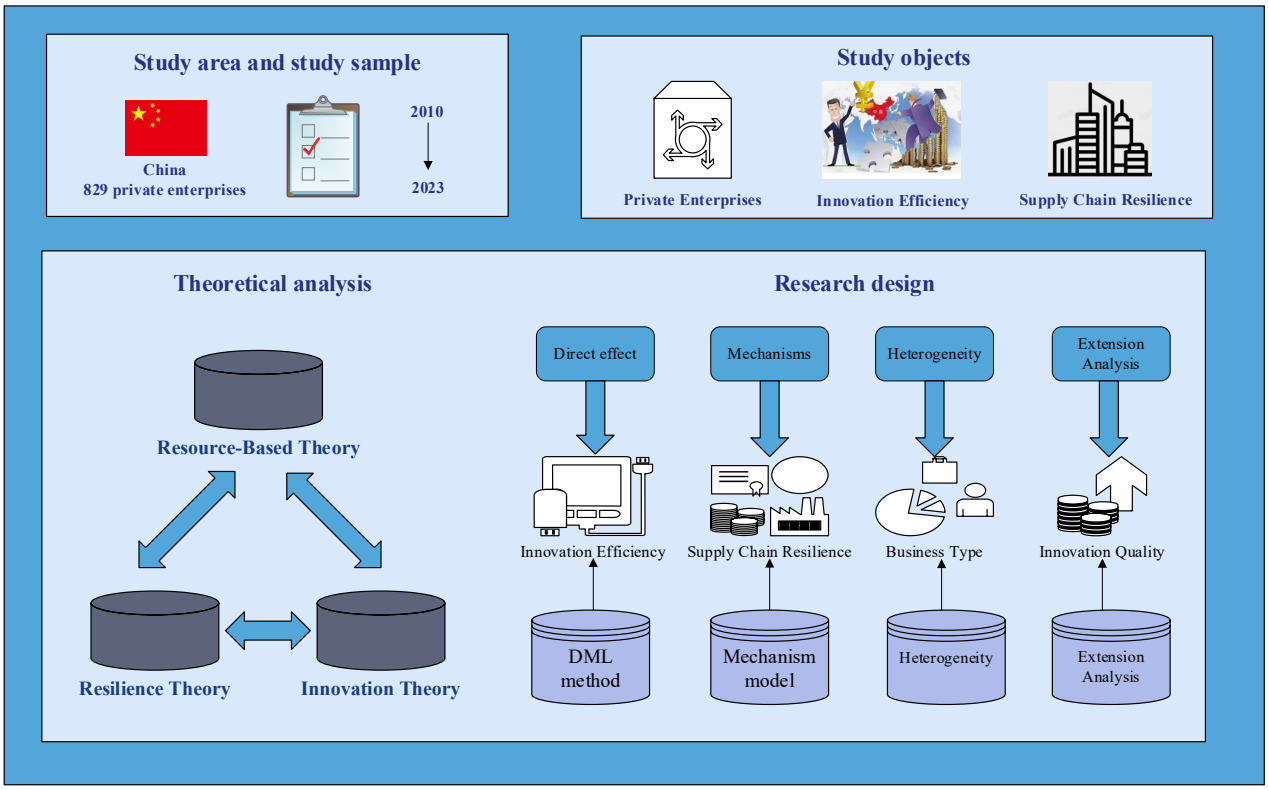
Can Artificial Intelligence Applications Enhance Innovation Efficiency in Private Enterprises: Evidence from China

Abstract: Based on a systematic review of the current state of artificial intelligence (AI) applications in China, we construct a Double Machine Learning (DML) model to empirically examine whether AI applications enhance the innovation efficiency (IE) of private enterprises (PEs), using data from 829 Chinese PEs between 2010 and 2023. The results reveal that AI significantly improves IE, with effects verified across both the input and output dimensions of the innovation process. This process relies heavily on strengthening the resilience of private-sector supply chains. Moreover, the innovation-enabling effect of AI is more pronounced in technology-intensive and capital-intensive PEs than in their labor-intensive counterparts. In addition, we find that AI not only enhances the IE of PEs but also improves their average and overall innovation quality, thereby achieving "both quality and efficiency." Based on the conclusions and case discussions, we have distilled a "technology-sharing-value" pathway for enhancing the IE of PEs. These findings enrich the existing literature and offer practical implications for PEs in emerging markets to optimize AI strategies and design more targeted application plans.

Keywords: Artificial intelligence; Private enterprise; Innovation efficiency; Supply chain; Innovation quality



Graphical abstract

1. Introduction

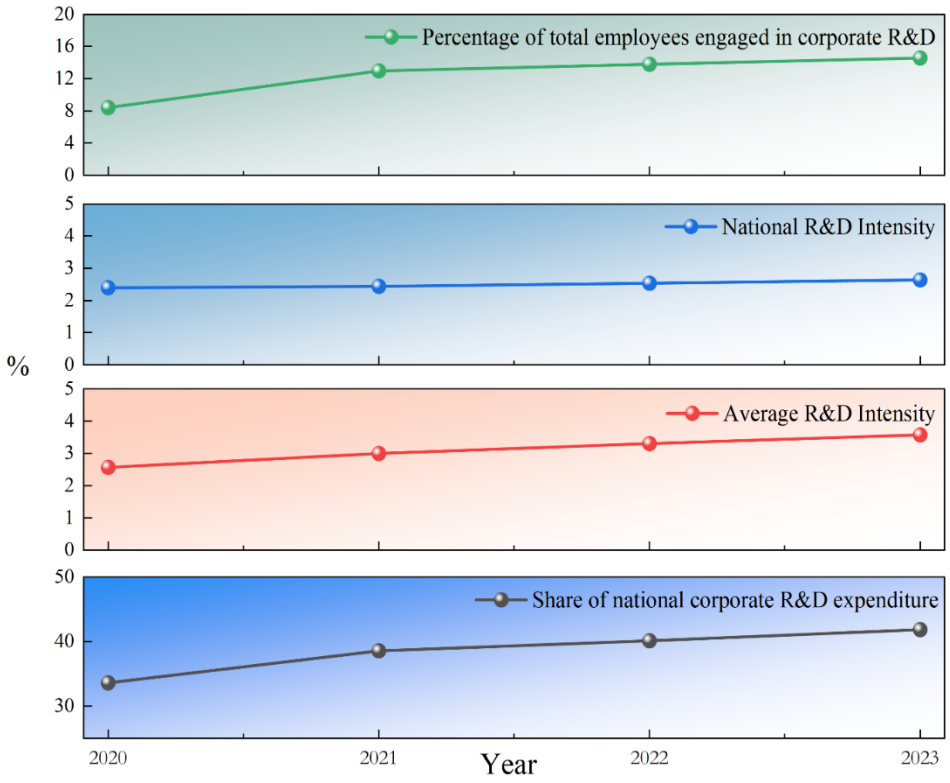
The new generation of information technologies, represented by AI, has been widely recognized across countries as a key engine for overcoming innovation and development bottlenecks (Mariani et al., 2023). In this process, PEs, as key agents of technology diffusion and market transformation, play an indispensable role in the innovation system. For example, in the United States, the vast majority of high-growth firms are private companies that drive the commercialization of frontier technologies such as AI and biotechnology. In Germany, small and medium-sized family-owned enterprises (the Mittelstand) constitute the core pillar of the national industrial innovation system. In South Korea, private technology firms continue to achieve breakthroughs in critical areas such as semiconductors and automation equipment. In China, PEs account for more than 70% of technological innovations and are increasingly emerging as the main force of the national innovation system.

The IE of PEs is generally defined as the socially optimal level of independent R&D investment (Jiang & Jiang, 2024). In the digital era, although PEs are increasingly active participants in the global innovation network, they continue to face persistent challenges in practice—such as delayed technology adoption and resource constraints, data silos and limited information sharing, weak technological accumulation, and underdeveloped internal management systems—which ultimately hinder their IE (Bhatti et al., 2025). In this context, the unique advantages of AI—such as optimizing

resource allocation and process efficiency, enhancing the efficiency and precision of decision-making, and facilitating cross-sectoral data sharing and collaboration—have made it an increasingly prevalent choice for PEs seeking to optimize innovation resources and improve IE (Kassa and Worku, 2025).

