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*Research article*

# How does artificial intelligence promote industrial upgrading? Evidence from China's practice of building the modern industrial system

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**Abstract:** Whether productivity gains from artificial intelligence (AI) translate into broader industrial upgrading remains unclear. Using panel data for 285 Chinese cities from 2011 to 2023, we examine this question in the context of China's modern industrial system, which emphasizes the coordinated development of the real economy, technological innovation, modern finance, and human resources. We construct a city-level index of modern industrial system development and measure local AI development using AI patent applications. An additional 1,000 AI patent applications is estimated to raise the MIS index by 0.367 points, equivalent to approximately 3.7% of its sample mean. The estimate remains stable across a range of robustness and endogeneity checks. Channel evidence suggests that AI facilitates technical-efficiency catch-up, improves the alignment of sectoral output and employment, and expands producer-service capacity. The estimated effect is stronger in less-developed regions and lower-tier cities and varies nonlinearly with the local industrial base, digital infrastructure, and governance intensity. Overall, the findings suggest that the broader industrial effects of AI depend on its diffusion across sectors and the complementary local conditions that support its productive use.

**Keywords:** artificial intelligence; industrial upgrading; modern industrial system; threshold effects

**JEL Codes:** O33, O14, R11, C33

## 1. Introduction

Artificial intelligence (AI) is increasingly viewed as a general-purpose technology with the potential to transform production, innovation, and firm organization. Recent evidence shows that AI can improve worker productivity, accelerate product innovation, and support firm growth (Noy and Zhang, 2023; Babina et al., 2024). Yet the aggregate implications of these gains remain uncertain. Productivity improvements within individual tasks or adopting firms do not necessarily translate into broad-based industrial upgrading. Understanding this transition from localized productivity gains to system-level industrial change is therefore central to evaluating the economic consequences of AI.

China provides a useful setting in which to examine this question. Industrial upgrading has long been a central component of the country's development strategy, but the current policy framework places increasing emphasis on the coordinated modernization of the broader industrial system. The concept of the modern industrial system refers to an industrial structure centered on a productive real economy and supported by technological innovation, modern finance, and human resources. *China's 15th Five-Year Plan (2026–2030)*[1] identifies the development of a modern industrial system and the strengthening of the real economy as major strategic priorities, while the *2026 Government Work Report*[2] links this agenda to industrial upgrading and the development of new quality productive forces. Rather than focusing solely on shifts in output from agriculture to manufacturing or from manufacturing to services, this framework emphasizes the joint development of productive capacity, innovation, factor allocation, and supporting institutions.

These policy priorities respond to persistent constraints on China's industrial upgrading. Productivity and technological capabilities remain uneven across regions and industries, while bottlenecks in core technologies and weak alignment between financial resources and productive investment may limit the conversion of innovation into sustained industrial development (Hang et al., 2024; Leng et al., 2023; Tan et al., 2025; Tian, 2025). AI may alleviate some of these constraints by improving prediction, information processing, automation, and organizational decision-making (Furman and Seamans, 2019; Agrawal et al., 2019). Its broader industrial effects, however, depend on the complementary investment and organizational adjustments required to translate technological advances into productive applications (Brynjolfsson et al., 2021).

Existing research provides limited evidence on how localized productivity gains from AI translate into broader industrial upgrading. Studies of industrial robots and automation document effects on productivity, employment, and firm organization, but these measures mainly capture embodied automation in manufacturing (Graetz and Michaels, 2018; Acemoglu and Restrepo, 2020; Koch et al., 2021). Research on digitalization similarly finds that digital development promotes industrial upgrading through innovation, infrastructure, and improved resource allocation, although

[1] The English webpage on the 15th Five-Year Plan is available at: https://english.www.gov.cn/2026special/2026npcandcpcc/6979af4fc6d00ca5f9a08cd6.

[2] See The State Council of the People's Republic of China, "Report on the Work of the Government 2026," available at: https://english.www.gov.cn/news/202603/13/content_WS69b4b130c6d00ca5f9a09dfc.html.

broad digital-economy measures do not isolate the contribution of AI (Xiong et al., 2023; Gong et al., 2023; Jin et al., 2024). More direct task- and firm-level evidence shows that AI can raise worker productivity and support firm growth and product innovation (Noy and Zhang, 2023; Czarnitzki et al., 2023; Babina et al., 2024). Recent provincial evidence from China further suggests that AI innovation promotes industrial upgrading and industrial-chain modernization, with its effects varying across institutional and factor conditions (Zhu and Zhang, 2026). Nevertheless, existing studies generally focus on productivity, conventional industrial-structure measures, or industrial-chain modernization. Whether local AI development contributes to the coordinated modernization of production, innovation, finance, and human resources at the city level remains less well understood.

Our paper examines whether and how local AI development contributes to broader industrial upgrading. We construct a city-level index of modern industrial system development that captures four dimensions (i.e., the real economy, technological innovation, modern finance, and human resources) and combine it with panel data for 285 Chinese cities from 2011 to 2023. Local AI development is measured by the number of AI patent applications associated with applicants in each city. The city-level setting allows us to exploit substantial variation in AI innovation and industrial development across regions and over time.

Using a two-way fixed-effects specification, we find that AI significantly improves the MIS. The estimate remains stable under alternative instrumental-variable specifications and across a range of robustness checks. Channel evidence suggests that AI supports technical-efficiency catch-up, improves the alignment of sectoral output and employment, and expands producer-service capacity. The estimated effect is stronger in less-developed regions and lower-tier cities and varies nonlinearly with the local industrial base, digital infrastructure, and governance intensity, indicating that the broader industrial impact of AI depends on both catch-up opportunities and complementary local conditions.

Our paper makes three contributions. First, it extends the literature on AI and productivity by examining whether gains associated with AI extend beyond individual workers and firms to the wider local industrial system. Second, it contributes to research on structural transformation by measuring industrial upgrading through the coordinated development of productive activity, innovation, finance, and human resources rather than through sectoral output shares alone. Third, it provides city-level evidence that the industrial effects of AI vary with initial development conditions and complementary industrial, digital, and institutional inputs.

The remainder of the paper is organized as follows. Section 2 discusses the policy background and related literature. Section 3 develops the conceptual framework and research hypotheses. Section 4 describes the data and variable construction. Section 5 presents the main empirical results and channel and heterogeneity analyses. Section 6 reports the threshold estimates, and Section 7 concludes the paper.

## 2. Policy background and literature review

### *2.1. Concept of modern industrial system*

The modern industrial system (MIS) is a policy concept formally articulated in China's national development strategy. It refers to a coordinated industrial system centered on the real economy and supported by technological innovation, modern finance, and human resources. Rather than emphasizing industrial scale alone, the concept highlights the quality, resilience, and coordination of industrial development, including the upgrading of traditional industries, the growth of emerging industries, and stronger linkages among production, innovation, finance, and skills.

The policy meaning of MIS has been progressively clarified in China's national planning documents. The outline of the *14th Five-Year Plan*[3] places the development of a modern industrial system within the broader objectives of strengthening the real economy, accelerating industrial upgrading, fostering strategic emerging industries, and improving the supporting conditions for industrial development. More recent policy documents further connect MIS development with digital transformation, new quality productive forces, and the modernization of industrial and supply chains.

Taken together, these policy documents define MIS as a broad framework for coordinated industrial modernization. Its emphasis is not limited to changes in sectoral composition, but extends to the interaction between productive capacity, technological innovation, financial support, and human resources. This policy framework provides the institutional context for examining how AI may contribute to industrial upgrading in China.

