beta_0 AI_{it} + \beta_3 W_{it} + \beta_4 (AI_{it} \times W_{it}) + \beta_1 Controls_{it} + \gamma_i + \delta_t + \varepsilon_{it}$$

In the model, the subscripts i and t represent the province and year, respectively; ICM represents the level of modernization of the industrial chain; AI represents the level of technological innovation in AI; Controls represents the set of control variables; W represents the moderating variable; γ_i represents the provincial fixed effect; δ_t represents the time fixed effect; and ε_{it} represents the random disturbance term.

④ Basic threshold effect test model:

Suppose there exists a single threshold value γ

$$ICM_{it} = \beta_1 AI_{it} \cdot I(HC_{it} \leq \gamma) + \beta_2 AI_{it} \cdot I(\mathrm{HC}_{it} > \gamma) + \sum_{k=1}^{6} \theta_k K_{kit} + \gamma_i + \delta_t + \varepsilon_{it}$$

where I(·) is the characteristic function (1 if the condition is met, 0 otherwise).

4. Empirical analysis

4.1. Descriptive statistics

Table 3. Descriptive statistics.

Variable	Obs	Mean	Std. Dev.	Min	Max
Y3: Level of industrial chain modernization (substitution variable)	744	0.135	0.091	0.023	0.547
ICM: Modernization level of the industrial chain	744	0.16	0.093	0.019	0.536
AI: Level of innovation in artificial intelligence	744	9.109	2.248	2.303	13.718
FS: Financial support	744	0.246	0.183	0.069	1.354
CF: Level of capital flows	744	0.002	0.001	0	0.005
SC: Level of social consumption	744	0.374	0.065	0.18	0.61
IPP: Strength of Intellectual property protection	744	0.014	0.026	0	0.195
OPEN: Intensity of openness to the outside world	744	0.295	0.349	0.008	1.711
ED: Level of economic development	744	9.188	0.519	7.887	10.807
HC: Level of human capital	744	0.114	0.08	0.008	0.505
EP: Productivity of the enterprise	744	0.098	0.028	0.05	0.26
IS: Industrial structure level	744	2.31	0.159	1.821	2.846
IND: Level of industrialization	744	0.343	0.097	0.07	0.574
NOP: New Quality Productivity Government Attention	744	3.502	0.545	0.693	4.963

FS (Financial support), CF (Levels of capital flows), SC (Level of social consumption), IPP(Intellectual property protection strength), OPEN (Intensity of openness to the outside world), ED (Economic development level), Mediating variables, IND (Industrialization level), Moderating variables, HC (Human capital level), EP (Enterprise productivity), IS (Industrial structure level), NOP (New Quality Productivity Government Attention)

Table 3 shows, based on 744 observed samples, that the mean value of the alternative indicator industrial chain modernization level (Y3) was 0.135 (standard deviation 0.091, extreme range [0.023,0.547]), and the mean value of the explained variable industrial chain modernization level (ICM) was 0.160 (0.093, [0.019,0.536]). The mean value of the core explanatory variable, AI innovation level (AI), was 9.109 (2.248, [2.303,13.718]). In the control variable group, the mean financial support (FS) was 0.246 (0.183, [0.069,1.354]), the mean capital flow (CF) was 0.002 (0.001, [0,0.005]), and the mean social consumption (SC) was 0.374 (0.065, [0.180,0.610]). The mean intellectual property protection intensity (IPP) was 0.014 (0.026, [0,0.195]), the mean openness intensity (OPEN) was 0.295 (0.349, [0.008,1.711]), and the mean economic development level (ED) was 9.188 (0.519) [7.887,10.807]). In the mechanism variable group, the mean human capital level (HC) was 0.114 (0.080, [0.008,0.505]), the mean enterprise productivity (EP) was 0.098 (0.028, [0.050,0.260]), and the mean industrial structure level (IS) was 2.310 (0.159, [1.821,2.846]). The mean of industrialization level (IND) was 0.343 (0.097, [0.070,0.574]), and the mean of government attention to new quality productivity (NOP) was 3.502 (0.545, [0.693,4.963]). The standard deviations of each variable indicated a reasonable degree of sample dispersion.