The private economy constitutes a vital component of China's overall economy and serves as the core of its innovation system. By the end of 2023, the number of PEs in China had exceeded 50 million, accounting for more than 90% of all firms. These enterprises contributed over 60% of national GDP, generated more than 70% of technological innovations, and provided over 80% of total employment (Huang and Véron, 2025) (Figure 1). However, PEs are currently confronted with an IE dilemma. Existing studies indicate that, on the input side, compared with SOEs and large foreign-funded firms, PEs are generally disadvantaged in financing channels, technological accumulation, and talent reserves, lacking the capital and expertise required to sustain high-level innovation (Liu and Suzuki, 2024; Sun et al., 2020). Moreover, their R&D investments are often short-term and fragmented, without systematic strategic planning or stable financial support. This hampers sustained technological accumulation and effective organizational learning, thereby weakening the foundations of innovation (Chen et al., 2024). On the output side, the innovations of many PEs remain concentrated in low value-added areas and incremental improvements, with a lack of breakthrough innovations in high-end industries and frontier fields, resulting in relatively low overall IE. Moreover, different types of PEs face varying resource

constraints—particularly small and medium-sized enterprises—while some larger firms have also struggled to realize their full innovation potential due to weak governance structures and short-sighted strategies (Keum, 2021). In addition, uncertainties in the external institutional and market environment further exacerbate this predicament. Limited market access, insufficient protection of property rights, and inconsistent policy implementation have weakened firms' confidence and capability to compete in high-technology sectors. At the same time, the sluggish global economic recovery, restructuring of industrial chains, and rising geopolitical tensions—together with domestic pressures such as intensified market competition and upgrading of demand structures—have further constrained innovation investment, amplifying uncertainty and transformation pressures in the innovation activities of PEs (Chen et al., 2024).



Source: General Federation of National Chambers of Commerce and Industry

Figure 1 Innovation of the top 1,000 private companies in R&D investment

AI, as a core driver of the new wave of technological revolution and industrial transformation, is increasingly emerging as a key force in empowering enterprise innovation. Existing research demonstrates that AI applications in areas such as intelligent manufacturing, product development, market analysis, and quality control can significantly enhance production efficiency and decision-making, help firms overcome technological bottlenecks, accelerate technology iteration and result transformation, and ultimately foster higher levels of innovation and development (Plathottam et al., 2023). At the same time, AI provides enterprises with intelligent support for technology foresight and product iteration through tools such as knowledge mapping, machine learning, and data mining, thereby enhancing innovation output and market responsiveness (Geurts et al., 2021).

Moreover, in PEs where resource constraints are particularly pronounced, AI technologies can lower trial-and-error costs, improve IE and output quality, overcome path dependence, and activate internal mechanisms of technological integration and knowledge sharing through process automation, intelligent recommendation, and assisted decision-making (Drydakis, 2022). However, scholars have also emphasized that the impact of AI on innovation is not unidirectional, as its application is accompanied by potential risks. On the one hand, excessive reliance on intelligent

algorithms may weaken firms' independent R&D capabilities, leaving them insufficiently resilient to sudden shocks (Macrae, 2025). On the other hand, the effects of AI adoption vary across firm types: for small and medium-sized PEs, the lack of digital infrastructure and expertise often results in a shallow adoption of AI technologies, which may even widen the innovation gap between them and larger firms (Schwaeke et al., 2025). Consequently, existing studies generally acknowledge that while AI can enhance IE, it also entails risks of path dependence, technological lock-in, and uncertainty, with its actual impact contingent upon the interplay between firms' internal governance capacity and the external institutional environment.

A large body of existing studies has explored the economic impact of AI, the various factors influencing firms' IE, and the interconnections between the two. However, fewer studies have examined micro-level firms such as PEs, and even fewer empirical studies have investigated the relationship between AI and the IE of PEs.

This paper develops a theoretical framework grounded in the resource-based view (RBV) and resilience theory, and employs a Double Machine Learning (DML) model to empirically examine the relationship between AI and the IE of PEs. Specifically, it seeks to address the following research questions:

（1）Does AI enhance the IE of PEs, and through what mechanisms?

（2）Does the effect of AI on IE differ across types of PEs?

（3）To what extent does AI influence not only the IE but also the innovation quality

of PEs?

The contributions of this paper are threefold. First, while existing studies have predominantly focused on manufacturing firms, new energy enterprises, or Internet companies, relatively few have examined the impact of AI on PEs. By centering on PEs, this study enriches the theoretical understanding of AI and innovation within the private sector. Second, instead of relying on traditional linear regression methods such as OLS or DID, we employ a Double Machine Learning (DML) framework combined with neural networks to identify the effects of AI on the IE of PEs from a multidimensional perspective. This methodological advancement not only broadens the research toolkit in this field but also enhances the robustness of our conclusions. Third, by deepening the analysis of AI's application effects at the micro level, this study provides theoretical support for fostering the integration of AI and the private economy, improving enterprise IE, and offering empirical references for policymakers in designing AI-driven innovation strategies.

The remainder of the paper is structured as follows. Chapter 2 presents the application of AI in China, Chapter 3 presents the theoretical analysis and research hypotheses. Chapter 4 outlines the research design. Chapter 5 reports the empirical analysis. Chapter 6 provides the discussion. Chapter 7 provides case studies. Chapter 8 concludes with policy implications and recommendations.

2. Application of AI in China

In recent years, with the ongoing implementation of China's AI + initiative, the AI industry in China is at a critical stage of large-scale application deployment (Zhang and Ding, 2025). The 2025 Computing Power Development Report indicates that, by the end of June 2025, China had 10.85 million active computing power center standard racks, with an intelligent computing power scale of 788 EFLOPS (exaflops per second). This has provided a strong core infrastructure system for the development of AI. According to estimates by the China Academy of Information and Communications Technology, the scale of China's AI industry exceeded 900 billion yuan in 2024, marking a year-on-year growth of 24%. By September 2025, the number of AI enterprises in China surpassed 5,300, accounting for 15% of the global total. The rapid development of AI has not only facilitated the intelligent upgrading of industries but has also become a key driver of the sustained growth of the digital economy (Mo and Liu, 2025). In 2024, the added value of China's core digital economy industries accounted for approximately 10% of its GDP, and this proportion is expected to continue rising steadily.

From the perspective of China's macro-level application efficiency in AI, its essence lies in the complex coordination and innovative integration of new production factors—such as data, algorithms, and computing power—with traditional factors at a higher dimensional level (Ma et al., 2025). AI has injected strong momentum into China's economic growth. It not only assists relevant entities in formulating "low-investment, high-output" production plans, but also substitutes capital for labor while

enhancing the coordination between various factors, thereby driving economic growth (Wang et al., 2025). The “Intelligent Computing Industry Development Report (2025)” indicates that, with AI accelerating the empowerment of industry applications and intelligent terminals, the intelligent computing power industry is set for explosive growth. By 2035, AI is expected to contribute over 11 trillion yuan to China’s GDP, accounting for approximately 4% to 5% of the total GDP. In 2024, China’s digital trade, driven by AI, reached a scale of 385.76 billion USD, growing by 5.2%, with a surplus of 55.37 billion USD. Among this, ICT services contributed nearly 60% to the growth, with computer services accounting for 9.3% of global exports.

In terms of the specific empowering effects of AI in China, AI reflects not only its “technological” dimension but also its “economic” dimension (Cheng et al., 2023). Firstly, AI has given rise to new forms of employment and, by breaking down information barriers, has enhanced the efficiency of labor market matching (Wang and Jiao, 2025). According to data from the Ministry of Human Resources and Social Security of China, between 2019 and 2022, the Ministry issued five batches of new occupations, totaling 74, with more than half of these roles involving frontier technologies in digital and intelligent fields. Positions such as algorithm engineers, data analysts, and AI product managers have seen rapid growth in recruitment demand. Under the empowerment of AI, labor forms are no longer constrained by specific spaces, equipment, or organizational models. Human-machine collaboration and remote work models have become increasingly common, significantly enhancing the flexibility,

intelligence, and autonomy of employment (Wang et al., 2024).