### *2.2. Determinants of industrial modernization*

Empirical research on China increasingly views industrial modernization as the outcome of interacting technological, financial, and institutional conditions rather than simply as a change in sectoral composition. One strand of this literature emphasizes digitalization and infrastructure. Xiong et al. (2023) show that the digital economy facilitates industrial-structure modernization through technological progress and improved factor allocation, although excessive credit expansion may weaken this effect. Gong et al. (2023) similarly find that new infrastructure promotes industrial upgrading by supporting innovation, human-capital accumulation, capital flows, and more efficient resource allocation. Service-sector evidence further shows that new digital infrastructure can raise total factor productivity through technological progress and human-capital accumulation, although its effects differ across regional economic and technological foundations (Hu et al., 2025a). Cross-country evidence likewise points to structural complementarities between digital connectivity and innovation capacity rather than a uniform effect of digitalization (Antohi et al., 2026). These studies suggest that new technologies affect industrial development not only by expanding technology-intensive activities but also by changing the conditions under which productive resources and innovative capabilities are developed and used.

A related strand highlights the importance of finance, innovation capacity, and local economic conditions. Evidence from Ren et al. (2023) and Shen et al. (2024) indicates that digital finance can support industrial upgrading by easing financial constraints and encouraging entrepreneurship and innovation. Policy finance can also facilitate industrial relocation by supporting transformation and upgrading in more-developed regions and reducing operating costs in less-developed regions (Zeng et al., 2025). Xu et al. (2024) further show that the effect of regional technological innovation depends on local marketization and openness. More generally, recent research shows that the informational

[3] The English version of the outline of the 14th Five-Year Plan is available at: https://english.www.gov.cn/w/14thfiveyearplan/.

contribution of modern finance depends on the value of financial data, the capacity to process complex financial information and extract informative signals, and the channels through which those signals are transmitted (Deng et al., 2025; Li et al., 2025b; Liu and Cambria, 2025; Li et al., 2026). Taken together, this literature indicates that technological advances are more likely to generate broader industrial gains when firms can finance adoption; resources can move toward more productive uses; and financial and institutional arrangements facilitate information transmission, innovation, and structural adjustment.

Existing studies, however, generally examine broad digitalization, infrastructure, finance, or technological innovation separately. They also tend to measure industrial upgrading through sectoral composition or related structural indicators. As a result, limited evidence is available on whether AI-specific technological advances contribute to the coordinated development of productive capacity and its supporting systems. The following section therefore turns to the potential effects of AI on MIS development.

### *2.3. AI and MIS: Optimistic and cautious views*

Artificial intelligence is closely related to MIS because it combines the attributes of an emerging industry and a general-purpose technology. As an emerging industry, AI is technologically intensive and has the potential to expand new sectors, generate new products and business models, and strengthen the broader innovation ecosystem. As a general-purpose technology, AI is applicable across a wide range of sectors (Bresnahan and Trajtenberg, 1995; Agrawal et al., 2023). By improving prediction, automation, data processing, and decision-making, AI may reshape production processes, firm organization, research and development (R&D) activities, and resource allocation.

A relatively optimistic strand of research emphasizes the productivity and innovation effects of AI-related technologies. Evidence on automation and industrial robots suggests that such technologies can raise productivity and reshape firm production structures (Graetz and Michaels, 2018; Koch et al., 2021). Recent firm-level studies further show that AI adoption is associated with higher productivity, firm growth, and product innovation (Czarnitzki et al., 2023; Babina et al., 2024). Evidence from China points in a similar direction. Xia et al. (2024) find that industrial intelligence promotes industrial-structure upgrading, industrial synergy, and the transformation of manufacturing and service sectors, while Zhang (2025) shows that AI development contributes to industrial-structure upgrading, with inclusive finance moderating this relationship. Using Chinese provincial data, Zhu and Zhang (2026) further show that AI innovation promotes industrial upgrading and industrial-chain modernization. The evidence therefore points to a potential role for AI in improving efficiency, expanding innovation, strengthening industrial linkages, and accelerating structural upgrading.

A more cautious strand of research stresses that the aggregate effects of AI are conditional rather than automatic. The task-based literature shows that automation may displace labor when new tasks and complementary capabilities do not expand sufficiently (Acemoglu and Restrepo, 2019, 2020). Agrawal et al. (2019) similarly argue that the labor-market implications of AI-based prediction are ambiguous because AI can either complement or substitute for human decision-making. More broadly, Acemoglu (2025) argues that current AI may generate limited macroeconomic gains if its main effect is to automate existing tasks rather than create new productive activities. The productivity J-curve perspective also suggests that the gains from general-purpose technologies may appear only after intangible investment, organizational adjustment, and complementary innovation have taken place (Brynjolfsson et al., 2021).

Taken together, existing studies show that AI can generate efficiency and innovation gains at the task and firm levels, but its system-level implications remain uncertain. Whether these localized gains contribute to MIS development depends on their realization in production, the reallocation of resources across sectors, and the complementary inputs that support their diffusion. The net effect of AI on coordinated industrial modernization therefore remains an empirical question.

## 3. Theoretical analysis and research hypotheses

### *3.1. AI and MIS development*

AI may contribute to MIS development through two complementary economic roles. First, AI is itself a technology-intensive industry. The expansion of AI-related activities creates new products and business models and increases demand for complementary inputs, including computing infrastructure, data services, software, and intelligent equipment. In this way, AI development can broaden the local base of high-technology production and innovation. This argument is consistent with innovation-driven growth theory, which emphasizes the creation of new products and industries through technological change (Aghion and Howitt, 1992), and with firm-level evidence linking AI investment to firm growth and product innovation (Babina et al., 2024).

Second, AI has the characteristics of a general-purpose technology. Its broad applicability allows it to be incorporated into production processes, service activities, and organizational decision-making. By lowering the costs of prediction and information processing and enabling new forms of automation, AI can facilitate process innovation, improve production coordination, and support organizational change across a wide range of existing industries (Bresnahan and Trajtenberg, 1995; Agrawal et al., 2019). Its economic effects are therefore not confined to firms that produce AI technologies but may also extend to firms and sectors that adopt them.

These two roles can reinforce one another. The growth of AI-related industries expands the supply of specialized technologies and inputs, while the diffusion of AI across existing sectors generates demand for these inputs and encourages complementary innovation. Realizing these gains requires investment in intangible capital and adjustments in business organization and production practices (Brynjolfsson et al., 2021). When such complementary changes occur, AI can strengthen both the technological capabilities and the productive performance of the local industrial system. We therefore propose the following hypothesis:

**Hypothesis 1:** AI advances the MIS development.

### *3.2. Multisector transmission mechanisms*

Productivity gains from AI at the task or firm level do not automatically translate into broader industrial upgrading. In a multisector economy, their aggregate effects depend on three interconnected margins: whether productivity gains are realized within sectors, whether labor and capital are reallocated toward more productive uses, and whether intermediate-input linkages propagate those gains across industries. Baqaee and Farhi (2020) show that aggregate productivity reflects both technical and allocative efficiency, while Jones (2011) emphasizes the role of intermediate inputs and production complementarities in transmitting localized productivity changes. Input–output evidence further shows that productivity gains can be redistributed across sectors through forward and backward linkages, regardless of where the initial shock originates (Rognini et al., 2025). Filippucci et al. (2026) further argue that the aggregate effects of AI depend on how heterogeneous productivity gains are distributed and combined across sectors. These margins reinforce one another: improvements in technical efficiency reshape relative sectoral returns and thereby influence factor allocation; producer services reduce the costs of technology adoption and structural adjustment; and broader AI adoption increases demand for specialized service inputs. We use this multisector perspective to organize the mechanisms linking local AI development to MIS development.

The first margin concerns the realization of AI-related productivity gains within existing production activities. Access to AI technologies does not by itself improve productive performance; firms must integrate them with existing capital, knowledge, and organizational practices. By lowering the costs of information processing, operational diagnosis, and experimentation, AI can help producers identify inefficiencies, improve process control, and use available technologies more effectively. Research on technology diffusion shows that productivity convergence depends not only on access to frontier technologies but also on their effective adoption and use (Kumar and Russell, 2002; Comin and Mestieri, 2018). AI may therefore facilitate technical-efficiency catch-up by moving local production closer to the best-practice frontier.

