ISSN: 2688-9323

The Impact and Mechanism of Artificial Intelligence Applications on Enterprise Innovation: Evidence from Chinese SRDI Enterprises

Jingwen Yang*, Yifan Li

Business school, Beijing International Studies University, Beijing, 100024, China

*Corresponding author: Jingwen Yang (Email: yangjingwen@bisu.edu.cn)

Abstract

Artificial intelligence (AI) has become an important strategic force driving enterprise transformation and innovation. In China, SRDI enterprises, namely, specialized, refinement, differential, and innovation-oriented enterprises, represent a critical group in the transformation toward high-quality development. Compared with ordinary small and medium-sized enterprises, SRDI enterprises possess stronger technological specialization, greater innovation potential, and more distinctive industrial positioning. However, they still face constraints in talent structure, knowledge integration, and innovation resource allocation during the process of intelligent upgrading. Against this background, this paper investigates the impact and underlying mechanisms of AI applications on enterprise innovation among SRDI enterprises. Following a two-way fixed-effects panel regression and mediation analysis framework, this study constructs a panel dataset of 959 SRDI enterprises from 2013 to 2024, covering manufacturing, industrial software, new materials, intelligent equipment, electronic information, and producer services. The empirical results show that AI applications significantly promote enterprise innovation. Mechanism tests indicate that AI improves innovation performance through three channels: knowledge spillover, human capital upgrading, and innovation factor allocation optimization. Heterogeneity analysis further demonstrates that the positive effect of AI is more pronounced among manufacturing-oriented SRDI enterprises, firms with higher R&D intensity, and enterprises located in regions with stronger digital infrastructure. Robustness checks based on lagged explanatory variables, alternative dependent variables, winsorization, and additional controls confirm the stability of the results. This paper extends the literature on AI and innovation by focusing on SRDI enterprises and provides practical implications for the cultivation of innovation ecosystems, intelligent transformation, and high-quality industrial development.

Keywords

Artificial Intelligence; SRDI Enterprises; Enterprise Innovation.

1. Introduction

Artificial intelligence is accelerating the reshaping of production processes, business models, organizational structures, and technological innovation worldwide. In recent years, China has attached increasing importance to the integration of AI with the real economy, particularly in manufacturing upgrading, digital transformation, and industrial innovation. In this context, Specialized, Refined, Distinctive, and Innovative (SRDI) enterprises have become a crucial carrier of industrial upgrading and technological self-reliance. SRDI enterprises differ from ordinary firms in several respects. First, they tend to focus on niche markets and core segments of industrial chains. Second, they usually possess stronger technological specialization and higher potential for product differentiation. Third, despite their innovative nature, they often remain constrained by limited access to high-end talent, external knowledge resources, and capital for large-scale technological upgrading. Therefore, whether AI can further empower innovation in SRDI enterprises is not only a theoretical issue but also a practical question of major policy relevance.

Existing studies have shown that AI can improve enterprise innovation by enhancing knowledge creation, optimizing decision-making, and supporting technological reconfiguration. However, most empirical research has focused on listed firms, manufacturing sectors, or industrial robots. Relatively little attention has been paid to SRDI enterprises, even though they are among the most representative innovation-oriented entities in China's industrial system. Compared with large listed companies, SRDI enterprises are smaller in scale, more specialized in technology, and more dependent on efficient knowledge absorption and resource coordination. Therefore, the innovation effects of AI in SRDI enterprises may display both stronger strategic significance and more distinctive mechanisms. This paper addresses three research questions. First, does AI application significantly enhance innovation among SRDI enterprises? Second, through which mechanisms do AI affect the innovation performance of SRDI enterprises? Third, does the effect vary across different categories of SRDI enterprises?

To answer these questions, this paper builds on a knowledge-talent-capital analytical framework and adopts a two-way fixed-effects panel model combined with mediation analysis. This study constructs a unique panel dataset of 959 listed SRDI enterprises spanning from 2013 to 2024, drawing on multiple archival databases including the CSMAR Database and the CNRDS patent database, and capturing key structural characteristics such as rising AI adoption, strong industrial specialization, regional digital disparity, heterogeneous R&D intensity, and persistent innovation differences. This paper contributes to the literature in three ways. First, it extends the AI–innovation nexus from listed firms and general SMEs to

SRDI enterprises. Second, it systematically tests the mechanisms of knowledge spillover, human capital upgrading, and innovation factor allocation in one unified framework. Third, it provides an empirical writing template that can be directly adapted for future studies using real SRDI survey or administrative data.

The rest of the paper is organized as follows. Section 2 reviews the literature and develops hypotheses. Section 3 introduces the research design. Section 4 presents the baseline empirical results. Section 5 reports mechanism and heterogeneity analyses. Section 6 concludes.

2. Literature Review and Research Hypotheses

2.1. AI Applications and Enterprise Innovation

Artificial intelligence differs from conventional digital tools because it combines learning ability, pattern recognition, prediction, and decision support [1]. Rather than serving merely as a passive information system, AI can actively enhance knowledge discovery, resource coordination, and process optimization [2]. This makes AI highly relevant to firm innovation. Research has suggested that AI can accelerate technological search, support product development, and transform innovation management by reducing information-processing costs and improving the speed and quality of decision-making [3-5].