Secondly, AI drives a systemic transition, from the optimization of the production factor structure and the leap in productivity to the restructuring of production relations (Cheng et al., 2024). On the one hand, in terms of productivity, AI facilitates the transition from informatization to digitalization, and ultimately to intelligent productivity. The "AI+" initiative is driving the manufacturing industry beyond automation, entering a new stage characterized by the integration of "perception, decision-making, and execution" (Chatterjee et al., 2021). At the same time, through technologies such as intelligent breeding, remote sensing monitoring, and precision irrigation, the application of AI enables refined management of agricultural production processes, reducing resource inputs while enhancing land productivity (Zhang et al., 2021). On the other hand, AI is driving a deep transformation in the internal production relations of the Chinese market. The role of elements such as knowledge, technology, management, information, and data is continually increasing, leading to a shift in their relationship with the power of physical capital. Centered around generative AI, new "intelligent-native" business models such as AIGC, AI programming assistants, and digital workers are reshaping content creation, software development, and business processes. These emerging forms of productivity, rooted in technological advancements, represent the most dynamic segment of the digital economy (Xiong et al., 2025), with projections indicating the creation of a trillion-dollar market.

Furthermore, AI technology is continually penetrating deeper into specific application scenarios. It is not only an efficiency tool but also a powerful "reconstructive force" for innovation ecosystems, giving rise to new growth poles (Han and Mao, 2024). From a macro perspective, "AI+" enhances government decision-making, strengthens risk prevention, and stimulates social innovation, systematically improving the operational efficiency and resilience of the economic system (Gao et al., 2025). At the meso and micro levels, the application and penetration rates of AI continue to rise in sectors such as manufacturing (Cheng et al., 2025). By July 2023, China had established nearly 8,000 digital workshops and intelligent factories, with over 2,500 intelligent factories reaching a maturity level of 2 or higher in terms of smart manufacturing capabilities. At the same time, according to forecasts by Deloitte Consulting, by 2025, the market sizes for three application scenarios—intelligent predictive maintenance, intelligent production scheduling, and intelligent quality control—are expected to reach 4.27 billion yuan, 2.97 billion yuan, and 2.32 billion yuan, respectively, with compound annual growth rates of 49%, 52%, and 51%. These developments lay a solid foundation for innovation and foster a favorable innovation ecosystem at the micro level.

Finally, in terms of AI support policies, since China first included AI in its national development priorities in 2016, the government has introduced several policies aimed at continuously promoting the development `of the AI industry and accelerating its integration with the real economy. In August 2025, the State Council issued the

"Opinions on Deepening the Implementation of the "AI +" Initiative, emphasizing the systematic promotion of AI"s extensive and deep integration with various sectors of the economy and society to establish new international competitive advantages. Under policy guidance and support, PEs, as a key force in driving AI development, actively engage in technological innovation and practical applications (Ding and Gao, 2025).

Recently, the Chinese government has implemented a range of measures to support various enterprises, including private companies, in deeply engaging with the "AI+" initiative. As of September 2025, the number of AI enterprises in China had surpassed 5,300, accounting for 15% of the global total. This has led to the formation of a comprehensive industrial system encompassing foundational infrastructure, model frameworks, and industry applications, significantly driving innovation in China's AI technologies, products, and applications.

However, AI still faces multiple challenges in its industrial applications in China. First, the risks associated with AI are characterized by diversity, complexity, and uncertainty, posing new demands for data security and governance (Wu, 2025). Second, there is a prominent mismatch between supply and demand for high-end AI talent. According to data from the Ministry of Human Resources and Social Security of China, the talent gap in the AI field has exceeded 5 million, with a supply-to-demand ratio of approximately 1:10. Third, the supply of high-quality datasets in vertical domains is insufficient, with data quality becoming a critical bottleneck in the transition of AI from

238 “usable” to “effective” (Wang and Zou, 2025). Fourth, there is a significant disparity
239 in digital infrastructure among enterprises. Many small and medium-sized enterprises,
240 particularly private firms, lack the necessary support in terms of data, capital, talent,
241 and technology, which hinders the widespread application of AI (Wang et al., 2023).

242 3. Theoretical analysis and research hypothesis

243 3.1 The Direct Impact of AI on the IE of Private Companies

244 The rise of AI has blurred the traditional boundaries between labor and capital.
245 Economic growth no longer depends solely on capital accumulation or labor input;
246 instead, the speed of algorithmic iteration and the quality of data have become new
247 indicators of growth, driving the technological frontier of industries outward
248 (Acemoglu, 2025). From the perspective of resource-based theory, AI is not merely a
249 general tool but also an internal resource with potential strategic value. When
250 effectively acquired and utilized, AI can empower innovation activities in key areas
251 such as knowledge acquisition, information processing, and process coordination,
252 thereby enhancing firms’ technological recognition capabilities and resource allocation
253 efficiency (Gao et al., 2025).

254 For PEs with relatively limited resources, AI can partially offset shortcomings in
255 production, financing, and technology application, thereby strengthening their capacity
256 for technological innovation in complex environments. Internally, leveraging AI for

data mining enables firms to rapidly collect and organize process-related technological data (Tian et al., 2023). At the same time, AI tools such as computer-aided design and visualization programs reduce reliance on physical prototypes and improve production efficiency (Zhang et al., 2022). Moreover, AI enhances process efficiency and predictive accuracy, enabling dynamic process coordination and intelligent decision support. This not only minimizes resource waste during R&D trial-and-error and solution adjustment stages but also alleviates innovation pressures stemming from limited capital investment, while shortening development cycles and facilitating faster product upgrades (Besiroglu et al., 2024). Finally, AI applications optimize internal collaboration mechanisms, strengthen cross-departmental knowledge flows and sharing, and create a more supportive environment for innovation activities (Olan et al., 2022).

When engaging with external innovation opportunities, AI enables PEs to identify prospects more rapidly through process automation and advanced intelligent analytics, thereby reducing the time-to-market for new technologies (Tian et al., 2023). In acquiring and processing external information, AI also helps to blur the boundaries of knowledge sharing within firms and strengthens their organizational capacity to search for and integrate external knowledge. This generates a complementary effect of knowledge coupling, facilitating the development of more effective innovation networks (Zhang and Yang, 2022). Moreover, AI is undeniably reshaping the redistribution of innovation resources within existing markets, narrowing the survival space of incumbent firms and compelling them to accelerate transformation in order to

sustain innovation. In the face of intensified market competition, PEs must continuously generate novel solutions in R&D, production, and sales to maintain competitive advantage and secure market resources, thereby improving their IE (Li et al., 2023).Therefore, this paper proposes the following hypothesis:

H1: AI has a significant positive effect on the IE of PEs.

3.2 The mechanism of AI's influence on the IE of PEs

Supply chain resilience (SCR), as defined by resilience theory, is widely recognized as a key capability that enables enterprises to cope with uncertain shocks and sustain innovation continuity. It not only focuses on immediate responses to unexpected events but also emphasizes forward-looking risk perception, flexible resource allocation, and continuous system operation (Sheffi, 2005). From a functional perspective, SCR has been categorized as resistance (Pettit et al., 2010; Sheffi and Rice, 2005), resilience (Christopher and Peck, 2004), and operational capabilities (Pettit et al., 2010). These capabilities provide firms with essential safeguards to maintain innovation continuity and system stability in uncertain environments.