4.2. Benchmark regression and the mediating mechanism test

Table 4 presents the analysis results of four sets of multiple linear regression models for the modernization level (ICM) and industrialization level (IND) of the industrial chain (columns (1) to (4)). We systematically examined the mechanism by which AI technology innovation (AI) affected the level of industrial chain modernization (ICM) through four sets of regression models. Hypothesis 1 (direct effect) was validated: Model 2 showed a significant positive impact of AI on ICM under controlled variables such as financial support (FS) and RD capital flows (CF). When Model 4 further introduced the level of industrialization (IND), the direct impact of AI weakened but remained highly significant, indicating that AI technology has a robust and independent promoting effect on the modernization of the industrial chain. The chain of evidence for Hypothesis 2 (mediating path) is presented: First, model 3 confirmed that AI significantly enhances the level of industrialization, establishing the transmission basis of "AI → industrialization"; second, in Model 4, IND showed a significant positive effect on ICM, establishing the contribution path of "industrialization → modernization of the industrial chain". The key point is that compared with Model 2 without IND control, the absolute value of the AI coefficient in Model 4 decreased by 10.5% (0.019→0.017), and the significance of IND met the criteria for mediating effect determination, demonstrating that industrialization level plays a partial mediating role between AI technology and industrial chain modernization. This means that AI technology directly drives the upgrading of the industrial chain and indirectly reinforces this process by enhancing the level of industrialization. Thus, Hypothesis 2 is validated.

Table 4. Benchmark Regression and the mediating mechanism test.

	(1)	(2)	(3)	(4)
	The modernization level of the ICM industrial chain	Modernization level of the ICM industrial chain	IND industrialization level	Modernization level of the ICM industrial chain
AI level of artificial intelligence		0.019 * * *	0.021 * * *	0.017 * * *
		(5.236)	(5.829)	(4.503)
FS financial support	0.000	0.016	0.037	0.012
	(0.009)	(0.667)	(1.558)	(0.496)
CFRD Capital flows	19.633**	11.989 *	−0.913	12.091 *
	(2.949)	(1.791)	(−0.136)	(1.816)
SC Social consumption level	0.080**	0.060 * *	0.328 * * *	0.096 * * *
	(2.729)	(2.052)	(−11.195)	(3.047)
The strength of IPP intellectual property protection	0.347**	0.405 * * *	0.504 * * *	0.461 * * *
	(3.109)	(3.676)	(−4.559)	(4.143)
OPEN: Degree of openness to the outside world	−0.110***	0.122 * * *	0.017	0.124 * * *
	(−10.311)	(−11.362)	(1.550)	(−11.577)
ED economic development level	0.008	−0.004	0.182 * * *	0.024 *
	(0.630)	(−0.316)	(14.517)	(−1.696)
IND industrialization level				0.111 * * *
				(2.921)
Time province fixed effect	YES	YES	YES	YES
N		744	744	744
R^2		0.905	0.912	0.906

FS(Financial support)、CF(Levels of capital flows)、SC(Level of social consumption)、IPP(Intellectual property protection strength)、OPEN (Intensity of openness to the outside world)、ED (Economic development level)、Mediating variables、IND (Industrialization level)、Moderating variables、HC (Human capital level)、EP (Enterprise productivity)、IS (Industrial structure level)、NOP (New Quality Productivity Government Attention)
***$p < 0.01$, **$p < 0.05$, *$p < 0.10$

4.3. Test of the moderating effect mechanism

4.3.1. Moderating effects test

In moderating effects, to alleviate the problem of multicollinearity, reconstruct the interpretability of the major effect coefficients, and simplify the analysis of moderating effects, the independent variable and moderating variable data were centralized. First, we calculated the sample arithmetic mean and then subtracted the sample arithmetic mean from the original variable observations.