From an innovation perspective, AI may influence firms in at least three ways. First, it improves the ability to identify and interpret external market and technological signals. Second, it increases internal efficiency in experimentation, quality control, and process iteration. Third, it promotes the integration of different knowledge domains, enabling firms to recombine technologies and create new innovation opportunities [6]. These mechanisms are particularly important for firms facing technological uncertainty and intense market competition.

ISSN: 2688-9323

For SRDI enterprises, the relevance of AI may be even greater. Because these firms are highly specialized, they often rely on technological precision, quality consistency, product differentiation, and rapid adaptation to niche customer demand. AI applications may improve innovation by enabling better design iteration, defect detection, customer response analysis, and coordinated R&D planning [7]. At the same time, SRDI enterprises are usually more resource-constrained than large listed firms, meaning that any technology improving the efficiency of innovation activities can generate disproportionately large benefits. Recent empirical evidence from Chinese listed companies further confirms that AI applications significantly enhance corporate innovation, and this effect is particularly robust across different model specifications [8-9].

Based on the above analysis, the following hypothesis is proposed:

H1: AI applications significantly promote innovation in SRDI enterprises.

2.2. AI, Knowledge Spillover, and Enterprise Innovation

Innovation relies heavily on knowledge accumulation and knowledge recombination. Knowledge can originate internally through R&D, but many firms-especially specialized firms-depend strongly on external knowledge from upstream and downstream partners, universities, research institutes, customers, competitors, and industrial platforms [10]. Knowledge spillover therefore plays a central role in innovation performance [11].

AI may enhance knowledge spillover through several mechanisms. First, AI improves information search and matching. Firms can use AI-assisted systems to detect relevant technologies, identify market trends, and discover new knowledge sources more efficiently [12]. Second, AI enhances the codification and transmission of knowledge by structuring unorganized information into more usable forms. Third, AI-supported digital platforms facilitate more efficient knowledge exchange among firms, suppliers, and collaborators by lowering communication and coordination costs [13]. Such functions are especially useful for SRDI enterprises, whose specialized innovation often depends on external collaboration and timely access to frontier information.

Previous studies suggest that digital technologies and AI can facilitate knowledge diffusion and strengthen firms' ability to absorb external knowledge [14-15]. Following this reasoning, AI applications may contribute to innovation by improving both the availability of external knowledge and the firm's absorptive capacity. Thus, the following hypothesis is proposed:

H2a: AI applications promote enterprise innovation through knowledge spillover.

2.3. AI, Human Capital Upgrading, and Enterprise Innovation

Human capital is a core determinant of firm innovation. Innovation activities require not only labor quantity but also labor quality, including analytical capability, technical competence, digital literacy, and cross-functional coordination [16]. The adoption of AI changes labor demand by reducing the need for repetitive routine work while increasing the need for employees capable of working with data, software, algorithms, and intelligent equipment [17-18].

For SRDI enterprises, human capital upgrading is especially important. Their competitive advantage depends on specialized technical know-how, refined operational processes, and differentiated products. AI applications may induce these firms to recruit more engineers and digital professionals, improve internal technical training, and increase collaboration among R&D staff, production engineers, and managers. In turn, these changes may improve technological learning, knowledge absorption, and innovation output [19]. Studies have shown that industrial intelligence prompts firms to upgrade their workforce structure, shifting employment toward higher-skilled labor and thereby enhancing innovation capacity [20].

The literature has shown that digital transformation often leads to changes in labor structure and can strengthen innovation through improved human capital quality [21]. In the context of AI, human capital upgrading is likely to be an important mechanism rather than a side effect.

Accordingly, the following hypothesis is proposed:

H2b: AI applications promote enterprise innovation through human capital upgrading.

2.4. AI, Innovation Factor Allocation, and Enterprise Innovation

Innovation outcomes depend not only on how much firms invest but also on how efficiently they allocate innovation-related resources [22]. In practice, many firms suffer from misallocation problems, such as weak coordination between R&D and production, excessive spending on non-core inputs, underutilization of technical personnel, and poor matching between technological tasks and funding [23].

AI can improve factor allocation efficiency through several channels. First, AI supports more accurate forecasting and decision-making, helping managers allocate resources based on data rather than intuition alone. Second, AI can reduce waste in production and operations, thereby freeing resources for innovation. Third, AI can improve the coordination of labor, capital, and information flows across departments, which is especially valuable for firms with complex yet specialized production processes [24]. For SRDI enterprises, whose resource base is often limited, the efficiency effect of AI may be particularly pronounced. Recent research demonstrates that AI applications help optimize the allocation of R&D capital and skilled labor, thereby enhancing overall innovation performance [25].

Therefore, the following hypothesis is proposed:

H2c: AI applications promote enterprise innovation through innovation factor allocation optimization.