The second margin concerns the allocation of labor and capital across sectors. The productivity gains generated by AI are unlikely to be uniform because industries differ in data intensity, technological compatibility, and their capacity for organizational adjustment. Improvements in technical efficiency therefore alter relative productivity and returns across sectors, and their aggregate contribution depends on whether factors move toward more productive uses. By improving demand forecasting, investment assessment, and the matching of inputs with production opportunities, AI can reduce information frictions that sustain inefficient allocations (David et al., 2016). Because cross-sector reallocation is an important source of aggregate productivity growth during structural transformation (McMillan et al., 2014), AI may contribute to MIS development by reducing mismatches between sectoral output and employment.

The third margin operates through producer services and intersectoral production linkages. The productive use of AI relies on complementary inputs, such as software, data processing, R&D, finance, logistics, and specialized business services. These services help firms adopt, adapt, and commercialize AI technologies while reducing the costs of organizational adjustment and cross-sector coordination. Producer services therefore support both the realization of productivity gains within firms and the reallocation of resources across industries. Related evidence from China shows that interregional peer learning can improve regions' positions in the digital value chain, highlighting how learning, policy attention, and coordination can extend digital capabilities through production networks (Li et al., 2025a). More broadly, intermediate inputs can transmit and amplify localized productivity improvements through production networks (Jones, 2011), while access to higher-quality service inputs can raise manufacturing productivity and facilitate industrial upgrading (Francois and Woerz, 2008; Arnold et al., 2016).

Taken together, the framework suggests that localized AI innovation is more likely to generate system-level industrial gains when its productivity effects are realized within production, accompanied by more efficient cross-sector factor allocation, and supported by complementary producer-service linkages. We therefore propose the following hypothesis:

**Hypothesis 2:** AI promotes MIS development through technical-efficiency catch-up, more efficient cross-sector factor allocation, and stronger producer-service linkages that support technology adoption and diffusion.

### *3.3. Threshold effects of complementary conditions*

The multisectoral transmission of AI-related productivity gains depends on complementary inputs that support their realization and diffusion within local industrial systems. General-purpose technology theory emphasizes that the economic returns to pervasive technologies are conditioned by downstream applications, complementary investment, and institutional adjustment (Bresnahan and Trajtenberg, 1995; Brynjolfsson et al., 2021). Recent evidence on advanced digital-technology adoption similarly highlights the importance of technology readiness and knowledge-management practices in translating technological capabilities into organizational applications (Jabeen et al., 2026). Translating AI innovation into system-level industrial outcomes therefore requires three basic forms of complementary capacity: an industrial domain in which AI can be applied, a digital foundation that enables its application, and an institutional environment that coordinates and supports the transformation process. At the city level, we define these requirements as industrial application capacity, digital-support capacity, and institutional-coordination capacity. Because deficiencies or imbalances in these complementary capacities may constrain the conversion of AI innovation into broader industrial upgrading, the effect of AI on MIS development may vary nonlinearly across their development levels.

Industrial application capacity constitutes the first dimension of local complementary capacity. AI generates economic value only when it can be embedded in a sufficiently broad range of production tasks and business processes. A stronger secondary-industry base provides production scenarios, process data, equipment, and demand for AI-enabled solutions, thereby expanding the scope for AI adoption and complementary innovation. Evidence on industrial intelligence similarly shows that the application of intelligent technologies can facilitate industrial upgrading and coordination between manufacturing and services (Xia et al., 2024). Recent evidence also suggests that the effects of AI innovation on industrial upgrading vary with institutional and factor conditions (Zhu and Zhang, 2026). When this industrial base is weak, AI innovation may remain disconnected from production activities. However, excessive dependence on traditional secondary industries may create structural rigidity and constrain the broader application of AI. The effect of AI on MIS development may therefore vary nonlinearly with industrial application capacity.

Digital-support capacity constitutes the second dimension. The effective application of AI requires digital connectivity, data-processing capacity, and specialized information services. A stronger digital-support environment can reduce data bottlenecks and facilitate the adoption and diffusion of AI technologies. Existing evidence shows that digital infrastructure contributes to industrial upgrading by improving resource allocation, technological innovation, and capital flows (Gong et al., 2023; Jin et al., 2024). Recent evidence indicates that the economic effects of new digital infrastructure vary across development stages and may be subject to threshold conditions (Hu et al., 2025b), consistent with the implementation costs, technical-skill shortages, and infrastructure constraints that continue to hinder the adoption of AI and related data technologies (Dos Santos and Dos Santos, 2025). When digital-support capacity is insufficient, AI innovation may not be translated effectively into productive applications. As this capacity develops, the relevant constraints can be relaxed, although large initial investments and adjustment costs may cause the marginal effect of AI to vary across development stages. Digital-support capacity may thus generate a nonlinear threshold effect.

Institutional-coordination capacity constitutes the third dimension. AI adoption may involve coordination failures related to public digital infrastructure, data standards, technology commercialization, and collaboration among firms and research institutions. Local governments can facilitate this process by coordinating public inputs, implementing technology policies, and reducing uncertainty surrounding emerging applications, consistent with the emphasis of the industrial-policy literature on information and coordination failures (Juhász et al., 2024). Consistent with this view, China's "Internet + Government Services" pilot shows that digital government can promote technological innovation and human-capital upgrading while reducing information asymmetry and agency costs (Lv and Xiao, 2026). Digital and inclusive finance may further complement these institutional functions by helping translate digital technologies into industrial upgrading (Ren et al., 2023; Shen et al., 2024; Zhang, 2025). Insufficient institutional-coordination capacity may impede this transformation.

Based on these arguments, we propose the following hypothesis:

**Hypothesis 3:** The effect of AI on MIS development varies nonlinearly with the local industrial base, digital infrastructure, and governance intensity.

## 4. Data and measurement

### *4.1. Measuring local AI development*

Existing studies differ in how they measure AI development, reflecting the diversity of AI technologies and applications. Although industrial robots are often used as a proxy for AI-related technologies in empirical research, robot-based measures mainly capture embodied and relatively mature automation applications in manufacturing. They therefore provide only a partial measure of AI development and are less suitable for evaluating AI's broader role in city-level industrial systems.

AI patents provide a suitable measure for our study because they capture AI-related technological innovation with potential application value and are not confined to particular production tasks or sectors. Following Zhai et al. (2023), we use the number of AI patent applications as the baseline measure of local AI development. Patent applications capture the breadth and timing of local inventive activity and therefore provide a relatively comprehensive measure of the scale and intensity of AI innovation. The data are obtained from the Artificial Intelligence Patent Database of the China Research Data Service Platform (CNRDS), which identifies AI patents using International Patent Classification codes related to AI technologies. We aggregate the identified patents to the city-year level according to the applicant's location.

To assess whether the results depend on this baseline measure, we also consider two alternative indicators. The number of AI patent grants provides a more selective, quality-oriented measure of inventive output because granted patents have passed the relevant examination process. The number of AI firms, by contrast, is a non-patent-based measure that captures the local presence of market participants engaged in AI-related production and commercialization.

Figure 1 reports annual AI patent applications and grants in China from 2000 to 2023. Since 2010, AI patent applications have grown rapidly, and the growth rate has increased over time, indicating that AI patenting activity in China expanded rapidly after 2010. The number of AI patent grants follows a similar pattern, and the number of patent grants follows a similar upward trend, while the gap between applications and grants narrows after 2020.

