The impact of artificial intelligence adoption on Chinese manufacturing enterprises’ innovativeness: new insights from a labor structure perspective

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Abstract

Purpose - This research aims to investigate the impact of artificial intelligence (AI) adoption on the innovation dynamics of Chinese manufacturing enterprises, with a specific focus on the intricate interplay with the labor structure.

Design/methodology/approach - Leveraging panel data of listed companies from 2010 to 2022, this study employs the two-way fixed effects (TWFE) model to examine the influence of AI adoption on Chinese manufacturing companies' innovativeness. Firm-level AI adoption is measured by constructing a three-dimensional attention, application, and absorption index.

Findings – The results indicate that: (1) AI adoption has a positive impact on both internal innovation capability and external innovation interaction. (2) AI adoption has dual effects on the education and skill structure of labor in manufacturing enterprises. (3) Enterprises with a highly educated and skilled workforce exhibit a stronger influence of AI adoption on innovativeness.

Originality/value: This research contributes to the academic and practical discourse by unveiling the underlying mechanisms of AI affecting innovation and introducing a new measurement of the AI adoption index. The findings emphasize the need for a highly educated and skilled workforce to navigate the complexities of AI-driven innovation, offering valuable theoretical and practical implications for policymakers and enterprises.

Keywords: Artificial intelligence adoption, Intelligent manufacturing, Enterprise innovation, Labor structure

1. Introduction

Artificial intelligence (AI) is recognized as a kind of transformative general-purpose technology (GPT) (Trajtenberg, 2018; Wen, 2021), making a paradigm shift in technical revolution and industrial development after steam power, electric power technology, and information technology. In recent years, AI has permeated various sectors, including intelligent robotics, autonomous vehicles, communications, social media, gaming, translation services, medical diagnostics, and even anti-spam measures. The emergence of generative AI, particularly with large language models (LLMs) like ChatGPT, is anticipated to induce disruptive and innovative transformations in the business landscape (Eisfeldt et al., 2023; Tyna et al., 2023). Consequently, Consequently, scholars have underscored the imperative of integrating AI into business operations to catalyze innovation (Chowdhury et al., 2023).

AI adoption and its impacts on business enterprises have garnered significant scholarly interest. The existing literature is predominantly bifurcated into two schools of thought. One perspective posits that AI has the potential to augment human productivity, enhance work quality, improve operational efficiency, stimulate economic growth, and inform decision-making processes (Agrawal et al., 2019a, 2019b; Babina et al., 2020; Haefner et al., 2021; Duan et al., 2019; Dwivedi et al., 2021). Conversely, the opposing viewpoint suggests that AI integration could diminish labor demand within production sectors, potentially leading to workforce displacement and escalating unemployment rates (Acemoglu and Restrepo, 2018; Aghion et al., 2020; Frey and Osborne, 2017; Tyna et al., 2023). For instance, Brynjolfsson et al. (2017) discovered that the present swift advancement of AI failed to enhance labor productivity, a phenomenon akin to the "Solow paradox."

As a kind of enabling technology and general-purpose technology (GPT), AI's development and proliferation are poised to exert a profound influence on enterprise innovativeness. While studies have indicated that AI can influence labor dynamics and boost productivity (e.g., Babina et al., 2024; Fügener et al., 2022; Wu and Zhuang, 2023), the granular mechanisms through which AI affects enterprise innovation remain underexplored. A limited number of researches have delved into the nexus between AI and innovation, with a focus on business model innovation (Lee et al., 2019), product innovation (Babina et al., 2024), medical innovation (Tsang et al., 2017), and enterprise innovativeness (Cockburn et al., 2018b). This study posits that AI's fundamental impact on innovation stems from its ability to revolutionize the scientific discovery and technological innovation process (Agrawal et al., 2024; Krenn et al., 2022), by enhancing human-machine collaboration (Chowdhury et al., 2022; Fügener et al., 2022). In the manufacturing sectors where intelligent transformation is prominent, AI not only serves as an enabling technology for mechanical product innovation, but also elevates the overall investment in research and development, product design, production, and management processes (Wu & Zhuang, 2023). China stands at the forefront of AI innovation and application scale. Data from the World Intellectual Property Organization (WIPO, 2021) reveals that over the past decade, China's AI-related patent applications have reached 389,571, constituting 74.7% of the global total and securing the top position globally. Additionally, the International Federation of Robotics (IFR, 2022) reports that China's industrial robot installations in 2021 reached 268,195 units, approximately half of the global total. The industrial milieu in China presents a plethora of application scenarios for diverse AI applications. This study aims to fill the research gap by examining the impact and mechanism of AI adoption on enterprise innovation, with a focus on labor force structure, utilizing data from Chinese manufacturing listed companies from 2010 to 2022.

One of the contributions of this study is to explain the mechanism by which AI impacts enterprise innovativeness based on complementary innovation of GPT theory. As previously discussed, while some studies have investigated the relationship between AI adoption and innovation, the internal mechanisms have often been overlooked (Erich, 2019; Haefner et al., 2021; Kakatkar et al., 2020). The GPT nature of AI-driven applications is posited to facilitate and enhance enterprise innovation across multiple channels (Babina et al., 2024). This study assesses enterprise innovativeness by considering three aspects: patent applications, citations, and industry-university-research cooperation, providing a comprehensive understanding of AI's impact on innovation. Furthermore, we investigate the dual mediation effects of the education and skill structures on the influence of AI adoption on enterprise innovativeness. This in-depth analysis illuminates the pathways through which AI adjusts labor structure to affect enterprise innovation (Liang et al., 2022; Malik et al., 2021).

Another contribution lies in the innovative methodologies employed to measure AI adoption. Previous studies mainly relied on indices such as the industrial robot penetration index (Acemoglu & Restrepo, 2020), AI-related investments (Aghion et al., 2020; Babina et al., 2024), or the number of patents obtained (Abadi & Pecht, 2020; Tamura, 2019) to measure AI adoption levels. This study introduces a novel three-dimensional AI adoption indicator at the enterprise level, diverging from previous single-dimensional approaches (Erich, 2019; Kakatkar et al., 2020). Inspired by the three stages of the digital divide—access, skills, and usage (van Deursen et al., 2021)—we measure AI adoption by considering attention, application, and absorption. This multidimensional framework transcends the limitations of conventional methodologies, offering novel insights into the complex effects of AI adoption on enterprise innovativeness.

In sum, the findings of this study carry significant implications for understanding AI's role in fostering enterprise innovation, potentially informing strategic decision-making and policy formulation in the context of AI adoption and innovation.

2. Theoretical analysis and hypotheses development

2.1 General-purpose technology (GPT)

According to the Organization for Economic Co-operation and Development, the AI system may generate predictions, suggestions, or judgments based on human-defined objectives (OECD, 2019). AI is essentially a kind of general-purpose technology (GPT) and key enabling technologies (KET) with the characteristics of enabling nature and innovation complementarity (Bekar et al., 2018; Martinelli et al., 2021). The increasingly popular generative AI, such as ChatGPT, also possesses general-purpose technological characteristics (Eloundou et al., 2023; Goldfarb et al., 2023). A typical characteristic of GPT is complementary innovation. Continuous refinement and positive feedback loops generate innovation spillover effects across various application domains. Based on the theoretical model of GPT (Helpman & Trajtenberg, 1996), we can derive the value creation within the innovation utility of enterprises following the adoption of AI. Due to the complementary innovative characteristics of GPT, there is a bidirectional interactive influence between AI and innovation in the manufacturing application field. On one hand, according to Moore's Law, AI technology updates quickly. The acceleration of AI technology speed brings innovation value to enterprises. This further enhances manufacturing enterprises' innovativeness. On the other hand, the advance in manufacturing technology expands the demand for AI technology applications, motivating developers to further promote AI technology. These complementarities can be termed as technological resonance, or "co-invention" (T. Bresnahan et al., 1996).