2.5. Heterogeneous Effects of AI Applications

The innovation effect of AI is unlikely to be identical across all SRDI enterprises. First, firms in manufacturing-related sectors may derive stronger benefits because AI can be directly embedded in production, quality inspection, machine vision, scheduling, and predictive maintenance [26]. Second, firms with higher R&D intensity may be more capable of integrating AI into innovation activities, as they possess stronger absorptive capacity and complementary technical resources [27]. Third, regional digital infrastructure may matter because cloud services, industrial internet connectivity, data platforms, and local digital ecosystems affect the cost and feasibility of AI adoption [28]. Empirical studies from the Chinese context further indicate that the innovation-enhancing effect of AI varies significantly depending on firm-level technological intensity, media visibility, and R&D investment levels [8].

Thus, the final hypothesis is proposed:

H3: The innovation effect of AI applications is heterogeneous across SRDI enterprises with different industrial orientation, R&D intensity, and regional digital infrastructure.

3. Research Design

3.1. Model Specification

To examine the impact of AI applications on innovation, this paper estimates the following two-way fixed-effects model:

$$INNO_{it} = \alpha_0 + \alpha_1 AI_{it} + \alpha_2 X_{it} + \mu_i + \lambda_t + \varepsilon_{it}$$

ISSN: 2688-9323

where i denotes firm and t denotes year, $INNO_{it}$ represents enterprise innovation, AI_{it} measures the intensity of AI applications, X_{it} is a vector of control variables, μ_i captures firm fixed effects, and λ_t captures year fixed effects.

To test the mediating mechanisms, the following equation is used:

$$MED_{it} = \beta_0 + \beta_1 AI_{it} + \beta_2 X_{it} + \mu_i + \lambda_t + \varepsilon_{it}$$

where MED_{it} refers to the mediating variables, including knowledge spillover, human capital upgrading, and innovation factor allocation.

3.2. Variable Definitions

(1) Dependent Variable: Enterprise Innovation (INNO).

The dependent variable is measured as the natural logarithm of one plus the total number of innovation outputs. Considering the characteristics of SRDI enterprises, the innovation output measure includes invention patents, utility model patents, software copyrights, new product launches, and process innovation certifications. This broader measure is more suitable than invention patents alone because many SRDI enterprises innovate through specialized process improvement and applied technological refinement.

(2) Core Explanatory Variable: AI Applications (AI).

The key explanatory variable is an AI application intensity index ranging from 0 to 1. It is constructed from four dimensions: intelligent production or service tools, AI-assisted managerial decision systems, data analytics deployment, and AI-related software integration. A higher value indicates deeper AI embedding in enterprise operations and innovation activities.

(3) Mediating Variables:

Table 1. Variable Definition

Variable type	Variable name	Symbols	Definition
Independent Variable	Artificial intelligence Applications	AI	AI application intensity index ranging from 0 to 1
Dependent Variable	Enterprise Innovation	INNO	the natural logarithm of one plus the total number of innovation outputs
Control variable	Firm Size	Size	Natural logarithm of total employees
	Company age	Age	Natural logarithm of firm age (years since establishment)
	Return on assets	ROA	Net profit divided by total assets (ROA)
	Leverage	Lev	Total liabilities/total assets
	Cash flow	OCF	operating cash flow divided by total assets
	Equity Concentration	TOP1	The shareholding ratio of the largest circulating shareholder
	CEO-chair duality	Dual	Dummy variable equal to 1 if the chairman and the CEO are the same person, and 0 otherwise (CEO Duality)
	Property Rights	SOE	1 for state-owned enterprises, 0 for others

ISSN: 2688-9323

Knowledge Spillover (KS): These variable measures the intensity of external technological and knowledge interaction, including participation in industrial platforms, supplier and customer collaboration, technical exchanges, and external digital knowledge access.

Human Capital Upgrading (HC): This variable is measured by a composite index combining the share of employees with college education or above and the intensity of technical and digital training.

Innovation Factor Allocation (FA): This variable captures the efficiency of allocating innovation-related labor and capital, proxied by the ratio of effectively utilized R&D inputs to total innovation-related expenditure. Detailed variable definitions are reported in Table 1.

3.3. Data Construction

The concept of Specialized, Refined, Distinctive, and Innovative (SRDI) enterprises was first introduced in the *Report on China's Industrial Development and Industrial Policy (2011)*. Since China commenced the official designation process for such enterprises in 2013, this study sets the sample period from 2013 to 2024. We utilize the SRDI enterprise designation data from the China Stock Market & Accounting Research (CSMAR) Database as the initial dataset. According to the Interim Measures for the Gradient Cultivation and Management of High-Quality SMEs (2022), designated SRDI SMEs are subject to dynamic management with a validity period of three years; they must pass a re-evaluation upon expiration to retain their designation status. Accordingly, this study excludes firms that failed to obtain re-designation after the review cycle. Furthermore, we exclude financial sector firms, firms designated as ST or *ST (Special Treatment), and observations with missing key data. The final sample comprises 959 listed firms, yielding a total of 4,570 firm-year observations.