In recent years, AI has been widely embedded across multiple key stages of the supply chain, significantly enhancing perception, responsiveness, and coordination. In the R&D process, AI enables enterprises to gain rapid insights into user needs and technological trajectories by integrating industry databases, market feedback, and

297 external patent information, thereby improving the accuracy of R&D topic selection,
298 pre-production resource matching, and reducing repeated trial and error (Madanchian
299 et al., 2024). In the production process, AI-driven intelligent manufacturing systems
300 enable dynamic optimization of production planning and process parameters,
301 strengthening firms' ability to regulate equipment conditions, adapt to order changes,
302 and adjust production rhythms in real time. This enhances both the stability and
303 elasticity of trial production for new products as well as overall output capacity (Ding
304 et al., 2023). In logistics, AI-powered predictive algorithms and path optimization tools
305 improve the agility of inventory management and transportation scheduling, mitigating
306 the risk of supply shortages and distribution disruptions that could otherwise hinder
307 innovation (Riad et al., 2024). In information flows, AI bridges communication barriers
308 along the supply chain, increasing the efficiency of cross-departmental and cross-
309 organizational collaboration through automatic identification and rapid-response
310 mechanisms, thereby reducing resource misallocations arising from information delays
311 or asymmetries (Teixeira et al., 2025).

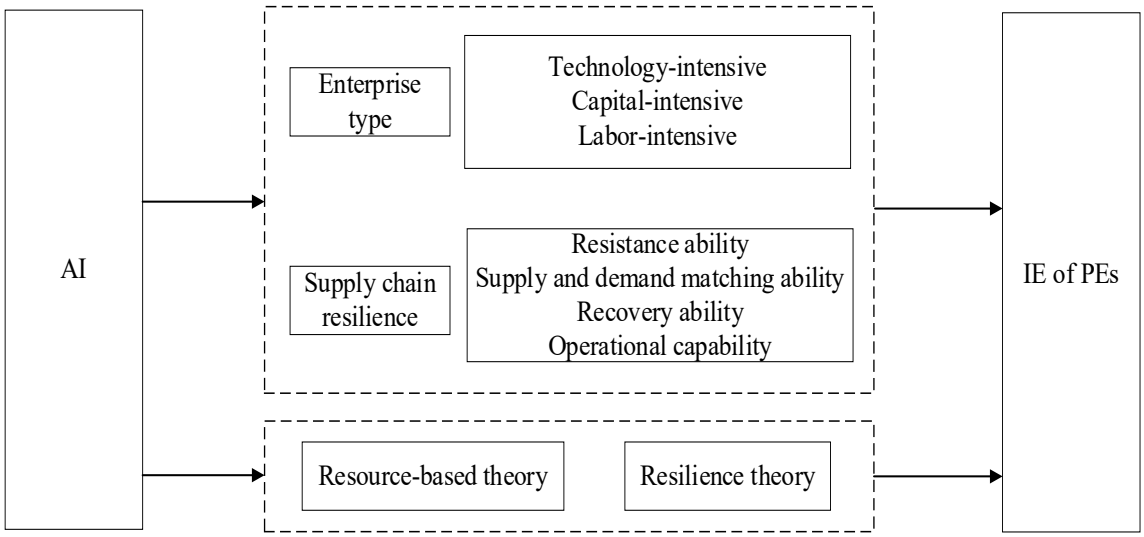
312 Some firms have already applied AI in practice to strengthen supply chain
313 coordination and responsiveness. For example, Haier Group's COSMOPlat industrial
314 internet platform leverages big data and AI algorithms to optimize order recognition
315 and production scheduling, enabling rapid demand feedback and flexible
316 manufacturing. Similarly, BYD, a leading new energy vehicle manufacturer, employed
317 AI to dynamically model and forecast supply chain risks amid the global chip shortage.

By optimizing procurement paths for battery raw materials and process parameter settings, BYD effectively mitigated production fluctuations and safeguarded the continuity of R&D and innovation activities. These cases demonstrate that AI supports firms in sustaining technological renewal and transformation under high uncertainty by enhancing prediction, scheduling, and collaboration within the supply chain (Sjodin et al., 2021).

For PEs with relatively limited resources and weak risk resistance, SCR not only mitigates disruptions in R&D, production, and logistics but also provides more stable and efficient support for technological transformation and commercialization, thereby continuously unlocking innovation potential in uncertain environments.Therefore, this paper proposes the following hypothesis:

H2: AI enhances the IE of PEs by strengthening SCR.

Figure 2 shows the theoretical research framework of this paper



331 Figure 2 Research framework

332 4. Research design

333 4.1 Model building

334 4.1.1 Baseline regression model

335 The IE of PEs is shaped not only by internal factors but also by the external
336 environment. Therefore, when examining the impact of AI on the IE of PEs, it is
337 essential to adopt a multidimensional perspective and account for the joint effects of
338 multiple factors. Traditional linear models, however, struggle to address challenges
339 posed by high-dimensional data, nonlinear relationships, and complex causal chains.
340 By contrast, DML isolates the effect of control variables on core variables through
341 machine learning models, generates residuals to disentangle causal relationships, and
342 employs cross-fitting to mitigate overfitting (Chernozhukov et al., 2018). This makes
343 DML particularly suitable for identifying the causal impact of AI on the IE of PEs.

Accordingly, we specify the following DML model:

$$Eff_{i,t} = \alpha_1 AI_{i,t} + g(X_{i,t}) + U_{i,t} \quad (1)$$

$$\mathrm{E}(U_{i,t} | IT_{i,t}, X_{i,t}) = 0 \quad (2)$$

Here, i and t denote firms and years, respectively; $Eff_{i,t}$ represents the innovation quality of firm i in year t; indicates the level of AI adoption； AI_{it} indicates the level of AI. X includes city fixed effects for the firm's location, year fixed effects, and firm fixed effects, whose influence on AI is estimated by the machine learning model g.We employ random forest as the specification for g. U denotes the random error term. In addition, to mitigate potential overfitting in the machine learning model, we apply K-fold cross-validation to improve the accuracy of coefficient estimation. The sample split ratio is set at 1:4, and the random seed is fixed at 42.

4.1.2 Mechanism testing model

To identify the mechanism through which AI influences the IE of PEs, and building on equations (1) and (2), we construct the following mechanism testing model:

$$M_{i,t} = \alpha_1 AI_{i,t} + g(X_{i,t}) + U_{i,t} \quad (3)$$

$$\mathrm{Eff}_{\mathrm{i,t}} = \alpha_2 \mathrm{M}_{\mathrm{i,t}} + \mathrm{g}(\mathrm{X}_{\mathrm{i,t}}) + \mathrm{U}_{\mathrm{i,t}} \quad (4)$$

In equation (3), denotes the mechanism variable, namely SCR; the definitions of the remaining variables are consistent with those above. Based on the theoretical framework, if and are both significantly positive, this would indicate that AI enhances the IE of PEs primarily by strengthening SCR.

4.2 Variable Selection

4.2.1 Explained variable: IE of PEs

（$innovation_{it}$）

IE reflects the capacity of firms to generate knowledge outputs and transform results under resource constraints. Existing studies generally acknowledge that the number of patent applications can, to some extent, represent a firm's innovation output, while R&D expenditures capture its resource inputs in innovation activities (Liu and Suzuki, 2024). Following Hall et al. (2010), this paper measures the IE of PEs using the ratio of the natural logarithm of the total number of invention, utility model, and design patent applications (plus one) to the natural logarithm of corporate R&D expenditures (plus one) , see Equ. (5). Figure 3 presents the distribution of IE for PEs across different years.

$$innovation_{it} = \frac{ln\left(Patent_{it}^{inv}+Patent_{it}^{um}+Patent_{it}^{des}+1\right)}{ln\left(R\&D_{it}+1\right)} \quad (5)$$