According to the innovation commons theory (Potts, 2018), the innovation network formed by AI results from collaborative innovation among multiple subjects such as enterprises, universities, users, developers, etc. It also activates other value interaction. Therefore, the application of AI technology can increase innovation resources and improve enterprises' innovation value.

2.2 The innovation driving function of AI

AI has an even more significant impact by serving as a new general-purpose "method of invention" that can reshape the nature of the innovation process and enterprise innovativeness (Cockburn et al., 2018a; Griliches, 1957). The application of AI can propel interconnection and communication among objects to a higher level of wisdom (Müller & Bostrom, 2016). As manufacturing enterprises popularize AI technology in production and management, the whole life cycle of the industry faces a new round of innovation. Specifically, it exhibits the following innovation-driven effects.

On one hand, AI exhibits the capability to accelerate the dissemination of knowledge and information, facilitating the discovery and incubation of new technologies. AI combined with big data analytics creates a scientific analysis of large data structures, which can help manufacturing enterprises obtain more information resources and dig deeply into them (Shukla et al., 2019). AI can rapidly mimic and learn from cutting-edge scientific advancements and identify issues in complex model designs, thus lowering trial-and-error costs. Statistics indicate a notable improvement in the accuracy of machine vision in pedestrian recognition, with error rates decreasing from 30 to 30 million frames. This development coincides with the increasing feasibility of autonomous vehicles (Brynjolfsson et al., 2017). Utilizing industry-level robot data, Liu et al. (2020) investigated that robotic applications promote innovation by accelerating knowledge creation and technology spillovers, enhancing learning and absorption capabilities, and increasing investment in research and development.

On the other hand, AI also has the potential to improve cooperation and communication within companies by connecting individuals or teams with the necessary skills or information. Human-to-computer interaction systems are widely applied to scientific research, product design, process simulation, and production simulation. AI aids scientists in formulating hypotheses and enhances knowledge production capabilities through effective search and recombination of a broader range of knowledge, substantially improving research efficiency (Agrawal et al., 2023). Further, AI is a predictive technology that demonstrates immense potential in experimental design and data processing (Agrawal et al., 2019b; Charness et al., 2023). It not only assists researchers in experimental design but also handles and analyzes experimental data, making the innovation process more efficient. For instance, AI can shorten the medicine research and development lifecycle, completing tasks that previously took years in a matter of weeks. Furthermore, enterprises leveraging AI applications can gather valuable insights from customers, suppliers, and supply chain partners (Min, 2010). AI algorithms assist in precisely understanding customer preferences, enabling personalization customization based on diverse customer demands, thereby expanding the product range (Mihet & Philippon, 2019). This fosters the creation of new business opportunities (Braguinsky et al., 2021) and optimizes product innovation, process innovation, and business model innovation (Babina et al., 2024; Haefner et al., 2021).

Therefore, AI can increase an enterprise's internal innovation capability while promoting external innovation interactions through strengthening communication and collaboration. Thus, we propose the following:

H1. *AI adoption has a positive impact on innovation capability (a) and innovation interaction (b).*

2.3 The impact of AI adoption on labor structure

The expanding use of AI in businesses will likely pose several organizational and managerial challenges. AI-based technologies have sparked controversy and an academic puzzle due to the prospect of human workforce replacement (Sun & Medaglia, 2019). Some studies suggest that adopting AI might have a substitution effect on employment. With the large-scale application of automation and AI technologies, the demand for the traditional labor force in various fields will decrease as machines replace many positions. Enterprises considering cost control may conduct a reduction in the scale of employment (David, 2017; Frey & Osborne, 2017). This "machine replacement" is an inevitable phenomenon.

According to the "*skill-biased technological progress*" (SBTC) hypothesis, the development of technology will decrease the demand for low-tech labor while maintaining or increasing the demand for high-tech labor (Neuberger-Fernandez & Barton, 2017). A study of the computerization of 702 occupations in the US found that about 47 percent of the workforce would be at risk of unemployment, with a higher risk of substitution for conventional occupations (Frey & Osborne, 2017). AI adoption by enterprises may feed back to the demand for skill levels, resulting in a declining share of low-tech jobs and rapid growth of high-tech jobs. Acemoglu and Restrepo (2020) confirmed that automation technology not only tends to use machines instead of low-tech labor but also creates new tasks for high-tech labor. They found that for every 1% increase in the number of robots in the United States, employment decreases by 0.18% to 0.34%. Enterprises may employ technicians specializing in AI-related tasks (Acemoglu et al., 2022). With the emergence of advanced AI technologies, the workforce with lower education and skill has become insufficient to meet the demands of businesses. Consequently, there is a growing demand for labor with higher education qualifications (Zhang et al., 2021). According to the above analysis, we propose the following:

H2. *AI adoption will decrease the proportion of low-tech personnel (a) and increase the proportion of high-tech personnel (b) in enterprises.*

2.4 AI adoption, labor structure, and enterprise innovativeness

Employees are an innovative company's most vital assets (Gupta & Singhal, 1993). Prior literature noted that employees' abilities affect firms' profits (Ada Leiponen, 2000). Moreover, the impact of the structure of employees on enterprise innovativeness is worth researching (Tajeddini, 2015a, b). Substantial evidence supports the notion that diverse knowledge and skills within an organization significantly contribute to its innovation potential (Herstad et al., 2019; Shin et al., 2012; Solheim et al., 2020). High-tech labor may have more research and development potential and productivity, while low-tech labor employees are comparatively less inclined to identify potentially beneficial research and development investment prospects (Aija Leiponen, 2005). There is a positive relationship between a larger pool of highly skilled personnel and the sustainability of innovation outcomes (Capozza & Divella, 2019; Chowhan et al., 2017). Technical personnel possess fundamental knowledge about technical and scientific domains, which they can impart to organizations.

In a work setting with AI adoption, collaboration between AI systems and human workers can create value for businesses and achieve more innovative outcomes (Chowdhury et al., 2022). Incorporating AI into business operations can enhance creativity and employee engagement by augmenting human capabilities, leading to higher performance and productivity (Jaiswal et al., 2022). AI can assist employees with their responsibilities and decision-making processes more efficiently, encouraging greater participation and creativity (Acemoglu et al., 2022; Filippetti & Guy, 2020). Employees are empowered to make informed decisions while developing their problem-solving skills by providing data analysis and insights through AI-powered systems. Additionally, using AI in fostering innovation enables employees to filter through vast amounts of data to identify patterns and trends that may lead to new avenues for innovation (Acemoglu & Restrepo, 2018). This promotes knowledge sharing and idea generation among employees (Chowdhury et al., 2022). Furthermore, labor performing repetitive low-tech tasks is susceptible to automation, while the utilization rate of high-tech labor with better digital skills is significantly enhanced. This ultimately reduces unit labor costs and unleashes the effects of technological innovation (Agrawal et al., 2019).

In conclusion, utilizing AI technology harnesses the potential of high-tech labor, replacing low-tech labor, thereby increasing innovation while improving employees' digital literacy. However, the impact of the labor structure of high-tech and low-tech personnel on enterprise innovativeness needs to be further confirmed. Therefore, we propose the following:

H3: *AI adoption influences enterprise innovation by replacing low-skilled labor and enhancing high-skilled labor.*

To sum up, our research hypotheses of this paper follow the theoretical logic shown in Figure Ⅰ.