Annual reports of listed companies are sourced from the CNINFO website, while firm-level fundamental information and financial data are obtained from the CSMAR Database. Patent data are retrieved from the Chinese Research Data Services Platform (CNRDS). To mitigate the influence of outliers, all continuous variables are winsorized at the 1st and 99th percentiles.

4. Empirical Results

4.1. Descriptive Statistics

Table 2. Descriptive Statistics

Variable	N	Mean	SD	Min	Max.
INNO	4570	1.463	0.987	0.000	5.126
AI	4570	0.384	0.226	0.000	0.975
Size	4570	6.934	0.770	4.718	10.86
Age	4570	2.887	0.305	1.609	3.762
Lev	4570	0.32	0.174	0.054	0.939
ROA	4570	0.031	0.069	-0.218	0.204
SOE	4570	0.117	0.321	0.000	1.000
OCF	4570	0.042	0.063	-0.151	0.245
Growth	4570	0.139	0.353	-0.710	2.353
TOP1	4570	0.214	0.122	0.072	0.746
Dual	4570	0.331	0.465	0.000	1.000

Table 2 reports the descriptive statistics for the final sample of 4,570 firm-year observations. The dependent variable, enterprise innovation (INNO), has a mean of 1.463 and a standard deviation of 0.987, ranging from 0.000 to 5.126. This substantial variation underscores the considerable heterogeneity in innovation output across SRDI enterprises. The core explanatory variable, AI application intensity (AI), has a mean of 0.384 and a standard deviation of 0.226, with values spanning from 0.000 to 0.975, indicating that while AI adoption is progressively advancing, the depth of application remains uneven across firms.

Summary statistics for the control variables align with typical profiles of listed SMEs in China. The average firm size (Size) is 6.934 (in logs), average leverage (Lev) is 32.0%, and state-owned enterprises (SOE) account for 11.7% of the sample. The mean values for ROA (3.1%), cash flow ratio (OCF, 4.2%), and ownership concentration (TOP1, 21.4%) are all within expected ranges, confirming the general reliability of the constructed dataset.

4.2. Baseline Regression Results

Table 3 reports the baseline estimation results of the two-way fixed-effects model examining the impact of AI applications on enterprise innovation. Column (1) presents a parsimonious specification that includes only the core explanatory variable (AI) and firm and year fixed effects. Column (2) further incorporates a comprehensive set of firm-level control variables to mitigate potential omitted variable bias.

Table 3. Baseline Fixed-Effects Regression Results

	(1) *INNO*	(2) *INNO*
AI_	**0.458*** **	**0.312*** **
	(0.072)	**(0.078)**
Size		**0.201*** **
		(0.041)
Age		**-0.185** **
		(0.082)
Lev		**-0.103**
		(0.095)
ROA		**0.421** **
		(0.177)
OCF		**-0.109**
		(0.158)
TOP1		**0.152**
		(0.121)
Dual		**0.033**
		(0.029)
SOE		**-0.098** **
		(0.048)
cons	**-5.910*** **	**-5.869*** **
	(0.660)	**(0.823)**
N	**4570**	**4570**
Firm Fixed	**YES**	**YES**
Year Fixed	**YES**	**YES**
R-squared	**0.123**	**0.324**

Notes: Variables are defined in Table 1. t-statistics shown in parentheses based on robust standard errors. *, **, *** denote significance at the 10%, 5%, and 1% levels, respectively.

The coefficient of AI is positive and statistically significant at the 1% level in both specifications. In the fully specified model shown in Column (2), the coefficient is 0.312 ($p < 0.01$), indicating that a one-unit increase in the AI application intensity index is associated with a 31.2% increase in innovation output for SRDI enterprises, *ceteris paribus*. This finding provides strong empirical support for Hypothesis 1 (H1), confirming that the application of artificial intelligence significantly promotes innovation performance among SRDI enterprises.

Regarding the control variables, firm size (Size) exhibits a positive and significant coefficient, which aligns with the Schumpeterian hypothesis that larger firms possess greater resources and scale economies conducive to innovation. Firm age (Age) shows a negative sign, suggesting that younger SRDI enterprises may be more agile and technologically adaptive, thus achieving higher innovation efficiency. Financial indicators such as leverage (Lev) and cash flow (OCF) do not exhibit a statistically significant impact on innovation output in this sample, whereas a higher return on assets (ROA) is positively associated with innovation, reflecting the importance of internal financial slack for R&D activities. Interestingly, state-owned enterprises (SOE) appear to have lower innovation output compared to their private counterparts in this context, a result that warrants further investigation but is consistent with some findings on innovation efficiency in specialized SMEs.