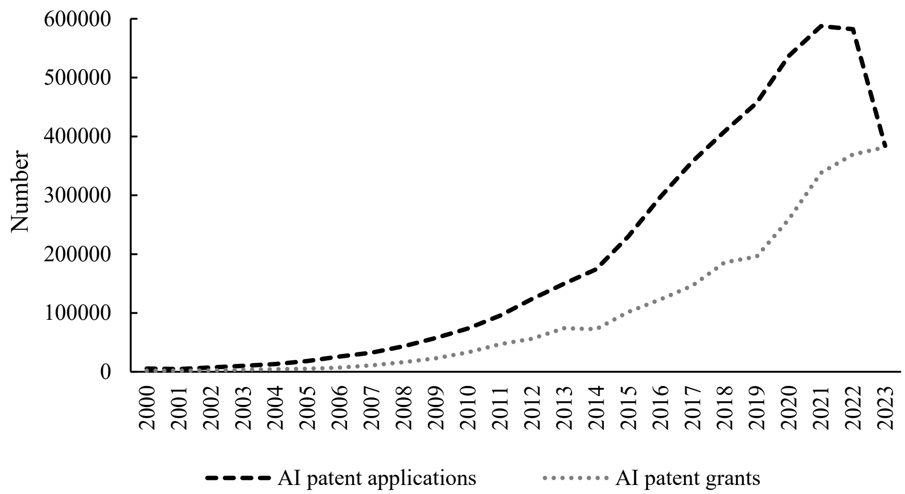


**Figure 1.** AI patent applications and grants in China, 2000–2023.

Figure 2 shows the regional distribution of AI patent applications in China from 2000 to 2023. Although AI has developed rapidly, regional imbalance remains pronounced. The eastern region accounts for a larger share of AI patent applications than all other regions combined. Even though the absolute gap across regions has widened, differences in relative growth since 2010 have eased this imbalance to some extent: the eastern region's share fell from more than 80% to 72.34% in 2023, while the shares of the central and western regions rose steadily, each reaching about 12% in 2023. The number of AI patent applications in the northeast also increased, but its share remained below 4% and showed no clear upward trend.

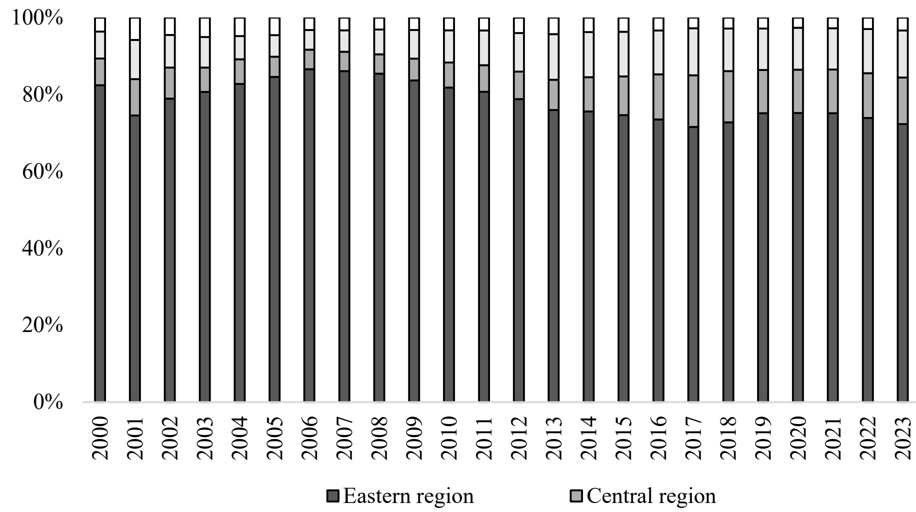


**Figure 2.** Regional distribution of AI patent applications in China, 2000–2023.

### *4.2. Construction of the MIS index*

The outline of the *14th Five-Year Plan* emphasizes the construction of MIS in which the real economy, technological innovation, modern finance, and human resources develop in coordination. Following this policy framework and drawing on recent research on the measurement of China's MIS (Han and Deng, 2025), we construct a city-level index system for MIS. Considering data reliability and availability, the index consists of four first-level dimensions: the real economy (*reco*), technological innovation (*tech*), modern finance (*dfina*), and human resources (*por*). These dimensions are further decomposed into eight subdimensions and 18 indicators.

Given data availability, this index system is used to evaluate the MIS development in 285 Chinese cities from 2011 to 2023. The specific indicators are shown in Table 1.

The digital financial inclusion index follows the measurement of Guo et al. (2020). The data for all indicators come from the China City Statistical Yearbook, China Regional Economic Statistical Yearbook, provincial and prefecture-level city statistical yearbooks, the EPS database, and statistical data released by provincial and municipal statistical bureaus. Some missing observations are filled using linear interpolation. To avoid relying on researcher-assigned weights, we use the entropy weight method to determine the baseline indicator weights. Because the resulting MIS index may nevertheless be sensitive to the aggregation method, we also reconstruct the index using equal indicator weights, equal weights across the four dimensions, and principal component analysis. The corresponding sensitivity results are reported in Section 5.4.1.

Table 2 reports the average scores of the MIS and its sub-dimensions from 2011 to 2023. At the national level, the average score of the MIS shows an overall upward trend and maintains a relatively stable growth rate. The real economy and technological innovation dimensions also show clear increases, although their levels remain relatively low. Modern finance grew rapidly from 2011 to 2017, but its growth slowed substantially after 2018. Human resources started from a relatively high level and maintained steady growth during the sample period.

**Table 1.** Index system for the MIS development.

| **First-level dimensions** | **subdimensions** | **Indicator** | **Measurement** | **Sign** |
|---|---|---|---|---|
| Real economy (*reco*) | Development level | Primary industry | Grain output per unit of cultivated land | + |
| | | Secondary industry | Secondary-industry value added/employment | + |
| | | Tertiary industry | Tertiary-industry value added/employment | + |
| | Development potential | Infrastructure | Road area per capita | + |
| | | Green development | Energy consumption per unit of GDP | - |
| | | Openness | Total imports and exports/GDP | + |
| Technological innovation (*tech*) | Innovation foundation | Innovation entities | Number of high-tech industrial firms | + |
| | | Digitalization | Existing firms in digital-economy industries | + |
| | Innovation input | R&D expenditure input | R&D expenditure/GDP | + |
| | | R&D personnel input | R&D personnel/total employment | + |
| Modern finance (*dfina*) | Financial structure | Value added | Financial-sector value added/tertiary-industry value added | + |
| | | Employment | Share of financial-sector employment | + |
| | Financial development | Bank fund-use efficiency | Loan balance/deposit balance | + |
| | | Insurance capital conversion rate | Insurance claims/premium expenditure | + |
| | | Digital financial inclusion | Digital financial inclusion index | + |
| Human resources (*por*) | Human capital | Education input | Education expenditure/general budget expenditure | + |
| | | Training scale | College students per 100,000 people | + |
| | Social security | Social security expenditure | Per capita fiscal social security expenditure | + |

The claims-to-premium ratio is interpreted here from the perspective of financial support for the real economy r ather than insurer profitability. A higher ratio reflects a stronger risk-compensation function of insurance funds, which helps stabilize households and firms and thus contributes positively to MIS construction.

**Table 2.** Mean scores of the MIS and sub-dimensions.

| **Year** | *MIS* | *reco* | *tech* | *dfina* | *por* |
|---|---|---|---|---|---|
| 2011 | 6.72 | 8.73 | 3.17 | 19.19 | 11.66 |
| 2012 | 7.30 | 8.88 | 3.46 | 23.24 | 12.27 |
| 2013 | 7.76 | 8.67 | 3.66 | 27.88 | 12.76 |
| 2014 | 8.11 | 8.96 | 3.90 | 29.25 | 13.07 |
| 2015 | 8.50 | 8.97 | 4.14 | 31.55 | 13.75 |
| 2016 | 9.04 | 9.21 | 4.55 | 34.23 | 14.20 |
| 2017 | 9.58 | 9.81 | 5.01 | 35.59 | 14.44 |
| 2018 | 10.21 | 10.85 | 5.46 | 36.36 | 14.92 |
| 2019 | 10.81 | 11.31 | 6.07 | 36.97 | 15.77 |
| 2020 | 11.43 | 11.62 | 6.62 | 38.17 | 17.05 |
| 2021 | 12.25 | 12.71 | 7.15 | 40.69 | 17.59 |
| 2022 | 12.63 | 13.40 | 7.21 | 41.39 | 18.67 |
| 2023 | 14.16 | 13.92 | 9.56 | 41.31 | 19.48 |

Table 3 reports the average scores of MIS across regions from 2011 to 2023. During the sample period, all regions improved significantly and maintained stable growth, but regional imbalance remained evident. Specifically, the eastern region had a significantly higher average construction level than other regions, reflecting its stronger industrial foundation and economic development. The central, western, and northeastern regions still lagged behind the east, although their relative gaps have continued to narrow.