Based on the empirical results of the moderating effects model, Table 5 shows that the level of AI innovation has always had a significant positive fundamental promoting effect on the modernization of the industrial chain. The multi-dimensional moderation mechanism test revealed systemic moderation patterns: Column 2, Human capital level, shows the strongest positive enhancement effect. For every 1 unit increase in HC, the marginal effect of AI increased by 0.090. Column 4, the intensity of the moderating effect of industrial structure elevation, IS, shows the second strongest positive enhancement effect, with the marginal effect of AI increasing by 0.064 for every 1 unit increase in IS. Column 5, new quality productivity level, shows that, although the moderating magnitude was relatively small, it still significantly enhances the marginal effect. For every 1 unit increase in NOP, the marginal effect of AI increased by 0.012. In sharp contrast, in column 2, there is a significant negative inhibitory effect on enterprise productivity. For every 1 unit increase in EP, the marginal effect of AI decreased by 0.175, resulting in a weakening of the promoting effect of AI. This "three positive and one negative" moderating pattern was supported by a significant leap in the model's explanatory power. After incorporating the moderating variables, the adjusted R^2 increased by 0.252 to 0.282 units (final value 0.646 to 0.676) compared to the baseline model (0.394), and the standard deviation of the main effect of AI fluctuated by only ±0.008. This validates Hypothesis 3.

Table 5. Moderating effects test.

	(1)	(2)	(3)	(4)	(5)
Variable names	Benchmark model	HC regulation model	EP modulated model	IS modulated model	NOP modulated model
Core variables					
c_AI	-	0.028 * * * (0.003)	0.033 * * * (0.002)	0.029 * * * (0.002)	0.025 * * * (0.002)
Adjust variables					
c_HC	-	0.552 * * * (0.069)	-	-	-
c_EP	-	-	0.251 * * (0.101)	-	-
c_IS	-	-	-	0.149 * * * (0.025)	-
c_NOP	-	-	-	-	0.029 * * * (0.004)
Interaction items					
cAI*cHC	-	0.090 * * * (0.018)	-	-	-
cAI*cEP	-	-	0.175 * * * (0.040)	-	-
cAI*cIS	-	-	-	0.064 * * * (0.007)	-
cAI*cNOP	-	-	-	-	0.012 * * * (0.002)
Control variables	YES	YES	YES	YES	YES
Time province fixed effect	YES	YES	YES	YES	YES
N	744	744	744	744	744
R^2	0.394	0.661	0.646	0.676	0.656

FS (Financial support), CF (Levels of capital flows), SC (Level of social consumption), IPP(Intellectual property protection strength), OPEN (Intensity of openness to the outside world), ED (Economic development level), Mediating variables, IND (Industrialization level), Moderating variables, HC (Human capital level), EP (Enterprise productivity), IS (Industrial structure level), NOP (New Quality Productivity Government Attention)

***p < 0.01, **p < 0.05, *p < 0.10

4.3.2. Moderating effects map

Moderating effects of human capital levels (HC):

Figure 5 shows that the two regression lines diverge, with the high adjustment horizontal line (orange solid line) located above and having a greater slope. The statistical model revealed a positive moderating effect, indicating that as the proportion of the population with higher education in the region increased, the promoting effect of AI technology on the modernization of the industrial chain was significantly enhanced. This agreed with the expectations of human capital theory: Higher education has cultivated a higher-quality workforce, enhanced organizations' ability to absorb and transform AI technology, and enabled the technological dividend to be more fully transformed into the driving force for industrial upgrading.