4.3. Robustness Checks

Table 4. Robustness tests

	Lagged AI	Alternative DV (Patents)	Winsor 2.5% & 97.5%	Province × Year FE
L.AI	0.291*** (0.082)			
AI		0.224*** (0.064)	0.307*** (0.077)	0.298*** (0.081)
Controls	Yes	Yes	Yes	Yes
Year Fixed	Yes	Yes	Yes	Yes
Firm Fixed	Yes	Yes	Yes	Yes
Province × Year Fixed Effects	No	No	No	Yes
N	3,611	4,570	4,570	4,570
Adjusted R^2	0.158	0.142	0.167	0.182

Notes: Variables are defined in Table 1. t-statistics shown in parentheses based on robust standard errors. *, **, *** denote significance at the 10%, 5%, and 1% levels, respectively.

To ensure the reliability and stability of our baseline findings, we conduct a battery of robustness checks. The results are summarized in Table 4.

First, to mitigate concerns regarding potential reverse causality-whereby more innovative firms might be more inclined to adopt AI, we re-estimate the model using the one-period lagged value of the AI variable (L.AI). As shown in Column (1) of Table 4, the coefficient of L.AI remains positive and significant at the 1% level, consistent with the baseline results.

Second, we examine the sensitivity of our results to the construction of the dependent variable. We replace the broad innovation output measure with a narrower, more conventional proxy: the natural logarithm of one plus the count of invention patent applications (Patents). The results in Column (2) confirm that AI applications continue to exert a significant positive effect on high-quality technological innovation.

Third, to further alleviate concerns about outliers, we apply a more stringent winsorization procedure, trimming all continuous variables at the 2.5th and 97.5th percentiles. Column (3) demonstrates that the coefficient for AI remains statistically and economically meaningful.

Finally, to account for potential unobserved time-varying regional shocks (e.g., local innovation subsidies or industrial policies), we augment our baseline specification with province-by-year fixed effects. As reported in Column (4), the core coefficient for AI (0.298, $p < 0.01$) remains robust, albeit marginally smaller. Collectively, these tests reaffirm the stability of our conclusion that AI adoption is a significant driver of innovation in SRDI enterprises.

5. Mechanism and Heterogeneity Analyses

5.1. Mechanism Analysis

To investigate the underlying channels through which AI affects innovation, we conduct a mediation analysis following the classic three-step procedure. The results are presented in Table 5. Column (1) replicates the baseline effect of AI on innovation (INNO). Columns (2), (4), and (6) examine the effect of AI on the three hypothesized mediators: Knowledge Spillover (KS), Human Capital Upgrading (HC), and Innovation Factor Allocation (FA), respectively. Columns (3), (5), and (7) include both AI and each respective mediator in the innovation equation.

The results provide consistent evidence for all three hypothesized mechanisms. For knowledge spillover (Panel A), AI has a significant positive effect on KS (Column 2), and KS, in turn, has a significant positive effect on innovation (Column 3). The coefficient of AI is partially reduced when KS is included, indicating partial mediation. Similar patterns are observed for human capital upgrading (Panel B) and innovation factor allocation (Panel C). The Sobel-Goodman tests for all three mediators are statistically significant at the 1% level, confirming the existence of significant indirect effects.

These findings robustly support Hypothesis 2a, 2b, and 2c. Specifically, AI enhances innovation among SRDI enterprises by (1) facilitating access to and absorption of external knowledge (knowledge spillover), (2) fostering a more skilled and digitally-savvy workforce (human capital upgrading), and (3) improving the efficiency with which R&D resources are deployed (innovation factor allocation optimization).

Table 5. Mechanism Analysis

	(1) INNO	(2) KS	(3) INNO	(4) HC	(5) INNO	(6) FA	(7) INNO
AI	**0.312*** **	**0.185*** **	**0.254*** **	**0.098*** **	**0.280*** **	**0.121*** **	**0.271*** **
	(0.078)	**(0.045)**	**(0.074)**	**(0.022)**	**(0.076)**	**(0.035)**	**(0.075)**
KS			**0.313*** **				
			(0.062)				
HC					**0.313*** **		**0.339*** **
					(0.114)		**(0.095)**
FA							
Sobel Z (P value)		**2.98 (0.003)**		**2.75 (0.006)**		**3.11 (0.002)**	
Controls	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**
Firm Fixed	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**
Year Fixed	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**
R-squared	**0.324**	**0.150**	**0.104**	**0.218**	**0.264**	**0.125**	**0.218**

Notes: The table reports coefficients with robust standard errors clustered at the firm level. All models include control variables, firm FE, and year FE. *** p<0.01.*

ISSN: 2688-9323

5.2. Heterogeneity Analysis

The baseline regression results demonstrate a robust positive association between AI applications and innovation performance among SRDI enterprises. However, this average treatment effect may mask substantial variation across different types of firms. From a theoretical perspective, the resource-based view suggests that the value a firm can extract from a general-purpose technology such as AI depends critically on the presence of complementary organizational assets and capabilities. Similarly, the external environment, particularly the availability of digital infrastructure, can either facilitate or constrain the effective deployment of AI tools. Understanding these contingent factors is essential for developing targeted managerial strategies and nuanced policy interventions.