**Table 3.** Mean scores of MIS by region, 2011–2023.

| **Year** | **Eastern region** | **Central region** | **Western region** | **Northeastern region** |
|---|---|---|---|---|
| 2011 | 9.48 | 5.70 | 5.30 | 5.82 |
| 2012 | 10.05 | 6.27 | 5.94 | 6.28 |
| 2013 | 10.47 | 6.81 | 6.40 | 6.67 |
| 2014 | 10.90 | 7.15 | 6.74 | 6.88 |
| 2015 | 11.45 | 7.49 | 7.09 | 7.06 |
| 2016 | 12.14 | 7.99 | 7.54 | 7.54 |
| 2017 | 12.94 | 8.56 | 7.93 | 7.78 |
| 2018 | 13.72 | 9.17 | 8.26 | 8.79 |
| 2019 | 14.45 | 9.65 | 8.71 | 9.73 |
| 2020 | 15.41 | 10.25 | 9.23 | 9.79 |
| 2021 | 16.50 | 11.10 | 9.92 | 10.19 |
| 2022 | 16.93 | 11.50 | 10.21 | 10.65 |
| 2023 | 19.15 | 12.90 | 11.36 | 11.74 |

## 5. Empirical analysis

### 5.1. Model specification, variable selection, and data sources

We estimate the following baseline specification:

$$MIS_{it}=\beta_0+\beta_1 AI_{it}+\sum_{j=2}^{n}\beta_j Control_{it}^{j}+\mu_i+\gamma_t+\epsilon_{it} \tag{1}$$

where $i$ denotes city, $t$ denotes year, the dependent variable $MIS_{it}$ denotes the construction level of the MIS of city $i$ in year $t$, the core explanatory variable $AI_{it}$ denotes the AI development level, $X_{it}$ is a vector of control variables, $\mu_i$ denotes city fixed effects, $\lambda_t$ denotes year fixed effects, and $\epsilon_{it}$ is the random disturbance term.

The dependent variable is the MIS development, measured by the index scores described in Section 4. The core explanatory variable is AI development, measured by the number of AI patent applications in each city from 2011 to 2023, measured in thousands of applications.

Following the literature, the control variables include: fiscal support (*fin*), measured by the ratio of local general budget expenditure to GDP; employment size (*labor*), measured by the logarithm of urban unit employment; foreign investment (*fdi*), measured by the ratio of actually utilized foreign investment to GDP; science and technology expenditure (*sci*), measured by the ratio of science expenditure to local general budget revenue; income level (*income*), measured by the logarithm of per capita disposable income; and consumption level (*consume*), measured by the ratio of total retail sales of consumer goods to GDP.

**Table 4.** Descriptive statistics.

| Type | Variable name | Symbol | Obs | Mea | Std. | Min. | Max. |
|---|---|---|---|---|---|---|---|
| Dependent variable | Modern industrial system development | *MIS* | 370 | 9.88 | 6.10 | 2.12 | 57.37 |
| Explanatory | Artificial intelligence | *AI* | 370 | 1.25 | 5.83 | 0.00 | 115.2 |
| Control variable | Fiscal support | *fin* | 370 | 0.20 | 0.10 | 0.04 | 0.92 |
| | Employment size | *labor* | 370 | 4.44 | 0.89 | 2.13 | 7.67 |
| | Foreign investment | *fdi* | 370 | 0.01 | 0.02 | 0.00 | 0.66 |
| | Income level | *income* | 370 | 10.34 | 0.34 | 9.33 | 11.40 |
| | Science and technology expenditure | *sci* | 370 | 0.02 | 0.02 | 0.00 | 0.26 |
| | Consumption level | *consume* | 370 | 0.38 | 0.11 | 0.05 | 0.84 |
| Mechanism variable | Technology catch-up effect | *EC* | 370 | 1.01 | 0.21 | 0.47 | 3.01 |
| | Industrial structure rationalization | *RIS* | 370 | 0.29 | 0.21 | 0.00 | 0.96 |
| | Producer services development level | *PS* | 370 | 0.17 | 0.10 | 0.00 | 0.93 |
| Threshold variable | Share of secondary industry | *construc* | 370 | 44.57 | 11.10 | 10.6 | 89.34 |
| | Digital infrastructure | *dig_infr* | 370 | 0.52 | 0.71 | 0.00 | 34.54 |
| | Local governance intensity | *gov* | 370 | 14.18 | 7.00 | 0.00 | 66.67 |

Based on data availability and statistical characteristics, we use panel data for 285 Chinese cities from 2011 to 2023 to empirically analyze the effect of AI on MIS. City-level AI patent data come from the CNRDS database. Other variables are collected from the CEIC economic database, EPS database, China City Statistical Yearbook, China Regional Economic Statistical Yearbook, and provincial statistical yearbooks. Some missing values are handled using linear interpolation. Descriptive statistics for all variables used in the empirical analysis are reported in Table 4.

### 5.2. Baseline regression results

Table 5 reports the baseline regression results. Column (1) controls only for city fixed effects, column (2) further controls for year fixed effects, volumn (3) adds control variables to column (1), and column (4) adds year fixed effects to column (3). The baseline results show that the coefficient on AI remains significantly positive after controlling for year fixed effects and adding control variables. The coefficient on AI is positive and statistically significant across all specifications. In the preferred specification, an additional 1,000 AI patent applications is estimated to increase the MIS index by 0.367 points. Given that the sample mean of MIS is 9.88, this coefficient corresponds to approximately 3.71% of the mean level of MIS, suggesting that the estimated relationship is also economically meaningful. Hypothesis 1 is therefore supported.

**Table 5.** Baseline regression results.

| **Variable** | **MIS** | | | |
|---|---|---|---|---|
| | **(1)** | **(2)** | **(3)** | **(4)** |
| *AI* | 0.5364*** | 0.3709*** | 0.3633*** | 0.3670*** |
| | (3.7426) | (3.8376) | (3.8021) | (3.8098) |
| *fin* | | | −0.8295 | −0.5699 |
| | | | (−0.7875) | (−0.4617) |
| *labor* | | | −0.3357* | −0.2461 |
| | | | (−1.9127) | (−1.3653) |
| *fdi* | | | −0.9075 | −0.0359 |
| | | | (−0.4259) | (−0.0211) |
| *sci* | | | 21.7318*** | 10.5370** |
| | | | (6.3228) | (2.5383) |
| *consume* | | | −1.5147* | 1.1224 |
| | | | (−1.8705) | (1.2536) |
| *income* | | | 6.8169*** | 1.2780 |
| | | | (31.0882) | (1.5692) |
| Constant | 9.2163*** | 6.5956*** | −59.2167*** | −5.3952 |
| | (51.6149) | (68.5132) | (−28.2339) | (−0.6755) |
| Observations | 3705 | 3705 | 3705 | 3705 |
| $R^2$ | 0.3016 | 0.8078 | 0.7837 | 0.8123 |
| City fixed effects | Yes | Yes | Yes | Yes |
| Year fixed effects | No | Yes | No | Yes |

Note: t-statistics are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. The same applies to the following tables.

*5.3. Endogeneity treatment*

The baseline regression results indicate a significant positive relationship between AI and MIS. However, the number of AI patent applications and the MIS development may suffer from endogeneity caused by reverse causality and related problems. To further identify the causal effect of AI, we use an instrumental-variable approach. Specifically, we use the one-period lagged AI variable and the Bartik variable as two alternative instruments and estimate two separate 2SLS regressions.