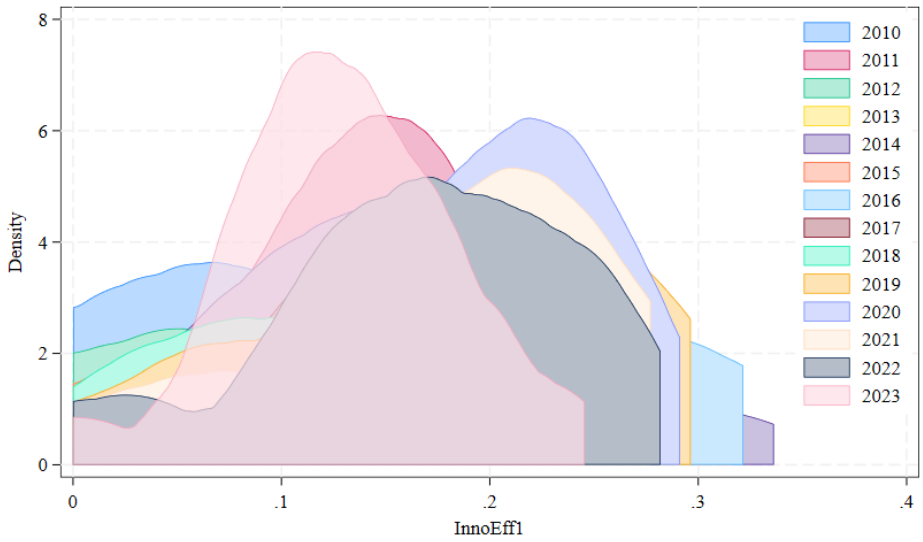


Figure 3. Kernel Density Distribution of IE of PEs

4.2.2 Core Explanatory Variable: AI

This paper follows the approach of Babina et al. (2023), which applies text analytics to measure AI based on corporate annual reports. The specific procedure is illustrated in Figure 4.

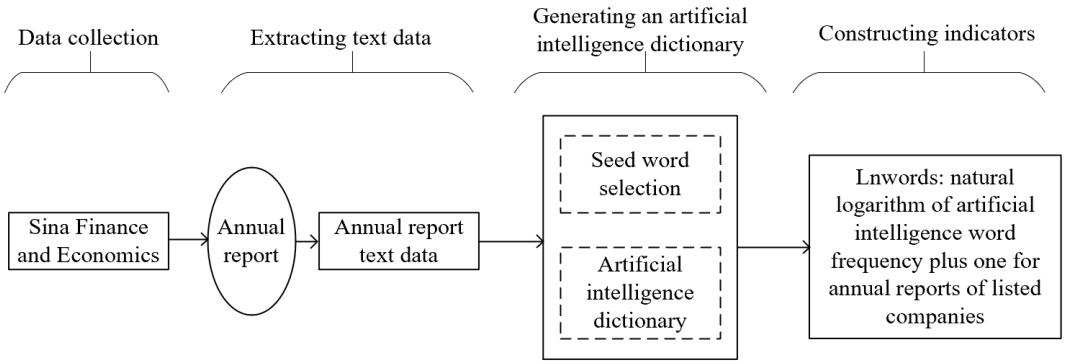


Figure 4. Construction Process of AI Metrics

4.2.3 Control variables

The innovation behavior of firms is shaped by internal factors such as resource endowment, managerial capacity, and technological base, making it necessary to control for key variables at the enterprise level. At the same time, the economic and institutional environment of the city in which a firm operates indirectly influences innovation outcomes through channels such as resource allocation efficiency, institutional incentives, and factor mobility, which requires the inclusion of city-level controls (Sun et al., 2020). Accordingly, this paper incorporates firm-level control variables including personnel, equipment, information, and organization, as well as city-level controls such as economic development, industrial structure, market competition, R&D environment, and financing constraints. The specific screening criteria are summarized in Table 1.

4.3 Data description and descriptive analysis

Considering data availability and consistency, samples with substantial missing values in key variables are excluded. The final dataset consists of panel data from 2010 to 2023 for empirical analysis. The data are primarily sourced from [data sources to be specified]. Descriptive statistics of the variables are presented in Table 1. The measurement of AI is conducted using Python, while the regression analysis is performed with Stata 18.0 and Python.

Table 1 Results of descriptive statistics of variables

	Variable	Definition	Obs	Mean	Std. dev.	Min	Max
Explained variable	IE	The ratio of the natural logarithm of the total number of invention patents, utility model patents, and design patents applied for plus one to corporate R&D expenditure	11606	0.158	0.081	0	0.407

		plus one						
Core explanatory variable	AI	Natural logarithm of AI-generated word frequency increase in listed companies' annual reports	11606	0.871	1.253	0	5.690	
Enterprise-level control variables		Company Size	11606	21.926	1.229	14.759	27.245	
	Personnel	Whether audited by one of the Big Four accounting firms	11606	0.023	0.155	-1	3	
		Annual salary disclosure method	11606	1.013	0.171	1	5	

	Total director compensation	11606	14.506	0.883	6.041	18.22
	Net fixed assets	11606	19.857	1.696	7.197	26.165
Equipment	Depreciation of fixed assets, depletion of oil and gas assets, depreciation of productive biological assets	11606	17.590	1.560	7.309	24.353
Information	R&D expenditure growth	11606	0.569	0.580	-3	3
	Investment expenditure ratio	11606	0.050	0.053	-0.431	0.474
	Intangible asset	11606	0.044	0.043	-0.005	0.680

		proportion					
		Shareholders' equity turnover ratio	11606	1.315	3.083	-59.621	106.791
	Organizat ion	Non-current asset turnover ratio	11606	2.799	45.495	-1.936	4458.976
		Asset-liability ratio	11606	0.400	0.463	-0.195	29.698
		Management expense ratio	11606	0.110	1.138	-65.548	55.458
		Capital intensity	11606	3.208	16.049	-25.748	915.475
	Economic developm ent	Regional GDP growth rate	11606	9.783	22.179	-530	1104.100
City-level control variables	Industrial structure	Share of tertiary industry in regional GDP	11606	54.252	13.120	-27.650	118.570
		Number of wholesale and	11606	7.637	1.240	1.609	10.549

	retail enterprises above					
Research and development environment	Citywide expenditures on science and technology	11606	12.894	1.702	5.545	16.214
Financing constraints	Citywide year-end balance of RMB loans from financial institutions	11606	18.597	1.365	12.526	21.258

5. Empirical analysis

5.1 Benchmark regression results

The results of the benchmark regression based on model (1) are presented in Table 2. Columns (1)–(3) report the estimates without controls, with firm-level controls, and with both firm- and city-level controls, respectively. When controlling for firm, city, and year fixed effects as well as incorporating both firm- and city-level control variables, the coefficient of AI is 0.00831 with a t-value of 10.33, significant at the 1% level. This

412 indicates that AI significantly enhances the IE of PEs, thereby providing empirical
413 support for hypothesis H1.

414 Table 2 Benchmark regression results

	Eff	Eff	Eff
AI	0.01120***	0.00836***	0.00831***
	（15.82）	（11.11）	（10.33）
Cons	0.00185**	0.00024	0.00065
	（2.44）	（0.42）	（1.12）
Firm Fe	YES	YES	YES
City Fe	YES	YES	YES
Year Fe	YES	YES	YES
Control-Firm	NO	YES	YES
Control-City	NO	NO	YES
N	11606	11606	11606

415 Note: *, **, *** indicate significant at the 10%, 5%, and 1% levels, respectively, with
416 t-values in parentheses. The following table is the same.

417 According to our definition of IE, its improvement cannot be separated from the
418 two dimensions of “input” and “output.” Accordingly, we decompose IE into
419 “innovation input” and “innovation output” to empirically examine the channels
420 through which AI exerts its effects. “Innovation input” is further divided into R&D

personnel input (measured by the total number of R&D employees in a firm) and R&D capital input (measured by the growth rate of innovation investment). "Innovation output" is divided into substantive innovation (measured by the natural logarithm of the number of invention patents granted plus one) and strategic innovation (measured by the natural logarithm of the total number of utility model and design patents granted plus one).

The regression results are reported in Table 3. With the exception of AI in the R&D capital input dimension, where the coefficient is insignificant (t = –0.76), the coefficients of AI in the other three dimensions are all significantly positive at the 1% level. This indicates that the improvement of AI on the IE of PEs is primarily reflected in talent aggregation on the input side and the enhancement of innovation output on the output side. These findings further confirm the enabling role of AI in improving the IE of PEs. Specifically, AI not only strengthens firms' capacity to pursue high value-added, breakthrough-oriented innovation but also enhances their ability to identify and capture market opportunities, thereby promoting the systematic advancement of technology commercialization.