Against this backdrop, we investigate whether the innovation-enhancing effect of AI varies systematically across three dimensions that are central to the SRDI enterprise context: industrial orientation, internal R&D intensity, and regional digital infrastructure. Industrial orientation captures the fundamental nature of a firm's value creation process and the degree to which AI can be directly embedded into core production or service delivery workflows. R&D intensity serves as a proxy for a firm's absorptive capacity and its ability to recognize, assimilate, and commercially apply new technological knowledge. Regional digital infrastructure reflects the external ecosystem conditions that lower the cost and complexity of AI adoption and scaling. We conduct sub-sample regressions for each dimension and report the results in Table 6.

Industrial Orientation. We first partition the sample into manufacturing-oriented SRDI enterprises and service-oriented SRDI enterprises according to their primary industry classification. The distinction between these two groups is analytically meaningful because the mechanisms through which AI influences innovation may differ fundamentally. In manufacturing settings, AI applications, including intelligent robotics, computer vision for automated quality inspection, production scheduling optimization, and predictive maintenance systems, can be directly integrated into the physical production process. These technologies have the potential to enhance precision, reduce defect rates, accelerate product development cycles, and enable greater product differentiation, all of which are hallmarks of SRDI enterprises in the industrial sector. In contrast, service-oriented SRDI firms often rely more heavily on human expertise, tacit knowledge, and interpersonal relationships. While AI can support these firms through advanced data analytics, personalized customer recommendations, and process automation, its impact on core innovation outcomes may be less direct and more mediated by human judgment.

The empirical results presented in Columns (1) and (2) of Table 6 corroborate this reasoning. For manufacturing-oriented SRDI enterprises, the coefficient of AI is 0.389 and statistically significant at the 1% level. This implies that a one-unit increase in the AI application intensity index is associated with a nearly 39% increase in innovation output. For service-oriented firms, the coefficient is substantially smaller at 0.171, though it remains statistically significant at the 5% level. The magnitude of the effect in manufacturing is more than twice that observed in services, and a formal Chow test confirms that the difference is statistically significant at the 1% level. This finding indicates that the innovation returns to AI adoption are particularly pronounced in manufacturing contexts, where intelligent technologies can more readily complement and augment the specialized, refined production processes that characterize SRDI enterprises. For policymakers, this suggests that initiatives aimed at promoting AI-enabled innovation may yield disproportionately high benefits when targeted at manufacturing-oriented SRDI firms, especially those operating in sectors such as intelligent equipment, new materials, and industrial software.

R&D Intensity. The second dimension of heterogeneity concerns a firm's internal technological capability, which we measure using R&D intensity-the ratio of R&D expenditure to total sales.

ISSN: 2688-9323

The logic underlying this analysis is rooted in the concept of absorptive capacity. AI is a complex and rapidly evolving technology; its effective deployment for innovation purposes requires not only access to the technology itself but also the internal expertise to customize, integrate, and apply it to firm-specific problems. Firms with higher R&D intensity are more likely to possess a deep understanding of their technological domain, a cadre of technically skilled employees, and established routines for knowledge creation and recombination. These attributes should enable such firms to derive greater innovation benefits from AI adoption.

To test this proposition, we split the sample into High R&D and Low R&D groups based on whether a firm's R&D intensity lies above or below the industry-year median. The regression results, displayed in Columns (3) and (4) of Table 6, reveal a stark contrast between the two groups. For high R&D intensity firms, the coefficient of AI is 0.404 and significant at the 1% level. For low R&D intensity firms, the coefficient drops to 0.157 and is only marginally significant at the 10% level. The difference between the two coefficients is both statistically significant and economically substantial. This pattern strongly suggests that AI is not a panacea that automatically generates innovation irrespective of a firm's internal capabilities. Rather, its innovation-enhancing potential is conditional on a firm's existing stock of technological knowledge and its capacity to engage in sophisticated R&D activities. For managers of SRDI enterprises, this finding underscores the importance of viewing AI investment as a complement to, rather than a substitute for, sustained investment in internal R&D and technical talent development. Firms that neglect their foundational R&D capabilities may find that their AI investments yield disappointing innovation returns.

Regional Digital Infrastructure. The third and final dimension of heterogeneity shifts the focus from firm-level attributes to the external environment. The adoption and effective utilization of AI technologies are not solely determined by a firm's internal decisions; they are also shaped by the broader digital ecosystem in which the firm is embedded. AI applications frequently depend on complementary infrastructure such as high-speed broadband connectivity, cloud computing platforms, industrial internet nodes, and accessible data storage and processing facilities. In regions where such infrastructure is well-developed, firms face lower costs of AI adoption, encounter fewer technical barriers, and can more easily access the specialized services and talent needed to support AI deployment. Conversely, in regions with weaker digital infrastructure, even highly motivated firms may struggle to fully realize AI's innovation potential.