Please place Figure I here

3. Methodology

This study utilizes panel data from Chinese manufacturing firms listed on the Shanghai and Shenzhen stock markets from 2010 to 2022, employing multiple regression analysis to identify the impact and underlying mechanisms of AI adoption on enterprise innovation. Python and machine learning techniques are used for data processing and index construction. Among them, the AI adoption index at the firm level is measured as the core explanatory variable with the entropy weighting method. In addition, multiple robustness tests are conducted to ensure the scientific rigor of causal inference.

3.1 Model settings

The research employed a two-way fixed effects (TWFE) model to investigate the impact of AI adoption on enterprises' innovativeness as follows:

$$Inno_{it} = \alpha_0 + \alpha_1 AIA_{it} + \alpha_x \sum Control_{it} + \theta_i + \lambda_t + \varepsilon_{it} \quad (1)$$

where $Inno_{it}$ contains two variables which respectively represent innovation capability and innovation interaction. AIA_{it} represents the index of AI adoption. $\sum Control_{it}$ represents the control variables. To mitigate the potential impact of omitted variables related to firm and industry characteristics on the effect of AI adoption on enterprises' innovativeness, this study controls for firm-fixed effects (θ_i)

and year-fixed effects (λ_t), and clustered the robust standard errors at the industry level.

To further test whether AI adoption can affect the labor structure of enterprises, we construct a mediation effect model.

$$LS_{it} = \beta_0 + \beta_1 AIA_{it} + \beta_x \sum Control_{it} + \theta_i + \lambda_t + e_{it} \quad (2)$$

LS_{it} indicates labor structure, including education structure and skill structure. β_1 examines the indirect effect of AI adoption on enterprise innovativeness by labor structure.

3.2 Data and measurement

We used unbalanced panel data from 2010 to 2022. The data of Chinese manufacturing listed companies in Shanghai and Shenzhen A-stock markets is collected through Wind and CSMAR databases. The data on patents comes from CSMAR and CNRDS databases, and some additional information is gathered from the State Intellectual Property Office (SIPO). The index of AI adoption combines three indicators, namely attention, application, and absorption. Among them, AI attention is measured by the word frequency of AI-related keywords captured by Python technology from annual reports of listed companies. The penetration rate of industrial robots is calculated from the IFR database. AI technology patent applications are identified by the international patent classification (IPC) code and obtained from the IncoPat database. To ensure the accuracy and authenticity of the research results, we eliminated samples with ST and ST* listed companies and with missing or wrong data, such as the number of assets and equity being less than zero. The continuous variables about the firm level have been subjected to a 1% winsorization.

3.2.1 Manufacturing enterprise innovativeness

The driving force of innovation not only emanates from the inherent capabilities of enterprises but also relies on the interaction with external resources. When measuring enterprise innovativeness, our study delves into two dimensions of innovation within manufacturing enterprises. The first pertains to innovation capability, gauged through patent applications, while the second focuses on innovation interaction, measured by patent citations and collaborative patents involving industry-university-research cooperation. In contrast to research and development investments, the number of patents offers a more intuitive reflection of the innovation level. Moreover, it makes a market signal for potential partners to obtain venture capital and show their competitive advantage to customers (Haeussler et al., 2014). This study excluded AI patent from the total patent applications, thus removing the influence of AI technology's inherent innovation. The number of citations not only reflects the quality of innovation (Pakes, 1984), but also indicates the commercial value of enterprise innovation and technological collaboration. In contrast, the number of patent citations can indicate the commercial value of enterprises' innovativeness and technological collaboration (Hall et al., 2005). Given the increasing complexity of technological innovation activities and the rise in technological convergence, enterprises find it increasingly challenging to achieve effective technological innovation solely relying on their internal resources and capabilities. This is where using external resources for collaborative research and development has emerged as a new trend (Chesbrough & Crowther, 2006). Among these, industry-university-research (IUR) cooperation stands out as a crucial form of collaborative innovation. This form of collaboration provides a comprehensive reflection of innovation interaction. To quantify the manufacturing enterprises' innovativeness, we employed the natural logarithm of the number of patents plus one as the dependent variable.

3.2.2 AI adoption index

The current mainstream methods for measuring micro-level AI adoption include the utilization of the enterprise industrial robot penetration index (Acemoglu & Restrepo, 2020), AI technology patent data (Hoedemakers, 2017; Mann & Püttmann, 2018), and AI investments (Aghion et al., 2020; Babina et al., 2024). However, single dimensional indicator is hard to capture an enterprise's actual AI adoption level fully. Drawing inspiration from the three stages of the digital divide—access, skills and usage (van Deursen et al., 2021), this study introduces the AI adoption Index, assessing the integration of AI with enterprises from three dimensions: attention, application, and absorption, as detailed in Table Ⅰ. Using the entropy weighting method, the core independent variable of an enterprise's actual AI adoption level is measured as follows.

Attention means the attitude of enterprises to adopt new technologies and business models of AI. AI attention is measured using AI-related keywords, as AI-related keyword disclosure can reflect enterprises' attention to AI (Q. Wu et al., 2023). Text analysis of annual reports has become a new method of econometrics. Following prior literature (F. Wu et al., 2021; Yang & Liu, 2018), we collected the annual report text of listed companies and counted the word frequency of AI-related keywords using Python and machine learning technology. This is because listed companies need to issue annual reports regularly, and the information in the annual reports of publicly traded companies reflects their strategic characteristics and future prospects. Further, the disclosure information is subject to public supervision. Therefore, this method of text analysis of annual reports is feasible and scientific. After reading the national policy documents and reports, we selected the relevant keywords related to AI, as shown in Table Ⅱ. The Jieba word function of Python was used to segment the annual report text of each listed company. Then, we cleaned the data and counted the word frequency of AI attention.

The penetration density of robots better reflects a country's actual level of AI application (Acemoglu & Restrepo, 2018). In the era of Industry 4.0, the concentrated embodiment of intelligent manufacturing lies in the widespread application of industrial robots. Industrial robots have had an early impact on the automation of manufacturing processes, leading to a substitution effect on labor structures. Following Acemoglu and Restrepo (2020), this paper employs the Bartik instrument (Bartik, 1991; Goldsmith-Pinkham et al., 2020) to construct a penetration index of industrial robots at the enterprise level in the Chinese manufacturing sector. The specific measurement method is outlined as follows:

In the first step, we calculate the industry-level penetration index of industrial robots, denoted as:

$$PR_{it}^{CH} = \frac{MR_{it}^{CH}}{L_{i,t=2010}^{CH}} \quad (3)$$

Here, MR_{it}^{CH} represents the stock of industrial robots in the industry i in year t in China, and $L_{i,t=2010}^{CH}$ represents the employment in the industry i in the base year 2010.

In the second step, we construct the enterprise-level penetration index of industrial robots as follows:

$$CHFexposure\ to\ robots_{jit} = \frac{PWP_{jit=2011}}{ManuPWP_{t=2011}} * \frac{MR_{it}^{CH}}{L_{i,t=2010}^{CH}} \quad (4)$$

Here, $\frac{PWP_{jit=2011}}{ManuPWP_{t=2011}}$ represents the ratio of the proportion of employees in the production department of enterprise j in the industry i in the year 2011 (base year) to the median proportion of employees in the production department of all manufacturing enterprises in the year 2011.

Absorption is defined as the capability of enterprises to effectively capture, transform, integrate and use internal and external knowledge to improve their competitive position (Cohen & Levinthal, 1990). Enterprises with higher absorptive capability are more likely to succeed in implementing new technologies and manufacturing practices (Agostini & Nosella, 2020). This paper adopts AI absorption as an indicator to characterize the capability of enterprises to integrate AI technology. This indicator includes the quantity of AI patents (Zhai & Liu, 2023) as well as research and development investments. We identify AI-related patents according to the IPC codes, which are detailed in Table Ⅲ. By matching AI patents from the IncoPat database with the patent information of listed companies, we aggregated company-level AI patents annually.