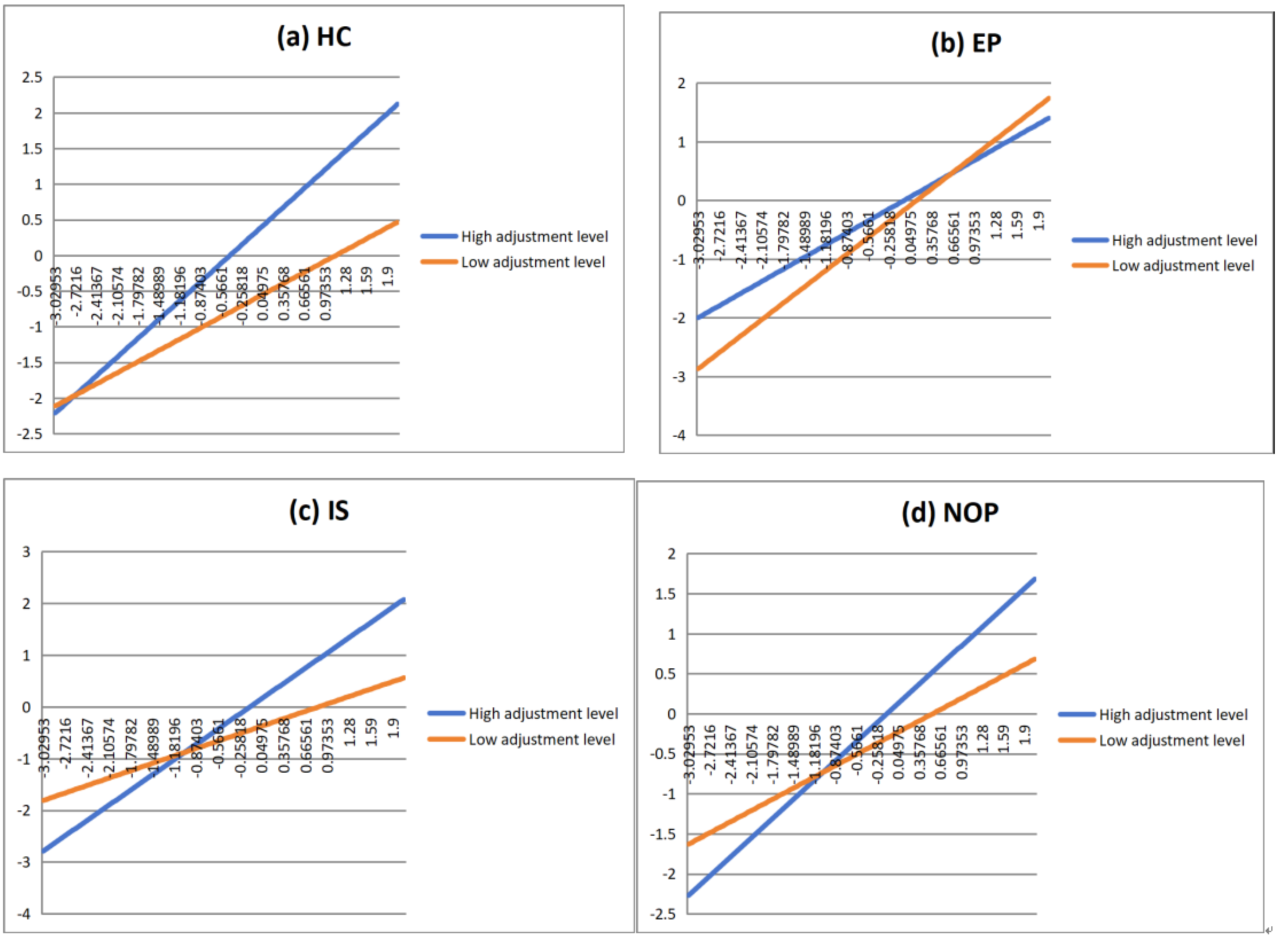

Figure 5. Moderating effects map.

The moderating effect of enterprise productivity (EP):

In Figure 5, the two regression lines show a unique convergence pattern, with the low moderating horizontal line (the blue dotted line) having a greater slope. The significant negative moderating effect (coefficient −0.1185) revealed the reverse moderating mechanism: AI showed a stronger marginal improvement effect in inefficient enterprises. This supported the "technology catch-up hypothesis" that efficiency lowlands can quickly make up for management shortcomings and achieve leapfrog development through the application of AI technology. Moreover, high-efficiency enterprises, being close to the boundaries of production possibilities, have relatively limited room for technological improvement.