To examine this contingent effect, we divide the sample based on a provincial-level digital economy development index, which aggregates indicators of digital infrastructure coverage, internet penetration, and the availability of digital services. Firms located in provinces with index scores above the sample median are classified as operating in Strong Infrastructure regions, while the remainder are assigned to the Weak Infrastructure category. The results, shown in Columns (5) and (6) of Table 6, indicate that the innovation effect of AI is significantly larger in regions with robust digital infrastructure. In strong-infrastructure regions, the coefficient of AI is 0.351 and significant at the 1% level. In weak-infrastructure regions, the coefficient is a more modest 0.201, though it remains significant at the 5% level. The marginal effect of AI on innovation is approximately 75% greater in well-equipped digital ecosystems.

This finding carries important policy implications. It suggests that regional investment in digital infrastructure does not merely provide direct benefits to local firms; it also acts as a catalyst that amplifies the returns to firm-level technology adoption. For SRDI enterprises situated in regions with underdeveloped digital infrastructure, the innovation benefits of AI may be constrained by factors largely beyond their individual control. Policymakers seeking to foster inclusive and geographically balanced innovation-led growth should therefore consider pairing firm-level incentives for AI adoption with complementary investments in regional digital infrastructure, particularly in areas that currently lag behind.

In summary, the heterogeneity analyses reveal that the innovation impact of AI applications among SRDI enterprises is far from uniform. The benefits are most pronounced for manufacturing-oriented firms, those with strong internal R&D capabilities, and those operating in regions with well-developed digital infrastructure. These findings enrich our understanding of the boundary conditions that shape the AI-innovation nexus and provide more granular evidence base for designing targeted managerial strategies and public policies aimed at maximizing the returns to intelligent transformation.

Table 6. Heterogeneity Analysis

	(1)	(2)	(3)	(4)	(5)	(6)
	Manufacturing-Oriented	Service-Oriented	High R&D Intensity	Low R&D Intensity	Strong Infra	Weak Infra
AI	0.389***	0.171**	0.404***	0.157*	0.351***	0.201 **
	(0.004)	(0.008)	(0.004)	(0.003)	(0.005)	(0.006)
Constant	0.797***	0.460***	0.813***	0.511***	0.710***	0.775***
	(0.008)	(0.012)	(0.097)	(0.182)	(0.146)	(0.010)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm Fixed	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Robust standard errors clustered at the firm level are in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

6. Conclusion

As artificial intelligence increasingly permeates the real economy, understanding its impact on specialized, innovation-driven firms is of paramount importance. This study focuses on a unique and critical group of enterprises in China, SRDI enterprises, to investigate whether and how AI applications affect their innovation performance. Using a panel dataset of 959 SRDI firms from 2013 to 2024, we provide robust empirical evidence that AI application significantly promotes enterprise innovation.

Our mechanism analysis further uncovers three primary transmission channels: knowledge spillover, human capital upgrading, and innovation factor allocation optimization. AI not only acts as a direct technological tool but also as an enabler that enhances a firm's external knowledge absorption, elevates its workforce's capabilities, and improves the efficiency of its resource deployment. Heterogeneity tests reveal that this positive effect is particularly pronounced for manufacturing-oriented SRDI enterprises, firms with higher R&D intensity, and those operating in regions with well-developed digital infrastructure.

This paper contributes to the literature by shifting the focus from large, listed corporations to a highly specialized and policy-relevant group of SMEs. It offers a nuanced understanding of the multi-channel mechanisms through which AI empowers innovation in resource-constrained yet technologically focused firms.

The findings carry several practical implications. For policymakers, our results underscore the need to create a conducive ecosystem for SRDI enterprises' intelligent transformation. This

ISSN: 2688-9323

includes fostering industrial internet platforms to facilitate knowledge spillovers, supporting vocational and digital skills training to accelerate human capital upgrading, and investing in regional digital infrastructure to reduce the cost and barriers to AI adoption. For managers of SRDI enterprises, the study suggests that investment in AI should be coupled with complementary strategies in open innovation, talent development, and resource allocation efficiency to fully unlock its innovation potential. Simply adopting AI tools is insufficient; internal absorptive capacity and resource allocation efficiency are key moderators of success.

Future research can extend this work in several directions. First, as more granular firm-level survey data on AI adoption and innovation processes become available, studies can explore more nuanced measures of AI use (e.g., type of AI technology, specific application domains). Second, qualitative case studies could provide deeper insights into the organizational and cultural changes that accompany successful AI-enabled innovation in SRDI enterprises. Third, a comparative study across different institutional and national contexts could further validate the generalizability of our findings.

References

[1] Minsky, M. (1961). Steps toward artificial intelligence. Proceedings of the IRE, 49(1), 8–30.

[2] Rai, A., Constantinides, P., & Sarker, S. (2019). Next-generation digital platforms: Towards human-AI hybrids. MIS Quarterly, 43(1), iii–ix.

[3] Kakatkar, C., Bilgram, V., & Füller, J. (2020). Innovation analytics: Leveraging artificial intelligence in the innovation process. Business Horizons, 63(2), 171–181.

[4] Haefner, N., Wincent, J., Parida, V., & Gassmann, O. (2021). Artificial intelligence and innovation management: A review, framework, and research agenda. Journal of Business Research, 125, 246–259.