First, we use the one-period lag of AI patent applications as the first instrumental variable. Lagged AI development is not directly related to the current construction level of the MIS but is correlated with current AI development. In addition, following Bonfiglioli et al. (2025), we construct a Bartik instrumental variable using a shift-share approach, as shown in Equation (2):

$$IV_{2,it}=AI_{i,2011}\frac{\sum_{j\neq i}AI_{j,t}}{\sum_{j\neq i}AI_{j,2011}} \tag{2}$$

where $AI_{i,2011}$ captures a city's initial exposure to AI development and the second component measures the cumulative national growth rate of AI patents in all other cities. Following the recent shift-share literature, the identifying variation mainly comes from the interaction between predetermined local exposure and aggregate national technology shocks. The 2011 AI exposure is predetermined relative to subsequent changes in the modern industrial system, and the leave-one-out national growth component reduces the possibility that a focal city mechanically drives the aggregate shock. Therefore, the instrument predicts current AI development through differential exposure to nationwide AI progress, while the exclusion restriction requires that it affects the modern industrial system only through local AI development.

**Table 6.** Instrumental-variable estimation.

| Variable | *MIS* | | | |
|---|---|---|---|---|
| | (1) | | (2) | |
| | First stage | Second stage | First stage | Second stage |
| $IV_1$ | 1.0031*** (46.7896) | | | |
| $IV_2$ | | | 0.7203*** (6.2325) | |
| $AI$ | | 0.3746*** (3.7747) | | 0.3817*** (4.1524) |
| Observations | 3420 | | 3705 | |
| $R^2$ | 0.4135 | | 0.4275 | |
| Control variable | Yes | Yes | Yes | Yes |
| City and year fixed effects | Yes | Yes | Yes | Yes |
| Kleibergen-Paap rk LM statistic | 3.490 | | 3.249 | |
| Kleibergen-Paap rk Wald F-statistic | 2189 | | 38.84 | |

Table 6 reports the two-stage least squares (2SLS) results. The coefficients of both instrumental variables are significantly positive at the 1% level. The Kleibergen-Paap statistics reject under identification and indicate that weak identification is unlikely to drive the estimates. Overall, the selected instruments are reasonable and reliable. The second-stage estimates remain positive and close to the baseline coefficient.

### *5.4. Robustness tests*

We conduct a series of robustness checks addressing the measurement of the key variables, the influence of extreme observations, sample composition, and model specification. We first assess whether the baseline result is sensitive to alternative constructions of the MIS index. We then use alternative measures of local AI development, winsorize the continuous variables, impose several sample restrictions, and introduce province-by-year fixed effects.

#### 5.4.1. Alternative constructions of the MIS index

The baseline MIS index is constructed using the entropy-weighting method. To assess whether the estimated effect depends on this particular weighting scheme, we reconstruct the MIS index using equal indicator weights ($MIS_{EW}$), equal dimension weights ($MIS_{DW}$), and principal component analysis ($MIS_{PCA}$). Specifically, $MIS_{EW}$ assigns equal weights to all 18 underlying indicators; $MIS_{DW}$ assigns a weight of 25% to each of the four dimensions and equal weights to the indicators within each dimension; and $MIS_{PCA}$ is based on the first principal component extracted from the standardized indicators. As reported in Table 7, the coefficient on AI is positive and statistically significant at the 1% level for all three alternative indices. The baseline finding is therefore not sensitive to the weighting or aggregation method used to construct the MIS index.

**Table 7.** Sensitivity to alternative constructions of the MIS index.

| **Variable** | $\boldsymbol{MIS_{EW}}$ **(1)** | $\boldsymbol{MIS_{DW}}$ **(2)** | $\boldsymbol{MIS_{PCA}}$ **(3)** |
|---|---|---|---|
| *AI* | 0.1237*** | 0.1546*** | 0.4105*** |
| | (4.0632) | (4.1413) | (3.9916) |
| Observations | 3705 | 3705 | 3705 |
| $R^2$ | 0.9043 | 0.8966 | 0.9072 |
| Control variable | Yes | Yes | Yes |
| City and year fixed effects | Yes | Yes | Yes |

#### 5.4.2. Restricting the sample to the post-2015 period

In May 2015, the State Council of China issued the *Made in China 2025* action program, which called for accelerating the integration of new-generation information technology and manufacturing technology and identified intelligent manufacturing as the main direction for deep integration between informatization and industrialization. To exclude the influence of this contemporaneous policy, we keep only the post-2015 sample and re-estimate the model. Column (1) of Table 8 shows that the coefficient on the core explanatory variable remains significantly positive at the 1% level, suggesting that the baseline result is not driven solely by pre-2015 observations.

#### 5.4.3. Winsorization

To remove the influence of extreme values, all continuous variables are winsorized at the 1st and 99th percentiles, and alternatively at the 5th and 95th percentiles. Columns (2) and (3) of Table 8 show that the coefficient on AI remains significantly positive at the 1% level after winsorization and the estimated coefficients are larger than those in the baseline regression.

#### 5.4.4. Using alternative AI measures

To examine whether the results depend on the patent-application measure, we replace it with the number of AI patent grants $AIgrant$ and the number of AI firms $AIfirm$. $AIgrant$ provides a more selective, quality-oriented patent measure, whereas $AIfirm$ captures local AI development from a non-patent-based industrial perspective. Columns (4) and (5) of Table 8 yield positive and statistically significant estimates for both measures, indicating that the main finding holds whether local AI development is measured by the number of patent applications, the quality-oriented dimension captured by patent grants, or the non-patent-based presence of AI firms.

#### 5.4.5. Excluding municipalities and provincial capitals

Municipalities and provincial capitals may differ from other cities in administrative rank, development policies, and resource allocation. To reduce the influence of these differences, we exclude Beijing, Tianjin, Shanghai, Chongqing, and all provincial capitals and then re-estimate the model. Column (6) of Table 8 shows that the estimated coefficient remains positive and statistically significant.

#### 5.4.6. Adding province-year interactive fixed effects

To control for unobservable province-level factors that vary over time, we further add province-year interactive fixed effects to the baseline specification. Column (7) of Table 8 shows that the estimated effect is stable in sign and magnitude.

**Table 8.** Additional robustness tests.

| **Variable** | ***MIS*** (1) | **(2)** | **(3)** | **(4)** | **(5)** | **(6)** | **(7)** |
|---|---|---|---|---|---|---|---|
| *AI* | 0.3408***<br>(3.5056) | 0.6224***<br>(9.1422) | 1.0175***<br>(6.5632) | | | 0.4656***<br>(17.4169) | 0.5455***<br>(7.8787) |
| *AIgrant* | | | | 0.5877***<br>(4.5116) | | | |
| *AIfirm* | | | | | 0.3166***<br>(15.1329) | | |
| Observations | 2565 | 3705 | 3705 | 3705 | 3705 | 3315 | 3627 |
| $R^2$ | 0.7588 | 0.8322 | 0.8016 | 0.8088 | 0.8184 | 0.8208 | 0.9744 |
| Control variable | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Province-year interactive fixed effects | No | No | No | No | No | No | Yes |
| City and year fixed effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes |

### *5.5. Empirical evidence on multisector transmission*

The multisector framework developed in Section 3.2 points to three areas in which the broader industrial effects of AI may become visible: productive efficiency, cross-sector allocation, and the complementary service capacity that supports technology adoption and diffusion. To examine these dimensions empirically, we consider changes in technical efficiency, the alignment of sectoral output and employment, and producer-service employment. These measures capture movement toward the best-practice production frontier, the correspondence between production and labor allocation across sectors, and the local availability of specialized service inputs. Taken together, they provide evidence on whether the observed patterns accord with the transmission mechanisms developed above.

#### 5.5.1. Technical efficiency: Technology catch-up

To examine the production-efficiency dimension, we follow Lyu et al. (2019) and measure technology catch-up ($EC$) using the technical-efficiency-change component of the DEA-Malmquist index. This component tracks changes in a city's production performance relative to the best-practice frontier, with an increase indicating improved technical efficiency and movement toward the frontier.