Please place Table I here

Please place Table Ⅱ here

Please place Table Ⅲ here

3.2.3 Labor structure

Labor structure is the mediator between AI adoption and enterprise innovativeness. The mediator is measured using two indicators. One indicator is education structure, reflecting employees' different educational backgrounds, measured by the proportion of high school degrees, college degrees, bachelor's degrees, and postgraduate qualifications. The other indicator is skill structure, measured by the proportion of production personnel, sales personnel, and technical personnel in the workforce.

Referring to the occupational classification provided by the statistical division of the International Labor Organization and the occupational categories introduced by

Filippetti and Guy (2020), the structure of low-tech personnel is represented by utilizing the proportion of employees having high school degrees and college degrees. Most employees included in this category were production personnel and sales personnel. The structure of high-tech personnel is expressed by the proportion of employees having bachelor's degrees and postgraduate qualifications. Most employees included in this category were technical personnel.

3.2.4 Control variables

We used control variables about enterprise innovativeness to mitigate the potential effects of omitted variables on estimation distortion (Tajeddini, 2015a, 2015b; Tajeddini & Trueman, 2012, 2014). Referring to previous literature (Bentley et al., 2013; Chen et al., 2022; Shi et al., 2020), enterprise size, enterprise age, return on assets, proportion of shares held by the largest shareholder, and growth rate of operating income were identified as potential control variables. To account for innovation disparities arising from distinct corporate ownership structures and industry heterogeneity, we further controlled ownership structure (i.e., stated-owned vs. private) and type of industry (i.e., high-tech vs. low-tech). The summary statistics about testing the effects of control variables are shown in Table Ⅳ.

Please place Table Ⅳ here

By analyzing the annual average growth trends by decomposing the AI adoption index and sub-indicators in Figure Ⅱ, it is evident that enterprises have sustained an upward trajectory in both AI attention and industrial robot penetration. This continuous elevation ensures the steady growth of the AI adoption index. Since 2016, there has been a significant breakthrough in AI technology, manifested in the explosive growth of AI patents. This surge has robustly propelled the diffusion of AI's general-purpose technologies, emerging as the core driving force behind enterprises' AI adoption. Since variable selection, we conducted correlation tests on the core and control variables, as shown in Table Ⅴ. The findings reveal a significant direct correlation among the core variables, while no multicollinearity issues were observed.

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Please place Table Ⅴ here

4. Empirical analysis

4.1 Estimation of benchmarks

Table Ⅵ illustrates how the adoption of AI directly affects enterprise innovativeness. The dependent variable for columns (1) and (2) is calculated using patent applications to represent the innovation capability, while the dependent variables for columns (3) to (6) are patent citation and IUR cooperative patent to represent the innovation interaction. The independent variables in columns (1), (3), and (5) employ the current period's AI adoption index, while columns (2), (4), and (6) incorporate a one-period lag to capture the lagged effects of AI on enterprise innovativeness. All models include control variables, fixed effects for firms, and years to ensure accuracy.

The results demonstrated that adopting AI has a statistically significant positive effect on enterprise innovativeness. This implies that the adoption of AI amplifies innovation capability and fosters innovation interaction among manufacturing enterprises in China. The coefficient in column (1) reveals that the effect of AI adoption on innovation capability is 3.599 and is statistically significant at the 1% significance level. After incorporating the lagged AI adoption index, this coefficient decreases to 2.865. The primary reason for this adjustment is the lingering influence of the previous period's AI adoption, exerting a coefficient effect of 2.906 on the current period's patent applications. This effect is equally applicable to innovation interactions. In column (3), the coefficient of AI adoption on patent citations reaches 4.572 and is statistically significant at the 1% significance level. In column (4), the lagged effect coefficient of AI adoption decreases to 0.849, which is significant at the 10% significance level. This indicates that AI adoption can expedite the diffusion of innovation resources, providing enterprises with greater convenience and speed in patent citations. As shown in columns (5) and (6), AI adoption also significantly promotes collaborative innovation involving industry, universities, and research institutions, strengthening the interaction among diverse innovation entities. The regression results support hypothesis 1a and 1b.

Additionally, the findings of our study also indicate that the size of enterprises has a positive effect on innovativeness. This suggests that larger enterprises may possess greater innovative capability, which could account for the observed trend. Companies with more extended periods of being publicly listed exhibit a higher frequency of mutual patent citations. In contrast, companies with shorter periods of being publicly listed engage more frequently in collaborative innovation with industry, universities, and research institutions. This reflects the divergent innovation interaction patterns among companies with different attributes.

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4.2 Robustness testing

To affirm the reliability of benchmark results, we replace both the independent and dependent variables. The independent variable is replaced by single-dimensional variable lagged by one period. The dependent variables are then replaced with the proportion of research and development investment to operating income, the logarithm of the number of invention patent applications, and innovation breadth. Innovation breadth is measured by the internal diversity of major group information within the IPC codes of patents. This metric reflects the enterprise's ability to strategically mobilize innovation resources across different domains, providing insight into the level of innovation interaction. The regression results with the replacement of new variables are shown in Table Ⅶ. The control variables and fixed effects of regressions are the same as the benchmark regression. The coefficient of new variables is all significant and positive.

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4.3 Endogeneity testing

This study has endeavored to meet endogeneity requirements in the application of AI. However, the reliability of benchmark regression results may still be affected by omitted variables and reverse causality issues. According to the Diffusion of Innovation (DOI) theory, omitted variables that influence the manner in enterprises' innovativeness, depends on individual or leadership's characteristics and the internal and external features of the organization (Savrul & Incekara, 2015). We have controlled for individual fixed effects and clustered at the industry level, covering most omitted variables related to individual characteristics of enterprises. However, the extent to which enterprises adopt AI may be an adaptive response to innovation capabilities. To address endogeneity issues, we employ external instrumental variables to mitigate this concern. We construct two instrumental variables following conventional practices (Acemoglu and Restrepo, 2020; Bartik, 1991). One is the installation data of industrial robots in the United States (IV_installusa). Another is the instrumental variable for the robot penetration of Chinese enterprises based on industry-level industrial robot data in the United States: IV_AIusa $= \left(PWP_{jit=2011}/ManuPWP_{t=2011}\right) \times (AIIN_{jt}^{US}/L_{jt=1990}^{US}$). Here, $AIIN_{jt}^{US}/L_{jt=1990}^{US}$ represents the robot penetration in industry j in the United States in year t. Both China and the United States are leading nations in global AI applications. While there is a certain correlation between the development of robotics in the two countries, the impact of American robot applications on Chinese enterprises' innovativeness is almost weak. This is evidenced by the lack of correlation with the original residual term, thus satisfying the relevance and exclusivity criteria for instrumental variables.

Table Ⅷ reports the regression results of the two instrumental variables. The results of the first stage of the instrumental variable model, presented in columns (1) and (2), indicate the reinforcement of the exogeneity of our instrumental variable, passing both the underidentification test and the weak identification test (p-values of the LM statistic and Wald F statistic are equal to 0). Despite mitigating endogeneity concerns through the two instrumental variable methods, the degree of AI adoption still significantly promotes both innovation capability and innovation interaction within enterprises. This confirms the robustness of the benchmark regression results in our study.

Please place Table Ⅷ here

5. Mechanism analysis

This section outlines our endeavor to elucidate the mechanism by which the adoption of AI affects innovation. Drawing from the theoretical analysis presented in Section 2, it can be posited that the adoption of AI has the potential to impact enterprise innovativeness by inducing changes in the composition of the labor structure. The impact mechanism of AI adoption was partitioned into two distinct routes and subsequently validated through the utilization of a mediation effect model, as presented in Table Ⅸ. In order to depict the influence of AI adoption on enterprise innovativeness under different labor structures, we used the heterogeneity test to tested hypothesis 3, as shown in Table Ⅹ.