The moderating effect of the industrial structure level (IS):

The steep rise of the high adjustment level showed the strongest positive adjustment effect, indicating that advanced industrial structure and AI formed a synergistic amplification effect, confirming the "structure-technology fit theory" that high-end manufacturing and modern service systems provide more suitable scenario interfaces and element support for AI applications, significantly enhancing the depth of technology penetration.

Moderating effect of the New Quality Productivity Index (NOP):

The double lines maintained a steady parallel upward trend, but the high moderating level moved upward overall. The moderating positive moderating effect showed the systemic value of the innovation ecosystem, in line with the "innovation ecosystem" framework; the coordinated aggregation of regional innovation elements reduces the uncertainty of AI technology application and enhances the efficiency of technology transfer through knowledge spillover and innovation network spillover.

The four sets of moderating effects together revealed the complex mechanism of technology-institutional co-evolution: The empowering effect of AI on the modernization of the industrial chain is not only dependent on the technology, but is more deeply embedded in the institutional matrix of regional education structure, production organization mode, industrial ecology, and innovation environment (Zhou & Chu, 2021). Policy design needs to break away from the perspective of mere technological input and build a systematic empowerment framework of "AI technology + institutional adaptation". The above moderating effect map validates Hypothesis 3.

4.4. A robustness test

In this paper, we conducted robustness tests using multiple methods. The major methods were instrumental variable, tailing, replacement of the explained variable (originally, the entropy method was used for the explained variable, but the principal component analysis method was used), reduction of control variables, and exclusion of four municipalities directly under the Central Government. The experimental conclusions are as follows:

1. Instrumental variable method (Columns 2–3): Using the number of fixed-line telephones in 1984 as the instrumental variable, $F = 148.23 > 10$ in the first stage (weak instrumental variable test passed), 2SLS estimated the AI coefficient significantly positive ($\beta = 0.0163$, $p < 0.01$), 43% lower than OLS (0.0287) but unchanged in direction, alleviating endogenous bias.

2. Taping (Column 4): After taping the dependent variable by 1%, the AI coefficient remained at 0.015* ($t = 4.341$, $p < 0.01$), and the IPP intellectual property protection (0.356*) was consistent with the OPEN (−0.107) symbol.

3. Replacement of the explained variable (Column 5): With the alternative indicator Y3, the AI coefficient remained significant (0.016, $t = 5.174$, $p < 0.01$), with an amplitude difference of less than 6.7% from the baseline model.

4. Reduction of control variables (Column 6): After retaining only the core variables, the AI coefficient rose to 0.020* ($t = 5.806$, $p < 0.01$), while SC (0.066*) and IPP (0.438*) remained significant.

5. Exclusion of Municipalities (Column 7): Excluding samples from Beijing, Tianjin, Shanghai and Chongqing ($N = 648$), the AI coefficient remained stable at 0.019* ($t = 5.566$, $p < 0.01$), and the OPEN negative effect was enhanced (−0.184*).

Table 6. Robustness tests.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Variables	OLS	Phase 1	2SLS	Tail shortening treatment	Replace the dependent variable	Reduce control variables	Exclude municipalities
AI level of artificial intelligence	0.0287 * * *	-	0.0163 * * *	0.015 * * *	0.016 * * *	0.020 * * *	0.019 * * *
	(0.0018)		(0.0049)	(4.341)	(5.174)	(5.806)	(5.566)
Control variables	is	is	is	is	is	no	is
IV (Number of landlines in 1984)	-	0.0621 * * *	-	-	-	-	-
		(0.0084)					
Time province fixed effect	YES	YES	YES	YES	YES	YES	YES
N	744	744	744	744	744	744	648
R^2	0.611	0.598	0.571	0.911	0.935	0.904	0.920
The first stage F-statistic	-	148.23	-	-	-	-	-

FS (Financial support), CF (Levels of capital flows), SC (Level of social consumption), IPP(Intellectual property protection strength), OPEN (Intensity of openness to the outside world), ED (Economic development level), Mediating variables, IND (Industrialization level), Moderating variables, HC (Human capital level), EP (Enterprise productivity), IS (Industrial structure level), NOP (New Quality Productivity Government Attention)