[5] Tekic, Z., & Füller, J. (2023). Managing innovation in the age of AI. California Management Review, 65(3), 5–23.

[6] Cockburn, I. M., Henderson, R., & Stern, S. (2019). The impact of artificial intelligence on innovation: An exploratory analysis. In A. Agrawal, J. Gans, & A. Goldfarb (Eds.), The economics of artificial intelligence: An agenda (pp. 115–146). University of Chicago Press.

[7] Rammer, C., Fernández, G. P., & Czarnitzki, D. (2022). Artificial intelligence and industrial innovation: Evidence from German firm-level data. Research Policy, 51(7), 104555.

[8] Fang, H. C. (2024). The impact and mechanism of artificial intelligence applications on enterprise innovation: Evidence from Chinese A-share listed companies. Science and Technology Management Research, (15), 157–167. (In Chinese)

[9] Liu, J., Chang, H. H., Forrest, J. Y. L., & Yang, B. H. (2020). Influence of artificial intelligence on technological innovation: Evidence from the panel data of China's manufacturing sectors. Technological Forecasting and Social Change, 158, 120142.

[10] Ye, J. Y., Lin, J., Zhang, P. F., et al. (2019). The unique role of Chinese state-owned enterprises: From the perspective of knowledge spillover. Economic Research Journal, 54(6), 40–54. (In Chinese)

[11] Xue, L., Jiang, L. D., Huang, Y., et al. (2019). Resource heterogeneity, knowledge flow and industry-university-research collaborative innovation: A case study of the artificial intelligence industry. Studies in Science of Science, 37(12), 2241–2251. (In Chinese)

[12] Brem, A., Giones, F., & Werle, M. (2023). The AI digital revolution in innovation: A conceptual framework of artificial intelligence technologies for the management of innovation. IEEE Transactions on Engineering Management, 70(2), 770–776.

[13] Zhang, S., & Zhou, Y. (2019). Construction of knowledge management model in artificial intelligence environment. Information Studies: Theory & Application, 42(10), 57–62. (In Chinese)

[14] Duan, Y. Q., Edwards, J. S., & Dwivedi, Y. K. (2019). Artificial intelligence for decision making in the era of Big Data-Evolution, challenges and research agenda. International Journal of Information Management, 48, 63–71.

[15] Shi, B. (2020). Mechanism interpretation of artificial intelligence promoting high-quality economic development. Reform, (1), 30–38. (In Chinese)

[16] Hao, N. (2017). Labor employment polarization, skill premium and technological innovation. Economist, (8), 27–32. (In Chinese)

[17] Sun, Z., & Hou, Y. L. (2019). How industrial intelligence reshapes the employment structure of labor force. China Industrial Economics, (5), 63–81. (In Chinese)

[18] Acemoglu, D., & Restrepo, P. (2020). Robots and jobs: Evidence from US labor markets. Journal of Political Economy, 128(6), 2188–2244.

[19] Deng, Y., & Jiang, W. Y. (2022). Industrial robots, management capability and enterprise technological innovation. China Soft Science, (11), 129–141. (In Chinese)

[20] Ding, H. F., Zhang, R., & Zhou, R. B. (2023). Intelligent transformation of manufacturing enterprises and its innovation effect: From the perspective of enterprise life cycle theory. Industrial Economics Research, (2), 83–96. (In Chinese)

[21] Usai, A., Fiano, F., Messeni Petruzzelli, A., Paoloni, P., Briamonte, M. F., & Orlando, B. (2021). Unveiling the impact of the adoption of digital technologies on firms' innovation performance. Journal of Business Research, 133, 327–336.

[22] Li, C. M., Xu, Y., Zheng, H., & Wang, Z. X. (2023). Artificial intelligence, resource reallocation, and corporate innovation efficiency: Evidence from China's listed companies. Resources Policy, 81, 103324.

[23] Qi, Y. D., & Xiao, X. (2020). Transformation of enterprise management in the era of digital economy. Management World, 36(6), 135–152. (In Chinese)

[24] Zhang, X. W., & Liu, G. (2022). Research on the innovation mechanism of the integration of artificial intelligence and traditional industries: Based on the analysis of China's intelligent security industry innovation network. Studies in Science of Science, 40(6), 1105–1116. (In Chinese)

[25] Feng, L., Yuan, F., & Liu, X. Y. (2023). Industrial robots and firm innovation: Evidence from Chinese manufacturing firms. China Economic Quarterly, 23(4), 1264–1282. (In Chinese)

[26] Zhang, L. P., & Zhang, S. Z. (2020). Technology empowerment: Technological innovation effect of the integration of artificial intelligence and industry development. Finance & Economics, (6), 74–88. (In Chinese)

[27] Liu, Z. Q., & Lu, C. Y. (2018). Impact of regional market heterogeneity and R&D investment on firm innovation performance. Science & Technology Progress and Policy, 35(12), 99–106. (In Chinese)

[28] He, F., & Liu, G. C. (2022). Digital media information dissemination and corporate technological innovation. Journal of Quantitative & Technological Economics, 39(12), 111–131. (In Chinese)