5.1 Education structure

In columns (1) to (4) of **Table Ⅸ**, the impact of AI adoption on the proportion of employees with different educational backgrounds is examined. We find that the coefficient for employees with a high school education or below is -24.297, significantly negative, while the coefficients for employees with associate degrees are negative but insignificant. In contrast, the coefficients for the proportions of employees with undergraduate and postgraduate degrees are respectively 11.196 and 5.930, both significantly positive. The reasons for the results may stem from the fact that AI demonstrates a comparative advantage over human labor in specific routine and repetitive tasks, typically carried out by less-educated and low-tech workers. Hence, the substitution effect on less-educated labor is more pronounced. Simultaneously, as automation replaces some labor positions, it also creates new positions that require higher levels of human skills. The development and maintenance of AI technologies demand highly skilled labor, increasing the demand for individuals with higher educational qualifications. Following the Smiling Curve Law, the value created at the research and development end far exceeds that in the production and assembly departments. AI aids companies in talent selection, and to achieve more excellent innovative value, firms tend to reduce the employment of less-educated labor with limited contributions to research and development and innovation and increase the hiring of highly educated talent.

5.2 Skill structure

In columns (5) to (8) of Table Ⅸ, AI adoption has a significant negative correlation with the proportion of mid-to-low-tech labor, including production personnel, sales staff, and finance personnel, while significantly increasing the proportion of research and development personnel. This reflects that AI exhibits the most substantial substitutive effect on mid-to-low-tech workers while concurrently demonstrating a complementary effect with highly skilled workers engaged in research and development activities. By replacing some production, sales, and finance personnel with AI, enterprises can save costs and redirect resources toward research and development expenditures. The traditional manufacturing industry considerably demands production personnel on the assembly line. However, enterprises are more likely to replace some personnel in simple and repetitive assembly line work after adopting AI technology and automated production lines. Yet, the mediation effect measured by sales personnel is untenable. AI technology will not necessarily replace the position of sales personnel. While AI avatars are employed on live streaming platforms for product marketing, breaking time and space constraints to enable continuous 24-hour broadcasting, online marketing still requires additional sales personnel to open new markets and provide personalized customer service. Sales personnel can also promote innovation interaction. As some researchers concluded (Deming, 2017), AI technology cannot wholly replace social activities that require human beings, and some jobs, like sales, that require social skills are difficult to replace. Column (8) shows a significant positive correlation between AI adoption and technical personnel at the 1% significance level. For better adoption of AI, enterprises need high-tech talents to provide a theoretical basis and more technicians in daily operations and maintenance of automation machines.

Under the advancement of AI technology, improvements in employees' structure also facilitate enterprise innovation. Human capital as the resource advantages underlying the competitiveness of the enterprises (Bogoviz & Ragulina, 2021), has become essential in fostering innovation in modern industries. Knowledge is diffused among individuals through interactions and more knowledge leads to the production of higher-quality innovations (Akcigit et al., 2018). Therefore, high-tech employees can better access external knowledge and make full use of existing resources, then make transformation and innovation of products and services (Tushman & Anderson, 2018). Furthermore, enterprise with a highly educated and skilled workforce may attracts more funding from governmental and financing entities, facilitating better innovation activities (González et al., 2016). Hypotheses 2a and 2b proposed above are all supported.

Please place Table Ⅸ here

5.3 AI-driven innovation based on labor structure

According to the grouped regression results based on labor structure, as shown in Table Ⅹ, enterprises with a higher proportion of high-tech employees exhibit a more substantial influence of AI adoption on technological innovation. In terms of educational background, for enterprises staffed with more employees holding graduate and postgraduate degrees, the coefficients of the impact of AI on innovation capability and innovation interaction are 3.717 and 4.731. In contrast, in enterprises where most employees have college and high school diplomas, the respective coefficient values are 2.836 and 2.872. Regarding skill levels, enterprises with a predominant presence of technical personnel experience a more pronounced impact of AI adoption. This impact is not only reflected in a substantial improvement in innovation capability (coefficient of 3.061) but also in the improvement of innovation interaction represented by patent citations (coefficient of 5.526) and patents with IUR collaboration (coefficient of 2.122). In contrast, enterprises with fewer technical personnel exhibit lower coefficients in innovation capability and insignificance in innovation interaction levels. This reflects that enterprises with a high proportion of high-tech employees often prioritize research and development activities. High-tech employees often possess complementary skills and work on interconnected projects that involve AI technologies. This interconnectivity fosters communication as team members share insights, challenges, and solutions related to AI adoption, creating a collaborative atmosphere for innovation and enhancing the overall innovation capability of the enterprise. The hypotheses 3 is thereby validated.

Please place Table X here

6. Discussion and implications

6.1 Discussion

This study provide novel empirical evidences that AI adoption significantly enhances enterprise innovation from multiple dimensions. The educational background and skill composition of employees are identified as pivotal mediating elements in this relationship.

Firstly, the integration of AI within business operations, particularly within the Chinese manufacturing sector, has been associated with a marked enhancement in innovation capabilities and interactions. This is primarily attributed to the complementary innovation of GPT, which foster a technological synergy between AI and manufacturing innovation. AI-based technologies facilitate the development of novel goods and procedures, thereby invigorating innovation within these enterprises (Dwivedi et al., 2021). Notably, the seamless integration of AI technology with production and management structures contributes to its popularity in manufacturing enterprises by fostering innovation. These findings align with the theory of AI and its enabling nature, which suggests that AI can enhance efficiency and stimulate corporate creativity (Agrawal et al., 2019a; Jaiswal et al., 2022). Integrating AI technologies with research and development processes has led to a surge in patent citations, indicating the increased relevance and applicability of these innovations. Furthermore, AI's facilitation of knowledge dissemination, automation of patent-related processes, and discovery of new insights has contributed to a more productive and efficient environment for industry-university-research (IUR) collaborations. AI applications in patent-related activities has fortified the nexus between industries, universities, and research entities, fostering a synergistic relationship that collectively propels innovation.

Secondly, AI heralds a transformation in the labor structure. Empirical evidence suggests that AI adoption exerts dual mediation effects on the educational and skill structure of the labor force within manufacturing enterprises. Aligning with the prevailing consensus in the literature (Acemoglu et al., 2022; Acemoglu & Restrepo, 2020; Aghion et al., 2019), this study posits that AI is likely to supplant low-tech labor while amplifying the demand for high-tech labor. There is a significant reduction in the percentage of employees with low education qualifications after adopting AI, while the proportion of employees with undergraduate and postgraduate degrees increased. Similarly, the result demonstrates a marked decrease in the proportion of production, sales, and financial personnel, coupled with a noteworthy increase in the proportion of technical personnel. This skill shift highlights the evolving requirements for specialized skills in response to AI adoption. However, this research presents a different perspective from recent literature on generative AI (Eisfeldt et al., 2023). Individual with medium to high skills and relatively higher wages are more likely to interact with LLMs and face a threat of substitution (Noy & Zhang, 2023; Tyna et al., 2023). While acknowledging the potential impact of this new type of AI on labor skills, this study does not deny the potential disruptions it may bring to low-skilled labor.