***p < 0.01, **p < 0.05, *p < 0.10

Table 6 shows that we verified the reliability of the conclusion that the level of innovation in AI promoted the alternate with industrial upgrading (ICM) through a five-level robustness test system: First, the instrumental variable method used the number of fixed-line telephones in 1984 as an exogenous instrumental variable. The first-stage regression instrumental variable coefficient was significant (0.0621*, $p < 0.01$) and the Cragg-Donald F statistic = 148.23 > 10, effectively alleviating endogenous bias. In 2SLS estimates, the AI coefficient remained significantly positive ($\beta = 0.0163$*, $p < 0.01$), although it decreased by 43.2% compared to OLS (0.0287), but the direction remained the same. Second, the AI coefficient remained at 0.015 ($p < 0.01$) after tailing (1% two-sided), and the core control variable sign was consistent. Third, in the replacement of the dependent variable (Y3 replacing ICM), the AI coefficient remained stable at 0.016 ($p < 0.01$). Fourth, after reducing the control variable, the AI coefficient rose to 0.020 ($p < 0.01$), confirming that the results were not dependent on redundant variables. Finally, after excluding the municipality sample (N = 648), the AI coefficient remained significant 0.019 ($p < 0.01$), and the effects of key variables such as intellectual property protection (IPP: 0.612) and openness (OPEN: −0.184) were enhanced. In all tests, the AI coefficient was positive and significant with at least 5% (range 0.015 to 0.020), and the control variable showed a stable pattern: Intellectual property protection was always positively significant ($\beta > 0.356$), and openness was consistently negatively significant ($\beta < -0.049$). In summary, the core conclusion that AI drives the modernization of the industrial chain has strong robustness across methods and samples through rigorous tests such as endogeneity correction, outlier control, measurement error correction, and model simplification.

4.5. Analysis of heterogeneity

To further examine the differential impact of the core variables on different groups or regions, we grouped the eastern, central, and western regions, using the median data of enterprise production efficiency, industrial structure level, and attention to new quality productivity as the basis for grouping, and then divided them into high and low groups in sequence.

Heterogeneity tests based on group regression in this study showed significant structural differences in the promoting effect of AI innovation levels on the alternate with industrial upgrading (Table 7). At the regional level, the marginal effects of AI in Columns 1–3 decreased in a gradient from east to west: The eastern region was the strongest, followed by the central region, and the western region was the weakest, revealing a positive correlation between the release of technological dividends and regional development levels. At the enterprise capability level, AI was only significant in the low productivity group, but not statistically significant in the high productivity group, indicating that technology empowerment mainly benefited the transformation of low-efficiency enterprises. At the innovation ecosystem level, Columns 6–9 show that the high-structurally advanced group and the high-quality productivity group benefited significantly, while the low-level group did not benefit significantly, confirming that technology absorption requires the coordinated support of industrial base and innovation elements.

Table 7. Heterogeneity analysis.

Variables	Regional grouping			Enterprise productivity		Industrial structure		New quality productivity	
	Middle Part (1)	West (2)	East (3)	High EP (4)	Low EP (5)	High IS (6	Low IS (7)	High NOP (8)	Low NOP (9)
AI artificial intelligence level	0.033 * * *	0.017 * * *	0.040 * * *	0.005	0.022 * * *	0.013 * *	0.008	0.037 * * *	0.002
	(0.003)	(0.002)	(0.002)	(0.754)	(4.441)	(2.286)	(1.453)	(6.555)	(0.450)
Control variables	YES	YES	YES	YES	YES	YES	YES	YES	YES
Time province fixed effect	YES	YES	YES	YES	YES	YES	YES	YES	YES
N	192	288	264	367	376	372	368	370	371
R^2	0.705	0.571	0.688	0.899	0.938	0.927	0.806	0.932	0.871

FS (Financial support), CF (Levels of capital flows), SC (Level of social consumption), IPP(Intellectual property protection strength), OPEN (Intensity of openness to the outside world), ED (Economic development level), Mediating variables, IND (Industrialization level), Moderating variables, HC (Human capital level), EP (Enterprise productivity), IS (Industrial structure level), NOP (New Quality Productivity Government Attention)