Table 3 Regression results of the impact of AI on innovation inputs and innovation outputs

	R&D staff	Increased investment in	Substantive innovations	Strategic innovation

		R&D		
AI	1.91700***	-2.239	0.15400***	0.14500***
	(12.77)	(-0.76)	(13.45)	(10.79)
Cons	-0.34200***	1.89800	-0.01960*	0.00606
	(-3.65)	(0.50)	(-2.50)	(0.60)
Firm Fe	YES	YES	YES	YES
City Fe	YES	YES	YES	YES
Year Fe	YES	YES	YES	YES
Control-Firm	YES	YES	YES	YES
Control-City	YES	YES	YES	YES
N	11606	11606	11606	11606

4.2 Heterogeneity

Established studies suggest that the impact of AI on corporate innovation may vary across industries. To examine this heterogeneity, we classify the sample by factors of production into three subgroups—technology-intensive, capital-intensive, and labor-intensive—and conduct regressions accordingly (Zhang et al.). This allows us to assess the industry-specific effects of AI on the IE of PEs.

Table 4 Results by factor of production

Sectors	Technology-	Capital-intensive	Labor-intensive

	intensive		
Segment code	N77 C36 M74 I65 C33 C35 C27 C29 C39 C38 C37 C41 C40	G56 D44 A04 B11 D45 B07 C22 C31 G55 C30 R86 C28 C26 C25	A01 A02 A03 A04 A05 B06 B08 B09 C13 C14 C15 C17 C18 C19 C20 C21 C23 C24 C32 C34 D46 E48 E49 E50 F51 F52 G53 G54 G58 G59 I63 I64 K70 L72 M73 M75 N78 P82 R87 S90
Sample size	1415	651	1173

Note: Some of the industry codes are derived from the "2012 SEC Guidelines for Listed Companies by Industry", and the classification results are obtained through SPSS19.0 clustering analysis.

The regression results are reported in Table 5. For technology-intensive PEs, the coefficient of AI is 0.00679 with a t-value of 8.40, significant at the 1% level. For capital-intensive PEs, the coefficient of AI is 0.00887 with a t-value of 3.20, significant at the 5% level. By contrast, for labor-intensive PEs, the coefficient of AI is only 0.00336 with a t-value of 0.41, which is not statistically significant. These findings

indicate that AI has a markedly stronger effect on improving the IE of technology-intensive and capital-intensive PEs compared with their labor-intensive counterparts.

Table 5 Results of heterogeneity analysis

	Technology-intensive	Capital-intensive	Labor-intensive
AI	0.00679***	0.00887***	0.00336
	（8.40）	（3.20）	（0.41）
Cons	0.00678	0.00608	0.00502
	（0.98）	（0.41）	（0.66）
Firm Fe	YES	YES	YES
City Fe	YES	YES	YES
Year Fe	YES	YES	YES
Control-Firm	YES	YES	YES
Control-City	YES	YES	YES

5.3 Mechanism analysis

To further verify the mechanism through which AI enhances the IE of PEs, and drawing on the theoretical assumption in H2, this paper subdivides SCR into four dimensions—resistance capacity, supply–demand matching capacity, resilience capacity, and operational capacity—following the criteria of Ivanov and Dolgui (2020). Based on equations (3) and (4), we then examine whether SCR serves as the transmission channel through which AI improves the IE of PEs.

The empirical results are shown in Table 6. In the dimension of resistance capacity, the coefficient of AI is 0.0295 with a t-value of 3.32, significantly positive at the 1% level, indicating that AI enhances firms' ability to maintain system stability when facing external shocks. In the dimension of supply–demand matching capacity, the coefficient of AI is –0.0150 with a t-value of –0.75, which is not statistically significant, suggesting that AI has not yet improved firms' ability to dynamically coordinate and allocate resources under fluctuating demand. In the dimension of recovery capacity, the coefficient of AI is –0.1188 with a t-value of –3.38, significantly negative at the 1% level, implying that current applications of AI may even hinder firms' ability to recover rapidly after shocks. In the dimension of operational capacity, the coefficient of AI is –0.0000531 with a t-value of –1.58, showing no significant direct effect. Further testing reveals opposite transmission effects of resistance and recovery capacities on IE: resistance capacity exerts a significantly positive effect on IE, with a coefficient of 0.00626 and a t-value of 4.42, indicating that it plays a crucial role in enhancing innovation stability and enabling high-quality outputs under the empowerment of AI; whereas recovery capacity has a significantly negative effect on IE, with a coefficient of –0.00253 and a t-value of –2.90, suggesting that once firms encounter shocks, their resilience remains limited, and AI alone may not offset the negative impacts of production line disruptions, resource mismatches, and information lags, but may instead reduce overall IE.

Table 6 Mechanism analysis results

	Resistance ability	Supply and demand matching ability	Recovery ability	Operational capability	Eff	Eff
AI	0.0295***	-0.0150	-0.1188	-0.00000531		
	（3.32）	（-0.75）	（-3.38）	（-1.58）		
Resistance ability					0.00626***	
					（4.42）	
Recovery ability						-0.00253***
						（-2.90）
Cons	-0.0199***	0.0493***	0.0175	0.00000465		
	（2.97）	（3.24）	（0.73）	（0.72）		
Firm Fe	YES	YES	YES	YES		
City Fe	YES	YES	YES	YES		
Year	YES	YES	YES	YES		

Fe						
Contro l-Firm	YES	YES	YES	YES		
Contro l-City	YES	YES	YES	YES		
N	7411	6455	2618	7036	7411	2618

485 5.4 Extensibility analysis

486 Together, innovation quality and IE constitute the core drivers of the sustained
487 growth of PEs (Dyer et al., 2024; Altuzarra, 2024). Having verified the role of AI in
488 improving the IE of PEs, we further investigate whether AI also enhances their
489 innovation quality—addressing the question of whether PEs can achieve both "quality"
490 and "efficiency" in innovation. Specifically, we assess the impact of AI on the
491 innovation quality of PEs from two perspectives: average innovation quality and overall
492 innovation quality. The regression results, reported in Table 7, show that the coefficients
493 of AI on both dimensions are significantly positive at the 1% level, indicating that AI
494 plays a significant role in promoting the comprehensive innovation output of PEs and
495 advancing systematic technological improvement.

496 Table 7 Results of the extensibility analysis

	Average quality of innovation	Overall quality of innovation
AI	0.0159***	0.248***

	（5.63）	（17.59）
Cons	-0.00045	-0.02510**
	（-0.20）	（-2.51）
Firm Fe	YES	YES
City Fe	YES	YES
Year Fe	YES	YES
Control-Firm	YES	YES
Control-City	YES	YES
N	11606	11606

5.5 Robustness check

To verify the reliability of the empirical results, we conduct five robustness tests. (1) Replacing the measurement of the explanatory variables. Since invention patents are widely regarded as the core of firms' competitiveness in innovation outcomes (Han et al., 2025), we construct an alternative measure of IE by weighting the total number of invention, utility model, and design patent applications in a 3:2:1 ratio, adding plus one, and taking the natural logarithm. This value is then compared with the logarithm of (R&D expenditures plus one), and the regression is re-estimated accordingly.

$$innovation_{it} = \frac{ln\left(3 \cdot Patent_{it}^{inv} + 2 \cdot Patent_{it}^{um} + 1 \cdot Patent_{it}^{des} + 1\right)}{ln\left(R\&D_{it} + 1\right)}$$

(2) Replacing the sample split ratio. The initial split ratio between the training set and the prediction set is changed from 1:4 to 1:6, and the regression is re-estimated.

(3) Replacing the measurement of the explanatory variable. Following Ren et al.

(2025), we expand the AI lexicon and re-run the regression.

(4) Replacing the algorithm. The random forest algorithm is substituted with neural network and XGBoost algorithms, and the regression is re-estimated. The results, reported in the table, show that the coefficients of AI remain significantly positive at the 1% level, confirming the robustness of our findings.