Thirdly, the increase in the proportion of high-tech employees is identified as a crucial mechanism through which AI drives innovation in manufacturing enterprises. Enterprises with a higher proportion of highly educated and highly skilled employees exhibit a more substantial influence of AI adoption on technological innovation. Although the labor resources required for fostering enterprise innovativeness are distinct, digital skills are indispensable for employees. Within China's educational system, individuals with higher education levels and technical expertise often have better learning conditions and possess higher digital skills, enabling them to master and apply new technologies more effectively. Analyzing and applying big data generated from manufacturing scenarios through AI technology is essential knowledge and capability for employees in the Industry 4.0 era (Di Maria et al., 2018). AI adoption enhances employees' digital skills, thus facilitating a beneficial interaction between technology introduction and skill development. Conversely, less-educated and low-skilled employees are insufficient to meet the demands of innovative development within enterprises. This inevitable trend puts an increased emphasis on employees with higher educational qualifications (Zhang et al., 2021).

In summary, the study's findings suggest a realignment in the demand for different educational and skill levels due to AI adoption, which is instrumental in fostering innovation. While concerns about job replacement arise with AI adoption, the findings also highlight the potential for new job opportunities arising from fostering innovation (Kumari et al., 2022). The deployment of AI is closely associated with changes in organizational employment structures and skill requirements in the workplace. These findings align with existing literature that supports the idea that a shift in personnel demand influences enterprise innovativeness (Acemoglu & Restrepo, 2018; Chowdhury et al., 2023; Solheim et al., 2020; Tajedini & Tajddini, 2018).

6.2 Theoretical implications

Our study significantly augments both the theoretical and empirical comprehension of the complex interplay among AI adoption, labor resources, and enterprise innovativeness in the AI-dominated era. This research innovatively extends the complementary innovation theory of general-purpose technologies (GPTs) to examine the impact of AI on enterprise innovation. The results of this study are consistent with prior literature that emphasized the favorable correlation between the adoption of AI and innovation (Babina et al., 2020; Bresnahan & Trajtenberg, 1995; Capozza & Divella, 2019; Cockburn et al., 2018b). Our study discusses enterprise innovation from multiple dimensions of innovation capability and innovation interaction, thereby enriching the innovation commons theory from an AI perspective (Potts, 2018). We have further substantiated the discovery that AI adoption is positively correlated with an increase in patent applications, citations, and industry-university-research (IUR) collaboration patents. The influence of AI adoption on both internal innovation capability and external innovation interaction is transformative. Internally, AI stimulates investment in research and development and continuous technological advancement, while externally, it integrates organizations into a broader innovation ecosystem, promoting collaboration and the exchange of valuable insights. AI acts as a kind of GPT that fosters ideation, collaboration, and problem-solving methods, thus creating an environment conducive to more efficient collaborative innovation. Unlike previous literature that predominantly utilized a single index to gauge the level of AI adoption in enterprises, this study introduces an innovative methodology to measure firm-level AI adoption. We construct a three-dimensional index encompassing attention, application, and absorption, amalgamating data from the industrial robot penetration index, AI-related keywords, and AI patents.

Furthermore, our study demonstrates the disruptive impact of AI adoption on educational and skill structures. Departing from prior research that focused on AI's role in substituting or enhancing labor skills (Acemoglu et al., 2022; Aghion et al., 2020; Agrawal et al., 2019a), we analyze the pivotal role of individuals with higher education qualifications and advanced skills in influencing the innovative activities of enterprises leveraging AI technologies. Enterprises with a high-tech employee structure exhibit stronger innovation capabilities and interactions. This analysis provides a theoretical framework for understanding human-machine collaborative innovation. Theoretical advancements in this domain offer valuable guidance for organizations in establishing inclusive and collaborative innovation ecosystems through the utilization of AI.

6.3 Policy recommendations

The findings of our research uncover Chinese practices, which have valuable implications for global dissemination. Firstly, we advocate for enterprises to actively embrace AI technology, leading to a transformative impact on the traditional manufacturing industry and facilitating intelligent upgrades. Strengthening proficiency in machine learning, data analysis, and utilization across various departments, including design, production, and sales, is crucial. This strategic adoption of AI enables enterprises to optimize their innovation processes, reduce research and development input costs, and enhance research and development efficiency. Further, government support is pivotal in driving the intelligent manufacturing strategy and backing the construction of intelligent factories and experiments.

Secondly, Policies must emphasize the importance of continuous education and skill enhancement to prepare the workforce for AI-driven industries. Recognizing the potential displacement of low-tech labor due to AI, it is crucial to design policies that facilitate the transition for affected workers. Retraining programs should focus on helping low-skilled workers acquire new skills to remain competitive in an AI-dominated labor market. Educational institutions should also update curricula to include AI-related topics and foster collaborations with industries to ensure students are equipped with relevant skills. Incentives such as scholarships and grants for students pursuing higher education in technical fields will address the growing demand for highly skilled workers in the AI era.

Thirdly, we propose enhancing technology communication and IUR cooperation based on AI adoption. Strengthening partnerships between industries, universities, and research entities is vital for fostering innovation. Policies should encourage collaborative AI-driven projects, with financial and structural support for initiatives involving joint R&D, knowledge sharing, and patenting. Innovation hubs and research incubators should be established to promote the cross-sector integration of AI technologies (Fan et al., 2023). This will further develop synergies between industries and academic institutions, leading to more rapid innovation growth.

6.4 Limitations and future research

In considering the limitations of this study and outlining potential avenues for future research, it becomes evident that while innovation patents offer valuable insights, they may not be the exclusive or optimal measures of enterprise innovation capability. To enhance the depth of our understanding, future investigations could advocate for a more expansive array of performance metrics. This broader spectrum should encompass not only innovation outputs but also incorporate factors such as employee satisfaction, customer experience, and societal impact. Embracing this comprehensive approach ensures a thorough and well-rounded evaluation of enterprise innovativeness.

An area ripe for further exploration lies in delving into the intricacies of human-AI collaboration dynamics. Future research endeavors could scrutinize the specific organizational structures and cultures that facilitate effective partnerships between humans and AI. This nuanced exploration promises to unveil valuable insights into optimizing collaborative efforts and harnessing the synergies between human intelligence and AI.

Furthermore, an in-depth examination of the long-term socioeconomic effects stemming from the adoption of various AI technologies, including but not limited to ChatGPT and advanced AI generative models, presents an exciting avenue for future inquiry. Understanding the profound and lasting impact of these technologies on societal and economic dimensions will be pivotal for crafting informed policies and strategies.

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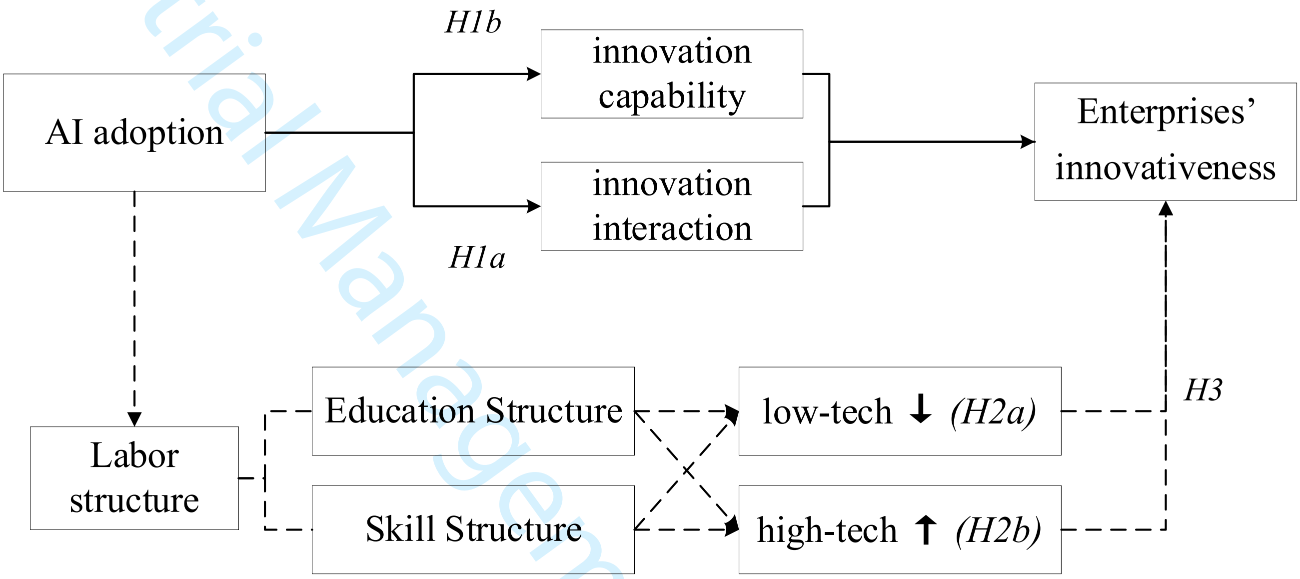