As reported in column (1) of Table 9, the coefficient on AI is 0.0009 and statistically significant at the 5% level. The positive estimate indicates that AI facilitates technical-efficiency catch-up. This pattern is consistent with the argument in Section 3.2 that AI-related gains become economically relevant when firms integrate AI with existing capital, knowledge, and organizational practices and use available technologies more effectively.

5.5.2. Cross-sector allocation: Industrial-structure rationalization

We next examine whether AI development is accompanied by changes in sectoral allocation. Following Xiong et al. (2023), industrial-structure rationalization ($RIS$) is measured using a Theil index constructed from differences between sectoral output and employment shares. A higher value indicates a larger mismatch between the sectoral distribution of production and employment, whereas a decline in the index indicates closer alignment.

Column (2) of Table 9 reports a coefficient of −0.0013, statistically significant at the 5% level. The negative estimate indicates that AI improves the alignment between sectoral output and employment. This result is consistent with the view that heterogeneous productivity gains from AI alter relative production opportunities across industries and are accompanied by a more efficient distribution of employment relative to economic activity.

5.5.3. Intersectoral diffusion: Producer-service capacity

Finally, we consider the complementary service capacity available to support the adoption and wider application of AI. Following Gao et al. (2020), producer-service capacity ($PS$) is measured by the share of producer-service employment in total urban unit employment. Producer services supply specialized inputs, including information processing, R&D, finance, logistics, and business support, that help firms adopt new technologies, adjust production processes, and coordinate activities across industries.

As shown in column (3) of Table 9, the coefficient on AI is 0.0023 and statistically significant at the 5% level. The positive estimate indicates that AI expands local producer-service capacity. This expansion is consistent with the development of an industrial environment better equipped to support the adoption, adaptation, and broader productive application of AI across firms and industries.

**Table 9.** Channel analysis of multisectoral transmission.

| **Variable** | ***EC*** **(1)** | ***RIS*** **(2)** | ***PS*** **(3)** |
|---|---|---|---|
| *AI* | 0.0009** | −0.0013** | 0.0023** |
| | (2.5475) | (−2.4635) | (2.5099) |
| Observations | 3705 | 3705 | 3705 |
| $R^2$ | 0.6182 | 0.0651 | 0.1946 |
| Control variable | Yes | Yes | Yes |
| City and year fixed effects | Yes | Yes | Yes |

*5.6. Regional heterogeneity tests*

Because regions and city tiers differ in factor endowments, marketization, and industrial structures, the effect of AI on MIS may be heterogeneous. We therefore examine heterogeneity across geographical regions and city tiers.

For geographical heterogeneity, the sample cities are divided into eastern, central, western, and northeastern regions according to the classification of the National Bureau of Statistics, and group regressions are conducted. Table 10 shows that AI has a significantly positive effect in all regions at the 1% level. The coefficient is smallest in the eastern region, larger in the central region, and largest in the western and northeastern regions, forming a clear gradient. This pattern reflects diminishing marginal effects in technology diffusion: in the more modernized eastern industrial structure, AI applications focus more on deepening and breaking through existing technological systems, with a limited short-term direct effect on industrial efficiency. In the central, western, and northeastern regions, where the existing technology stock and development level are lower, AI can generate a more evident catch-up effect.

**Table 10.** Heterogeneity of geographical location.

| **Variable** | ***MIS*** | | | |
|---|---|---|---|---|
| | **Eastern region** | **Central region** | **Western region** | **Northeastern region** |
| *AI* | 0.2879*** | 0.8177*** | 1.1522*** | 1.1072*** |
| | (3.7405) | (9.6780) | (9.6883) | (3.5151) |
| Observations | 1105 | 1040 | 1118 | 442 |
| $R^2$ | 0.8754 | 0.9060 | 0.8636 | 0.6914 |
| Control variable | Yes | Yes | Yes | Yes |
| City and year fixed effects | Yes | Yes | Yes | Yes |

To clarify regional heterogeneity further, we examine the heterogeneous effect of AI across city tiers. Specifically, based on the *Ranking of Cities' Business Attractiveness in China 2023* published by the Rising Lab[4], the sample cities are divided into first-tier cities, second- and third-tier cities, and fourth- and fifth-tier cities, and group regressions are performed. The results in Table 11 are similar to those in Table 10: AI shows a significant enabling effect across all city tiers, but the effect size differs substantially. The coefficient is lowest for first-tier cities, higher for second- and third-tier cities, and highest for fourth- and fifth-tier cities. This reflects both diminishing marginal effects in AI diffusion and the weaker industrial foundations of non-first-tier cities, where factor substitution costs are lower and AI's enabling effect is therefore more pronounced.

The heterogeneity results display a clear regional and city-tier gradient consistent with catch-up dynamics. In less-developed regions and lower-tier cities, lower initial technology levels and less mature industrial structures leave greater scope for AI to improve productive efficiency and facilitate structural adjustment. In the more developed eastern region and first-tier cities, existing production systems are generally closer to the technological frontier, and AI is more likely to deepen established capabilities whose contribution may emerge more gradually in aggregate MIS indicators. The larger coefficients observed in lagging areas thus reflect their greater marginal upgrading potential, while the realization of this potential continues to depend on the availability of local digital and institutional complements.

[4] See Yicai's New First-Tier Cities Research Institute, "New First-Tier Cities' Attractiveness Ranking Indicators," available at: https://www.datayicai.com/cityindex.

**Table 11.** Heterogeneity of city tier.

| Variable | *MIS* First-tier cities | Second- and third-tier cities | Fourth- and fifth-tier cities |
|---|---|---|---|
| *AI* | 0.1549* | 0.5920*** | 2.1059*** |
| | (2.0987) | (3.0957) | (2.7717) |
| Observations | 247 | 1287 | 2171 |
| $R^2$ | 0.9212 | 0.8986 | 0.7723 |
| Control variable | Yes | Yes | Yes |
| City and year fixed effects | Yes | Yes | Yes |

## 6. Further analysis

To examine how local complementary conditions shape the effect of AI on MIS development, we estimate a panel threshold model using three theoretically motivated threshold variables: the share of the secondary industry, digital infrastructure development, and local governance intensity. The share of the secondary industry (*construct*) is defined as secondary-industry value added divided by GDP. Digital infrastructure (*dig_infra*) is measured by the number of firms in information-infrastructure industries relative to GDP, following the *Statistical Classification of the Digital Economy and Its Core Industries (2021)*[5]. Local governance intensity (*gov*) is proxied by the share of employment in public management and social organizations in total urban unit employment.

The double-threshold model is specified in Equation (3):

$$MIS_{it}=\beta_0+\beta_1 AI_{it}\cdot I(q_{it}\le\kappa_1)+\beta_2 AI_{it}\cdot I(\kappa_1<q_{it}\le\kappa_2)+\beta_3 AI_{it}\cdot I(q_{it}>\kappa_2)+\sum_{j=4}^{n+2}\beta_j\, Control_{it}^{j}+\gamma_t+\epsilon_{it} \tag{3}$$

where $q$ is the threshold variable, $\kappa_1$ and $\kappa_2$ are threshold values, $I(.)$ is the indicator function, and the other variables are defined as in Equation (1).

We first test the threshold effects of the selected variables. Table 12 reports the bootstrap tests for threshold effects. For each threshold variable, the null hypothesis of no threshold is rejected for both the single- and double-threshold specifications, whereas the addition of a third threshold is not statistically supported. The subsequent analysis therefore uses double-threshold models for *construct*, *dig_infra*, and *gov.*

Table 13 reports the panel threshold estimates. Column (1) reports the baseline coefficient for comparison, while columns (2)–(4) allow the coefficient on AI to vary across the three regimes defined by each threshold variable.