We also conduct an endogeneity test to address potential endogeneity concerns in the model. Following the approach of Chernozhukov et al. (2018), we construct the following endogeneity test model.

$$Eff_{i,t} = \alpha_1 AI_{i,t} + g(X_{i,t}) + U_{i,t} \quad (6)$$

$$IV_{i,t} = m(X_{i,t}) + V_{i,t} \quad (7)$$

Among them, we select corporate audit opinion as the instrumental variable (Table 8). The test results show that the coefficients of AI in the two-step regression remain significantly positive at least at the 10% level, indicating that our empirical findings pass the endogeneity test and demonstrate strong credibility.

Table 8 Assignment methods

Type of opinion	Assign value
Standard unqualified opinion	1
Qualified opinion	2
Unable to express an opinion	3
Unqualified opinion plus matter paragraph	4
Qualified opinion plus matter paragraph	5

6. Disccusion

First, our empirical results show that AI significantly enhances the IE of PEs. The possible explanations are as follows. First, as a general-purpose enabling technology with sensing, learning, and prediction functions, AI substantially improves data processing and information integration capabilities in resource-constrained PEs, thereby optimizing the R&D process and improving the quality of innovation-related decision-making (Peretz-Andersson et al., 2025). Second, the adoption of AI enables firms operating in highly uncertain and dynamically changing markets to achieve greater resource allocation efficiency, increase responsiveness and fault tolerance during the innovation process, and consequently enhance the stability of innovation outputs and the efficiency of results transformation (Kaplan and Haenlein, 2019). Finally, AI stimulates organizational learning and cross-departmental knowledge sharing by reconfiguring internal knowledge synergy networks, breaking “path dependence” and “organizational inertia,” and thereby fostering technological breakthroughs and institutional innovation (Abou-Foul et al., 2023).

Second, our findings indicate that AI has a significant positive effect on the number of R&D personnel in the innovation input chain, but not on the growth rate of R&D investment. In the innovation output chain, AI significantly promotes both substantive and strategic innovations. The underlying reasons are as follows. First, AI improves the efficiency of human resource allocation and talent utilization, which increases the demand for high-quality R&D personnel and optimizes the human capital

545 structure (Murugesan et al., 2023). However, firms tend to optimize the use of existing
546 resources to improve IE rather than simply increasing R&D expenditures. This "quality
547 over quantity" strategy explains the insignificant effect of AI on the growth rate of R&D
548 inputs (Leung and Sharma, 2021). Second, in terms of innovation outputs, AI
549 significantly contributes to both substantive and strategic innovations. Leveraging its
550 advantages in knowledge mining, market information identification, and cross-sector
551 collaboration, AI shortens R&D cycles, accelerates innovation response, and increases
552 the success rate of technology commercialization (Füller, 2022). Moreover, by enabling
553 real-time data analysis and predictive decision-making, AI allows firms to gain a
554 competitive edge in both breakthrough and strategic innovations, thereby facilitating
555 the systematic transformation of technological achievements (Babina, 2024).

556 Again, we find clear industry heterogeneity in the impact of AI on the IE of PEs:
557 while AI significantly enhances the IE of technology-intensive and capital-intensive
558 firms, it has not yet produced a positive effect in labor-intensive firms. The reasons are
559 twofold. First, technology-intensive firms typically rely on highly complex
560 technological systems and specialized processes in their production and management,
561 and thus possess stronger absorptive capacity and greater willingness for organizational
562 learning (Joshi and Das, 2025). As a result, once AI is introduced, its perceptual and
563 predictive advantages can be rapidly embedded into the innovation process, unleashing
564 stronger synergies and knowledge transformation in product R&D, algorithmic
565 modeling, and high-end manufacturing, thereby improving IE (Mubarak et al., 2021;

Wang and Zhong, 2024). Second, capital-intensive firms usually enjoy stronger financial resources and infrastructural conditions, which allow them to support the software and hardware environments required for AI. Through AI-assisted decision-making, they can optimize equipment investment, energy efficiency management, and process reengineering, indirectly improving the allocation of innovation resources and output efficiency (El-Kassar and Singh, 2019). By contrast, labor-intensive firms depend primarily on low-cost labor, with relatively rigid management styles, technological paths, and organizational structures. Their absorptive and adaptive capacity for advanced digital technologies such as AI is weaker, making it difficult for them to achieve effective technological transformation and organizational reconfiguration in the short run, which explains why their IE is less influenced by AI (Lin and Wu, 2025).

Meanwhile, we find that AI improves the IE of PEs by enhancing supply chain resistance. This effect may stem from differences in the maturity of various supply chain dimensions. The strengthening of resistance capacity primarily arises from AI's advantages in real-time monitoring of raw material supply, predicting the impact of unexpected events, optimizing order scheduling, and implementing risk-avoidance strategies, which together enhance firms' stress-resistance in highly uncertain environments and reduce the disruption of production interruptions and resource wastage on innovation activities (Belhadi et al., 2024). By contrast, the insignificant effect of supply–demand matching capacity may reflect the weak technological

foundations and insufficient data accumulation of SMEs in AI-driven precision marketing, customer data mining, and rapid response mechanisms (Le Dinh et al., 2025). Regarding resilience, the negative effect of AI may indicate that excessive reliance on AI systems reduces recovery ability when technical failures or data anomalies occur; in addition, SMEs' limited investment in security redundancy and emergency response mechanisms further constrains recovery after crises (Culot et al., 2024). As for operational capacity, the insignificant effect may be explained by two factors: first, some PEs neglect the construction of traditional fallback paths and emergency response mechanisms after adopting AI, resulting in insufficient manual intervention and dispatching capacity in unexpected situations (Richey et al., 2025); second, most AI systems emphasize front-end early warning and production optimization, but their adaptability and flexibility in post-disaster recovery and resource reallocation remain limited, especially in SMEs, where model complexity and high technical thresholds restrict their ability to quickly recover from extreme conditions (Hokmabadi et al., 2024).

Finally, we find that AI enables PEs to achieve both the "quality" and "efficiency" of innovation. This result is consistent with Rammer et al. (2021), who argue that AI not only enhances IE but also improves innovation quality, underscoring its deep-rooted enabling effect. The reasons may be twofold. First, AI improves resource allocation efficiency and R&D responsiveness through optimized data analysis and process automation, allowing firms to identify innovation opportunities more accurately, reduce

608 trial-and-error costs, and thereby enhance average innovation quality (Bouschery et al.,
609 2023). Second, the embedding of AI strengthens internal knowledge integration and
610 cross-functional collaboration, promotes organizational learning and technological
611 reconfiguration, and enhances the overall synergy and breakthrough capacity of the
612 innovation system, thereby improving overall innovation quality (Ritala et al., 2024).

613 7. Case studies

614 AI is not only a technological tool in the innovation processes of PEs but also a
615 key strategic resource within their innovation systems (Wang et al., 2023). An overview
616 of the application of AI in empowering the innovation practices of PEs and enhancing
617 their IE reveals three main stages: technological accumulation, shared integration, and
618 value creation.

619 In the technological accumulation phase, China's rapid progress in social
620 intelligence has provided a strong "technological foundation" for PEs to adopt AI. By
621 2024, intelligent computing power accounted for 32% of the total computing capacity.
622 As of March 2025, the penetration rate of 5G users in China had reached 75.9%.
623 Furthermore, breakthroughs in computing power and algorithm innovation form the
624 foundation for technological advancements and the core of technical implementation in
625 PEs. Investment in computing power has become a key driver of their intelligent
626 transformation (Cheng et al., 2024). For example, in 2023, Baidu established an
627 intelligent computing center project in Ya"an, which not only includes the construction
628 of physical data centers and intelligent computing infrastructure but also offers a

comprehensive solution encompassing AI software and hardware ecosystems, represented by large models. This solution supports the computational tasks and industrial applications of large models across various business scenarios in the era of intelligent computing. Finally, PEs primarily deploy AI services in the areas of content generation, customer insights, and internal automation. According to the "2025 China Entrepreneur Survey Report on AI Applications", 41.41% of enterprises prefer public API integration, 34.38% configure customized models, and 30.47% use embedded tools, reflecting a tiered AI deployment strategy of "API → tools → customization → open source."