Figure I.
Hypothesized Model

Source(s): Authors' own creation

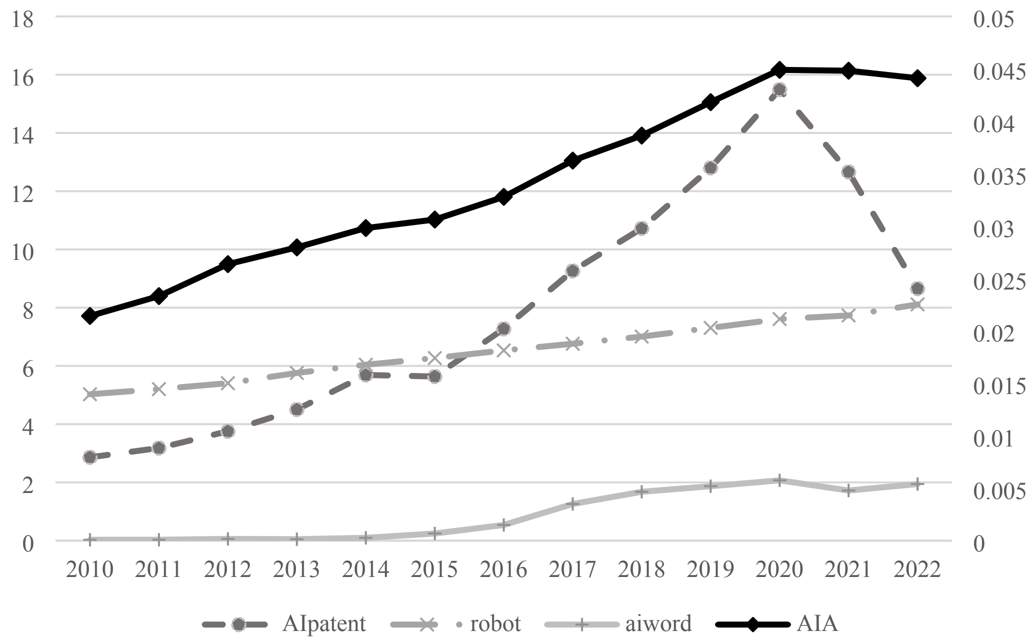

Figure Ⅱ.
Time trend chart of enterprise AI adoption index

Source(s): Authors' own creation

Table I.
The indicators of AI adoption index

AI Indicators	Indicator description	Data source
Attention	The logarithm of the number of artificial intelligence keywords disclosed in the enterprise annual report.	Calculated from the CSMAR database
Application	Penetration rate of industrial robots.	Calculated from the IFR database
Absorption	Logarithm of AI technology patent applications.	Calculated from the IncoPat database
	Research and development expenditure accounts for the proportion of total assets	Calculated from the CSMAR database

Source(s): Authors' own creation

Table II.

Keywords related to artificial intelligence

	AI
Keywords	intelligence, artificial intelligence, intelligent manufacturing, intelligent technology, image understanding, machine learning, deep learning, semantic search, speech recognition, natural language processing, face recognition, biometric technology, neural network, face recognition, intelligent robot, industrial robot, intelligent data analysis, automation, authentication, autonomous driving, smart, smartification, automated, investment decision support system, numerical control, integration, intelligent office, AIoT, intelligent Internet of things, smart medicine, UAV, intelligent driving, intelligent medical treatment, smart home, intelligent education, intelligent finance, intelligent security, smart retail, business intelligence, industrial intelligence, mobile intelligence, intelligent control, intelligent terminal, smart mobility, smart management, smart factory, smart logistics, smart manufacturing, smart warehousing, smart technology, smart devices, smart production, intelligent networked, intelligent system, automation, automatic monitoring, automated control, automated detection, automated production, numerical control, integration, integrated solutions, integrated control, integrated systems, industrial cloud, future factory, intelligent fault diagnosis, etc.

Source(s): Authors' own creation

Table Ⅲ.
The patent details of AI technology

AI technology name	IPC code
Deep Learning Technology	G06K9 G06F17 G06Q10 G06N3 G06T7 H04L29 GO6F16 G05B13 G06F19 G06Q30
Speech Recognition	G10L15 G06F17 G06F3 G10L25 G06K9 H04L29 HO4MI G10L17 G05B19 G10L21
Natural Language Processing	G06F17 G06F16 G06K9 G10L15 G06F9 G06Q10 H04L29 G09B5 H04L12
Computer Vision	G06K9 G06T7 G06F17 G06T5 G06T3 G06F3 HO4N5 G06T17 G06F21 G06F9
Intelligent Driving	G05Dl G08G1 B60W30 B64C27 G06K9 G06T7 B60R16 G05B19 B64C39
Cloud Computing	H04L29 G06F17 HO4L12 G06F9 G06Q10 GO6F3 G06F21 G06Q30 G06F11 G06F16 G01C21
Intelligent Robot	B25J G05D G05B B62D A47L A6IH GO6F B23K B65G G06K

Source(s): Authors' own creation

Table Ⅳ.
Descriptive statistics of variables

Variables	Variable explanation	*N*	Mean	SD	Min	Max
Inpatent	log of the total number of patent applications (except AI patent) plus 1	22004	2.854	1.875	0	7.22
Incite	log of the total number of patent citation plus 1	22849	1.25	1.61	0	9.64
IUR	log of the total number of industry-university-research cooperative patent plus 1	7348	0.21	0.57	0	5.38
AIA	Index of AI adoption	20100	0.04	0.03	0.00	0.15
Size	log of the number of assets	22873	21.98	1.16	19.84	25.56
Age	log of length of time for enterprise listing	22873	1.83	0.97	0	3.30
ROA	net profit /total assets	20789	0.06	0.05	0	0.25
TOP1	number of shares held by the largest shareholder / total number of shares	22873	34.09	14.10	9.03	72.29
Growth	growth rate of operating income	20788	0.20	0.38	-0.38	2.67
SOE	state-owned enterprise is 1, otherwise it is 0	22316	0.26	0.44	0	1
HighTech	High-tech industry is 1, otherwise 0	22316	0.26	0.44	0	1
Education structure	proportion of high school degree	11844	52.31	21.37	0.02	100
	proportion of college degree	18864	23.72	10.80	0.61	102.35
	proportion of bachelor's degree	19849	20.91	13.54	0.16	100
	proportion of graduate degree	15720	4.21	5.87	0.03	71.60
Skill structure	proportion of production personnel	21284	54.47	19.44	0.10	96.20
	proportion of finance personnel	20330	2.35	1.61	0.03	47.06
	proportion of sales personnel	21377	11.59	12.87	0.06	92.33
	proportion of technical personnel	21583	19.01	13.10	0.12	94.25

Source(s): Authors' own creation

	lnpatent	*lncite*	*IUR*	*AIA*	*Size*	*Age*	*ROA*	*TOP1*	*Growth*	*SOE*	*HighTech*
Inpatent	1										
Incite	0.43***	1									
IUR	0.34***	0.17***	1								
AIA	0.41***	0.32***	0.21***	1							
Size	0.16***	0.50***	0.28***	0.27***	1						
Age	0.03***	0.43***	0.20***	0.06***	0.48***	1					
ROA	0.01*	-0.08***	-0.02	0.05***	-0.01	-0.17***	1				
TOP1	0.02***	-0.04***	-0.01	-0.03***	0.07***	-0.13***	0.09***	1			
Growth	0.11***	-0.02***	-0.03**	0.00	0.06***	-0.05***	0.24***	-0.01	1		
SOE	0.11***	0.22***	0.16***	0.04***	0.33***	0.45***	-0.13***	0.11***	-0.05***	1	
HighTech	0.43***	0.10***	-0.02	0.19***	-0.01	-0.05***	-0.02***	-0.05***	0.04***	0.01	1

Table Ⅴ. Correlation tests

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Source(s): Authors' own creation

Table Ⅵ.