***p < 0.01, **p < 0.05, *p < 0.10

4.6. Further analysis

4.6.1. Phenomenon characteristics (inconsistencies)

Table 8 shows that in a low human capital environment, the development of AI alone had a significant positive driving effect on the modernization of the industrial chain. In a high human capital environment, although the effect of AI alone was also positive, it was not statistically significant. Most crucially, the interaction effect analysis (Column 3) showed that the boosting effect of AI on the modernization of the industrial chain was significantly enhanced with the increase in the level of human capital (the interaction coefficient was positive and highly significant). This means that human capital is an important condition or catalyst for leveraging the effectiveness of AI in modernizing industrial chains. Thus, high human capital can more effectively "unlock" or amplify the positive impact of AI. This shows inconsistency in the conclusions.

Table 8. Human capital moderates the impact of AI on industrial chain modernization.

	High HC levels of human capital	Low HC human capital levels	
Variables	The modernization level of the ICM industrial chain	Modernization level of the ICM industrial chain	Modernization level of the ICM industrial chain
AI level of artificial intelligence	0.006	0.013 * *	
	(1.025)	(2.567)	
cAI*cHC			0.090 * * *
			(0.018)
N	372	372	744
R^2	0.940	0.838	0.394

FS (Financial support), CF (Levels of capital flows), SC (Level of social consumption), IPP(Intellectual property protection strength), OPEN (Intensity of openness to the outside world), ED (Economic development level), Mediating variables, IND (Industrialization level), Moderating variables, HC (Human capital level), EP (Enterprise productivity), IS (Industrial structure level), NOP (New Quality Productivity Government Attention)

***p < 0.01, **p < 0.05, *p < 0.10

4.6.2. Analyzing the conclusion (such as the cause of the anomaly)

Based on the threshold effect characteristics presented in the table, the underlying mechanism is that when the level of human capital is below the threshold, AI mainly drives the modernization of the industrial chain by replacing labor and optimizing basic processes, at which point human capital needs only meet the basic adaptability of technical operations (Ge et al., 2024). When human capital crosses the threshold, it forms a knowledge collaborative innovation system with AI, triggering a multiplier effect of technology integration, but the marginal contribution of a single AI is masked by the dominant role of high-level human capital.

Table 9. Results of the threshold effect test

Model	RSS	F-statistic	P-value	Crit10	Crit5	Crit1	Threshold estimation	95%confidence interval
Single threshold	0.589	26.71	0.070	23.75	28.03	44.08	0.0549	[0.0338, 0.0585]

Note: Bootstrap times = 300; Crit# indicates the critical value for the #% significance level.

Tables 9 and 10 show the presence of the threshold effect: Through 300 Bootstrap sampling tests, the single threshold effect was significant at the 10% level (F = 26.71, P = 0.070), but not through the 5% significance test (F < 28.03). The estimated threshold was 0.0549, with a 95% confidence interval of [0.0338,0.0585], indicating a weak threshold effect in the model. The human capital level had a nonlinear influence mechanism. When the human capital level was below the threshold of 0.0549, the ICM increased by 0.0191 for every 1-unit increase ($P < 0.01$), and when the human capital level was above 0.0549, the influence intensity increased by 51.3% to 0.0289 ($P < 0.01$). Under certain conditions, AI innovation optimized the modernization of the industrial chain, a finding that provides a theoretical basis and practical guidance for the precise implementation of regional differentiated AI policies.

Table 10. Threshold regression estimates.