Furthermore, the co-development of "human-machine collaboration" capabilities has become a critical foundation for AI capability building in PEs (Kardush et al., 2022). For example, Aima Technology, a PE that has ranked first in the China Brand Power Index (C-BPI) for electric bicycle brands for 13 consecutive years, integrates the concept of granular computing. It categorizes relevant factors in decision-making scenarios into distinct data modules based on approximate, fuzzy, functional, and distance relationships. Using human-curated experience and knowledge, it compresses and expresses data to construct a sales forecasting model, thereby enabling effective mapping from data to scenarios. Practices such as the "RPA Digital Employee Solution" implemented by TBEA further support this point.

In the shared integration phase, PEs have gradually established a unified mechanism of "product-user-scenario" integration in their operational practices. Firstly,

650 the diversified interactive data generated from continuous product-user interactions
651 across multiple scenarios enables enterprises to uncover high-value innovation
652 opportunities. For example, in response to the growing demand for green products and
653 increasing pressure for green transformation, leading manufacturers such as Midea and
654 BYD have actively integrated AI into their green technology systems. This integration
655 has enabled multidimensional applications, including emissions monitoring, optimal
656 energy consumption scheduling, and green supply chain collaboration. Secondly, from
657 the perspective of dynamic capabilities theory, AI technology enhances digital
658 adaptability, providing fundamental support for a company's ability to perceive,
659 collaborate, and reconfigure resources in dynamic environments. This significantly
660 improves the company's innovation flexibility and efficiency (Gao et al., 2025). For
661 example, Inspur Group, in collaboration with JD Technology Group, developed the
662 "TianShu" server. Its rapid elastic scaling capability, based on the cloud computing
663 platform, can handle peak loads of hundreds of millions. Finally, AI has enhanced
664 enterprises" market perception capabilities, establishing a pathway driven by the
665 enterprise itself, with a closed-loop flow of data, technology, talent, scenarios, products,
666 and other elements. This pathway helps enterprises achieve sustainable technological
667 breakthroughs and the transformation of business value.

668 In the value creation phase, on the one hand, AI has established a new model of
669 production (Xu and Tian, 2025). Big data analytics and machine learning technologies
670 effectively mine, process, and utilize the vast amounts of data and information

671 generated within PEs, thereby transforming them into new forms of production assets.
672 At the same time, in the production process, the deep integration of smart devices,
673 machine learning algorithms, data models, and natural language processing can help
674 PEs forecast and optimize the demand and supply of various production resources. This
675 enables companies to overcome the limitations of traditional manufacturing models,
676 achieving flexible and efficient production goals, enhancing the effectiveness and
677 utilization of production assets, and improving IE. For example, Huawei utilizes neural
678 network algorithms for defect detection and classification, combining grayscale
679 distribution models with various image processing techniques to achieve accurate
680 defect identification and categorization. This application of AI technology enhances IE
681 in manufacturing. On the other hand, AI accelerates the processes of knowledge
682 creation, diffusion, and spillover (Gelashvili-Luik et al., 2025). AI has demonstrated
683 outstanding performance in applications such as automatic summarization, question-
684 answering systems, and knowledge graphs, significantly enhancing knowledge
685 production efficiency. It facilitates the interconnection of information across various
686 stages of research, development, production, and marketing in PEs, increasing their
687 knowledge stock and activities, and enabling thorough preliminary accumulation for
688 technological innovation. At the same time, the application of AI has overcome the
689 contextual limitations of knowledge sharing, reducing the cost of information exchange
690 and knowledge flow between enterprises. This has helped PEs break down “data silos”
691 within their innovation systems. For example, JD Cloud has introduced a new

development model through the collaboration of the “Intelligent Agent + Code Platform.” JoyAgent 3.0, as a production-grade intelligent agent platform, integrates internal knowledge bases, business processes, and data systems within enterprises, assisting in the completion of complex decision-making tasks.

8. Research findings and policy recommendations

This paper uses data from 829 PEs in China from 2010 to 2023 to analyze the impact of AI on IE. The empirical results lead to the following conclusions. First, the benchmark regression indicates that AI significantly improves the technological and IE of PEs. Second, in the innovation input chain, AI has a significant positive effect on the number of R&D personnel, while in the innovation output chain, AI significantly promotes both substantive and strategic innovation. Third, the heterogeneity analysis shows that, compared with labor-intensive firms, AI exerts a stronger positive effect on technology-intensive and capital-intensive firms. Fourth, the mechanism analysis reveals that AI enhances the IE of PEs by strengthening supply chain resistance, but it also exerts a significantly negative effect by reducing SCR, thereby lowering IE. Fifth, AI improves both the overall innovation quality and the average innovation quality of PEs while simultaneously enhancing their IE. Finally, based on case studies of PEs in China, we have distilled a pathway for enhancing innovation efficiency through AI empowerment, structured around technological accumulation, shared integration, and value creation.

Our theoretical contributions are summarized as follows. First, while most studies

on the economic consequences of AI and innovation focus on the regional level (Ge et al., 2025) or specific industries such as manufacturing (Tian et al., 2023) and new energy (Xu and Lin, 2025), little attention has been paid to PEs, and even less to their IE. This paper examines the economic consequences of AI for the IE of PEs, thereby extending the research boundary of AI, advancing the theoretical understanding of enterprise innovation, and enriching antecedent research on IE.

Second, by applying the resource-based view and resilience theory, we construct an analytical framework of "AI – SCR – IE of PEs," which explores the internal logic of how AI affects the IE of PEs. This provides a new perspective for studying the transmission mechanisms linking AI to enterprise innovation outcomes.

Finally, this paper confirms the heterogeneous impact of AI on the IE of different types of PEs and demonstrates that while AI enhances the IE of PEs, it also improves their innovation quality. This contribution provides a feasible analytical perspective for understanding the practical effectiveness of AI-enabled innovation in enterprises.

Based on the above findings, this paper offers the following policy recommendations:

First, the policy support system for the application of AI in PEs should be further strengthened. At present, many SMEs face financial constraints and high technical thresholds when introducing AI. It is recommended that the government lower the initial costs of intelligent transformation through measures such as financial subsidies, preferential loans, and tax incentives. In addition, a comprehensive service mechanism

encompassing technical consulting, data integration, and system implementation should be established to improve the accessibility, universality, and adaptability of AI.

Second, the deep integration of AI with the core internal processes of PEs should be promoted. Enterprises should be guided to establish digital supply chain management systems to improve responsiveness to upstream procurement, downstream sales, and external environmental changes, thereby enhancing the robustness and adaptability of their innovation systems. At the same time, efforts should be made to accelerate the cultivation, introduction, and mobility of AI-related talent, foster collaboration and knowledge transfer among universities, research institutions, and enterprises, and address structural challenges such as insufficient manpower, skill mismatches, and low retention rates during the process of intelligent transformation.

Finally, differentiated paths of intelligent transformation should be developed to promote the orderly adoption of AI across different types of PEs. For technology-intensive and capital-intensive firms with strong financial and technological endowments, policy support should emphasize breakthroughs in deep integration and self-developed algorithms. By contrast, for labor-intensive firms, the priority should be the promotion of standardized and lightweight AI solutions to lower adoption thresholds and mitigate the risks of resource mismatches and systemic instability.

This study also has certain limitations. On the one hand, due to data availability, the empirical analysis is based only on listed PEs, which to some extent weakens the generalizability of the findings. Future research could incorporate data from unlisted

PEs to further validate the conclusions. On the other hand, although the DML approach enables us to obtain more reliable empirical results, the economic significance of the coefficients cannot be directly interpreted. Future studies could enhance interpretability by applying explainable machine learning methods such as SHAP to further test and refine the empirical results.

Declaration of competing interest

The authors declare there is no conflict interest.

Data availability

Data will be made available on request.

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