Benchmark estimation

	Innovation capability		Innovation interaction			
	(1)	(2)	(3)	(4)	(5)	(6)
	lnpatent	*lnpatent*	*lncite*	*lncite*	*IUR*	*IUR*
AIA	3.599***	2.865***	4.572***	3.446***	1.840***	1.588***
	(0.695)	(0.613)	(0.909)	(0.427)	(0.553)	(0.428)
L.AIA		2.906**		0.849*		1.089**
		(1.172)		(0.438)		(0.433)
Size	0.508***	0.468***	0.405***	0.390***	0.031	0.020
	(0.062)	(0.060)	(0.054)	(0.020)	(0.032)	(0.023)
Age	-0.012	-0.095	0.926***	1.200***	-0.164***	-0.246***
	(0.073)	(0.070)	(0.084)	(0.043)	(0.053)	(0.049)
ROA	0.631*	0.766	-0.262	-0.186	0.041	0.069
	(0.358)	(0.452)	(0.266)	(0.212)	(0.206)	(0.230)
TOP1	-0.000	-0.004	-0.001	-0.000	0.000	-0.001
	(0.003)	(0.003)	(0.002)	(0.001)	(0.002)	(0.002)
Growth	-0.037	-0.019	-0.175***	-0.148***	-0.021	-0.015
	(0.029)	(0.032)	(0.023)	(0.021)	(0.018)	(0.024)
SOE	0.152	0.154	0.036	0.044	-0.022	-0.062
	(0.097)	(0.132)	(0.067)	(0.053)	(0.038)	(0.057)
HighTech	0.231	0.077	0.176*	0.262***	-0.092	-0.092
	(0.196)	(0.176)	(0.095)	(0.091)	(0.058)	(0.132)
Year FE	√	√	√	√	√	√
Firm FE	√	√	√	√	√	√
Constant	-8.640***	-7.365***	-9.693***	-10.039***	-0.129	0.337
	(1.291)	(1.309)	(1.315)	(0.443)	(0.660)	(0.516)
$Adjust-R^2$	0.550	0.564	0.798	0.815	0.423	0.442
N	18838	14742	19572	15336	6658	5575

Notes: Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Source(s): Authors' own creation

Table Ⅶ.
Robustness test of substituting variables

	(1) *RD*	(2) *Invention*	(3) *Breadth*	(4) *RD*	(5) *Invention*	(6) *Breadth*
L.lnword	0.001**	0.042**	0.004*			
	(0.000)	(0.016)	(0.002)			
L.lnAI_patent				0.001*	0.123***	0.015***
				(0.000)	(0.016)	(0.002)
Control Variables	√	√	√	√	√	√
Year FE	√	√	√	√	√	√
Firm FE	√	√	√	√	√	√
Constant	0.039**	-7.906***	0.064	0.045***	-6.934***	0.198
	(0.017)	(1.595)	(0.172)	(0.016)	(1.471)	(0.202)
$Adjust - R^2$	0.831	0.720	0.418	0.831	0.725	0.420
N	17352	17352	16703	17369	17369	16720

Notes: Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Source(s): Authors' own creation

Table Ⅷ.
Robustness test of instrumental variable method.

	The first stage		*The second stage*			
	(1)	(2)	(3)	(4)	(5)	(6)
	AIA	*AIA*	*lnpatent*	*lnpatent*	*lncite*	*lncite*
IV_installusa	0.001***					
	(0.000)					
IV_AIusa		0.234***				
		(0.032)				
AIA			32.17**	6.858**	119.92***	108.73***
			(17.07)	(3.71)	(18.12)	(15.54)
Control Variables	√	√	√	√	√	√
Year FE	√	√	√	√	√	√
Firm FE	√	√	√	√	√	√
Anderson canon LM	42.661	83.83				
Cragg-Donald Wald F	43.216	58.506				
Observations	3969	4113	3969	3969	4113	4113

Notes: Standard errors in parentheses.* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Source(s): Authors' own creation

	Education Structure				*Skill Structure*			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Highschool	*college*	*undergraduate*	*graduate*	*production*	*sales*	*finance*	*technology*
AIA	-24.297^{**}	-4.739	11.196^{**}	5.930^{***}	-10.685^{*}	-5.875^{**}	-1.535^{*}	23.972^{***}
	(10.476)	(4.338)	(4.135)	(2.122)	(5.759)	(2.336)	(0.779)	(6.595)
Control Variables	√	√	√	√	√	√	√	√
Year FE	√	√	√	√	√	√	√	√
Firm FE	√	√	√	√	√	√	√	√
Constant	93.140^{***}	18.527^{**}	10.944	-4.668	48.561^{***}	28.014^{***}	6.707^{***}	3.828
	(13.654)	(7.713)	(7.560)	(3.102)	(7.229)	(5.987)	(1.203)	(5.485)
Adjust R^2	0.817	0.736	0.874	0.911	0.869	0.895	0.698	0.811
N	10413	16416	16972	13323	18358	18410	17598	18584

Table Ⅸ.

Mechanism analysis

Notes: Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Source(s): Authors' own creation

Table X.

Heterogeneity testing

	High-education		Low-education		High-Skilled			Low-Skilled		
	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*	*(7)*	*(8)*	*(9)*	*(10)*
	lnpatent	*lncite*	*lnpatent*	*lncite*	*lnpatent*	*lncite*	*IUR*	*lnpatent*	*lncite*	*IUR*
AIA	3.717***	4.731***	2.836**	2.872**	3.061***	5.526***	2.122**	2.474*	2.726***	1.205
	(1.018)	(1.019)	(1.167)	(1.119)	(0.992)	(0.939)	(0.788)	(1.220)	(0.783)	(0.780)
Control Variables										
Year FE										
Firm FE										
Constant	-9.612***	-10.025***	-6.410***	-10.286***	-10.704***	-9.552***	-2.379	-7.943***	-8.787***	0.012
	(1.756)	(1.508)	(1.513)	(1.981)	(2.401)	(2.501)	(1.547)	(1.456)	(1.354)	(0.774)
Adjust R^2	0.514	0.792	0.665	0.834	0.546	0.832	0.524	0.572	0.810	0.409
N	12775	13258	5701	5959	6998	2629	1281	11235	16275	5169

Notes: When the number of employees with undergraduate and graduate degrees exceeds those with college and high school diplomas, the enterprise is classified as 'High-education'; otherwise, it is classified as 'Low-education.' If the number of research and development personnel exceeds the sum of production, sales, and financial staff, it is categorized as 'High-skilled'; otherwise, it is 'Low-skilled.' The reason for non-reporting of IUR patent data in the sample grouped by educational background is due to the presence of missing values. The regression coefficients for the groups have all passed inter-group difference tests. Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Source(s): Authors' own creation