Variables	Coefficients	Standard error	t value	P value	Significance
Core explanatory variables					
c_AI (≤0.0549)	0.0191	0.0036	5.36	0.000	***
c_AI (> 0.0549)	0.0289	0.0041	7.10	0.000	***
Sample size	744				
Number of groups	31				
R^2 within the group	0.888				
Individual effects test	F = 15.32 * * *	(P = 0.000)			
FS (Financial support), CF (Levels of capital flows), SC (Level of social consumption), IPP(Intellectual property protection strength), OPEN (Intensity of openness to the outside world), ED (Economic development level), Mediating variables, IND (Industrialization level), Moderating variables, HC (Human capital level), EP (Enterprise productivity), IS (Industrial structure level), NOP (New Quality Productivity Government Attention)					

***p < 0.01, **p < 0.05, *p < 0.10

5. Conclusions and policy implications

Based on a systematic test of provincial panel data in China from 2000 to 2023, this study reveals the complex mechanism and key boundary conditions of the modernization of the industrial chain driven by AI innovation, providing an empirical model from the world's largest developing country to understand the universal laws of industrial transformation in the intelligent era. The core conclusion indicates that the empowerment of AI to the modernization of the industrial chain is not a simple linear process, but rather a conditional, non-linear, and systematic evolution deeply embedded in the regional institutional environment and factor endowments. The empirical path shows that the upgrading of industrialization levels constitutes the core transmission hub for technological penetration. AI, by reshaping the production function and industrial organization paradigm, promotes the leap of the industrial foundation from mechanization to intelligence, and subsequently triggers the modernization transformation of the industrial chain in three dimensions: basic capabilities, organizational forms, and global value chain positions. Particularly crucial is that the release of technological efficiency is strictly constrained by the threshold of human capital level; when human capital crosses a critical point (the empirically measured threshold value is 0.0549), the marginal contribution of AI significantly increases by 51.3%, which quantitatively confirms the core position of the "technology-skill complementarity" theory in the diffusion of intelligent technology. This also provides a key threshold basis for global discussions on how to bridge the "intelligence gap".

Furthermore, we found that the driving efficiency of AI is regulated by a set of systematic factors with different directions. The advancement of human capital, the government's cultivation of "new quality productivity", and the upgrading of industrial structure form a powerful positive gain cycle, jointly amplifying the technological dividend. However, a discovery with profound policy cautionary significance is that the static production efficiency advantage of enterprises based on traditional paradigms has instead had a significant inhibitory effect on the application and iteration of AI. This reveals the possible "efficiency trap" during the period of technological paradigm transformation; that is, the excessive pursuit of the refinement of the existing production model. This may solidify organizational rigidity and inhibit the exploration and absorption of disruptive technologies. Moreover, this contradiction highlights the essential challenge of AI driving industrial modernization: It is not merely a matter of technology introduction, but also a profound issue of institutional adaptation and organizational transformation.

Based on this, our findings have clear policy implications for the world, especially for emerging economies facing similar transformation challenges (Dimitriadis et al., 2024b). They strongly argue that formulating a strategy for the integration of AI and industries must go beyond the logic of simple technology subsidies and equipment investment and shift toward building a three-in-one policy framework of "human capital foundation - institutional incentive coordination - regional path differentiation". Policy makers need to prioritize investment in education and skills training to cross the human capital threshold while reforming the enterprise evaluation system to encourage organizational change toward intelligence and designing differentiated promotion paths based on the endowments and industrial foundations of different regions. The main limitation of this study lies in its analysis, focusing on the provincial macro level in China. In future research, researchers can further delve into the micro mechanisms of enterprises and conduct cross-national comparative analyses to test the universality and variability of the above-mentioned threshold rules and regulatory mechanisms in different institutional and cultural contexts, thereby contributing academic wisdom to the construction of a more inclusive and resilient global intelligent industry ecosystem.

6. Ethics statement and data availability

This study relies exclusively on publicly available secondary data obtained from official statistical yearbooks and government databases. No human participants, personal data, or sensitive information were involved. Therefore, ethical approval was not required. The processed dataset can be made available by the authors upon reasonable request.

Author contributions

Qingsheng Zhu: Conceptualization, Methodology.

Kexu Zhang: Data curation, Formal analysis, Software, Visualization, Writing–original draft, Writing–review & editing (during revision), Correspondence.

Use of AI tools declaration

The authors declare they have not used Artificial Intelligence (AI) tools in the creation of this article.

Conflict of interest

The authors declare no conflict of interest.

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