Column (2) of Table 13 uses *construct* as the threshold variable. When the secondary-industry share is below 24.23%, the estimated effect of AI is 0.1942. The coefficient increases to 0.6060 when *construct* lies between 24.23% and 35.84% and then declines to 0.4719 once it exceeds 35.84%. All three coefficients are statistically significant at the 1% level. The results indicate that the effect of AI is

[5] See National Bureau of Statistics of China, Statistical Classification of Digital Economy and Its Core Industries (2021), available at: https://www.stats.gov.cn/sj/tjbz/gjtjbz/202302/t20230213_1902784.html.

weakest in cities with a relatively small secondary-industry base and strongest at intermediate levels of industrial development. A plausible explanation is that a minimum industrial base is needed to provide production tasks, data, and demand for AI applications. Beyond the second threshold, the smaller coefficient may reflect diminishing marginal returns to AI or structural rigidities associated with a high concentration of secondary-industry activity. Nevertheless, the effect remains larger than that in the lowest regime, indicating that AI continues to generate substantial industrial gains in cities with a well-established industrial base.

**Table 12.** Threshold-effect test results.

| **Threshold variable** | ***construct*** | | | ***dig_infra*** | | | ***gov*** | | |
|---|---|---|---|---|---|---|---|---|---|
| Threshold model | Single | Double | Triple | Single | Double | Triple | Single | Double | Triple |
| | 22.81 | 24.23 | 24.23 | 0.7836 | 0.7836 | 0.7836 | 7.3315 | 6.8611 | 6.8611 |
| Threshold value | | 35.84 | 35.84 | | 1.0103 | 0.798 | | 7.3315 | 7.3315 |
| | | | 48.53 | | | 1.0103 | | | 8.6565 |
| F-statistic | 744.92 | 106.49 | 29.94 | 153.38 | 200.80 | 65.20 | 602.82 | 310.13 | 51.76 |
| p-value | 0.0000 | 0.0140 | 0.5660 | 0.0180 | 0.0040 | 0.3840 | 0.0000 | 0.0000 | 0.5600 |
| Iterations | 500 | 500 | 500 | 500 | 500 | 500 | 500 | 500 | 500 |
| Search points | 300 | 300 | 300 | 300 | 300 | 300 | 300 | 300 | 300 |

Column (3) of Table 13 reports the estimates for *dig_infra*. The effect of AI is 0.4639 when *dig_infra* is below 0.7836, decreases to 0.3049 between 0.7836 and 1.0103, and rises to 0.6834 above the second threshold. This nonmonotonic pattern suggests that the productivity effects of AI do not increase uniformly during the early stages of digital-infrastructure expansion. Initial investment, adjustment costs, and incomplete complementary services may temporarily limit the conversion of AI innovation into industrial outcomes. Once digital infrastructure exceeds the upper threshold, the substantially larger coefficient indicates that stronger connectivity, data-processing capacity, and digital-service support enhance the productive application and diffusion of AI.

Column (4) of Table 13 uses *gov* as the threshold variable. The estimated effect of AI is 0.4482 below the first threshold of 6.8611, falls to 0.3123 between 6.8611 and 7.3315, and increases sharply to 0.9371 above the second threshold. The larger effect in the upper regime suggests that stronger local coordination and implementation capacity may improve the provision of public digital infrastructure, facilitate technology commercialization, and reduce coordination frictions surrounding AI adoption.

Overall, the threshold estimates reveal substantial heterogeneity in the causal effect of AI across local economic and institutional environments. The effect is relatively limited when the industrial base or complementary conditions are insufficient but becomes larger once the relevant support capacity reaches a higher level. The nonmonotonic estimates also indicate that improvements in complementary conditions may involve transition and adjustment costs. These findings support the view that the industrial effect of AI depends not only on technological development itself, but also on the local capacity to apply, absorb, and diffuse AI technologies.

**Table 13.** Panel threshold regression results.

| Variable | *MIS* (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| *AI* | 0.3670*** (3.8098) | | | |
| AI: first interval | | 0.1942*** (26.5606) | 0.4639*** (11.0555) | 0.4482*** (9.2217) |
| AI: second interval | | 0.6060*** (9.9723) | 0.3049*** (4.7625) | 0.3123*** (7.1650) |
| AI: third interval | | 0.4719*** (13.2463) | 0.6834*** (11.7681) | 0.9371*** (13.4090) |
| Observations | 3705 | 3705 | 3705 | 3705 |
| $R^2$ | 0.8123 | 0.8482 | 0.8291 | 0.8518 |
| Control variable | Yes | Yes | Yes | Yes |
| City and year fixed effects | Yes | Yes | Yes | Yes |

## 7. Conclusions and policy implications

Using panel data for 285 Chinese cities from 2011 to 2023, this paper examines the effect of local AI development on the development of China's modern industrial system. We construct a city-level MIS index covering the real economy, technological innovation, modern finance, and human resources, and measure AI development using AI patent applications. The baseline estimates show that an additional 1,000 AI patent applications increases the MIS index by 0.367 points, equivalent to approximately 3.7% of its sample mean. The estimated effect remains stable after addressing potential endogeneity and across a range of robustness checks.

The channel analysis places this effect within a multisector productivity framework. AI facilitates technology catch-up by helping local producers move closer to the best-practice production frontier, improves industrial-structure rationalization by reducing mismatches between sectoral output and employment, and expands the producer-service capacity that supports technology adoption and intersectoral diffusion. These findings suggest that the industrial effects of AI extend beyond productivity improvements within individual firms or production activities. Their broader contribution also depends on the reallocation of productive factors and the availability of complementary service inputs through which technological gains can spread across industries.

The estimates also reveal substantial heterogeneity in the effect of AI. The effect is larger in the central, western, and northeastern regions than in the eastern region and is stronger in lower-tier cities than in first-tier cities. This pattern is consistent with greater opportunities for technology catch-up in cities that begin farther from the production frontier. The threshold estimates further show that the effect of AI varies nonlinearly with the secondary-industry share, digital infrastructure, and local governance intensity. The effect is therefore not determined by AI innovation alone, but also by the industrial, digital, and institutional conditions that shape the adoption and diffusion of AI technologies.

The results have several policy implications. First, policies designed to support AI development should place greater emphasis on the conversion of technological innovation into productive use.

Expanding AI patenting and research capacity is unlikely to generate broad industrial gains unless firms can adopt the resulting technologies and integrate them with existing production processes. Policies that facilitate technology transfer, commercialization, workforce training, and access to specialized software and data services can strengthen the link between AI innovation and real-sector productivity.

Second, the cross-sector effects of AI require complementary improvements in factor allocation and producer services. Barriers that prevent labor and capital from moving toward more productive activities may limit the aggregate gains from AI, even when individual firms experience substantial productivity improvements. The development of software, R&D, logistics, finance, data processing, and other producer services can also reduce adoption costs and extend AI-related capabilities to a broader range of firms and industries. AI policy should therefore be coordinated with policies that improve factor mobility and strengthen the supply of specialized intermediate services.

Third, regional policy should take differences in initial conditions into account. The larger estimated effects in less-developed regions and lower-tier cities suggest that AI can contribute to technological catch-up, but realizing these gains requires sufficient absorptive capacity. Support for digital connectivity, technical training, technology transfer, and access to producer services may be particularly important in these areas. At the same time, the threshold results do not imply that the estimated threshold values should be treated as fixed policy targets. Rather, they indicate that the effect of AI varies with local industrial structures and complementary capacities. Policy design should therefore respond to local constraints instead of applying a uniform model of AI-led industrial development.

## Author contributions

Qinghe Song: Investigation, methodology, writing—review.

Luge Ma: Conceptualization, data collection, data analysis, writing—original draft, writing—review and editing.

## Use of AI tools declaration

The authors used AI tools only for language editing and grammar review during the preparation of this manuscript. The authors are fully responsible for the content of this publication.

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## Conflict of interest

All authors declare no conflicts of interest in this paper.

## Data Availability Statement

The data used in this study are obtained from commercial database, and are available from the corresponding author upon reasonable request.

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