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Artificial Intelligence Adoption and Innovation Outcomes: Mechanisms and Empirical Evidence

Ansel Mirek
University of Nebraska at Kearney, Kearney, USA
ansel950@unk.edu

Abstract:

The integration of Artificial Intelligence (AI) technologies has become a key driver of enterprise innovation in the digital economy. However, the impact of AI adoption on the innovation quality (INQ) of firms remains underexplored. This study investigates how AI adoption influences INQ and reveals the underlying mechanisms that mediate this relationship. Using panel data from Shanghai and Shenzhen A-share listed firms from 2010 to 2021, the paper employs fixed-effect and robustness regression models to empirically analyze the effects of AI adoption on INQ. The results show that enterprise AI adoption significantly enhances INQ at the 1% confidence level, and this positive relationship remains robust across multiple model specifications and subsample tests. Mechanism analysis further demonstrates that innovation cooperation (IC) plays a mediating role in this relationship, suggesting that AI adoption promotes collaborative innovation and thus improves INQ. Moreover, heterogeneity analysis reveals that the positive effect of AI on INQ is more pronounced among state-owned enterprises, firms located in eastern regions, and those operating in regions with stronger intellectual property protection (IPP). These findings provide new empirical evidence that AI technologies not only improve innovation efficiency but also elevate innovation quality by enhancing cooperation, knowledge sharing, and resource integration. The study offers valuable implications for policymakers and managers seeking to leverage AI for sustainable innovation-driven development.

Keywords:

Enterprise innovation; Innovation cooperation; Digital transformation; Heterogeneity analysis.

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1. Introduction

The innovation quality (INQ) of an enterprise has a crucial impact on its development[1]. In today's competitive market environment, companies must rely on high-quality innovation to create a differentiated competitive advantage if they want to stand out. In the long term, high- quality innovation is the core driver of sustainable development, which can help companies consolidate existing markets, explore new markets, and achieve sustainable development[2]. However, according to the National Innovation Index Report released by the Chinese Academy of Science and Technology for Development, although Chinese enterprises have maintained growth in innovation capacity, the quality of innovation still lags behind that of developed countries. In terms of patents, although China has surpassed the United States in the number of annual patent applications, the United States has a more comprehensive distribution of patent technology fields and high quality, while China's patent structure is relatively simple and low quality[3]. This gap in INQ has had a significant impact on the development and competitiveness of Chinese enterprises. First, due to the low INQ, Chinese enterprises face greater competitive pressure in the international market, and it is difficult to gain more market share. Secondly, the gap in INQ makes it difficult for enterprises to compete with international leading enterprises in terms of product-added value and brand influence, thus affecting the profitability of enterprises. Therefore, for Chinese enterprises, improving the INQ is more important than ever[4]. In today's wave of digital transformation, enterprises are increasingly recognizing the importance of artificial intelligence (AI) as a key technology to drive innovation and enhance competitiveness[5]. From intelligent customer service to automated production lines, from data analytics to predictive models, AI technology is reshaping business models and market strategies[6]. However, despite the promising applications of AI, its actual impact on the quality of enterprise innovation is still a question worthy of in-depth discussion. On the one hand, AI technology can help companies process large amounts of data more efficiently, optimize decision-making processes, and accelerate product iteration cycles[7]. On the other hand, the adoption of AI technology can also bring complex issues such as pressure for organizational change, the increasing cost of technology, and the need for employees to upgrade their skills. Therefore, exploring the relationship between AI adoption and enterprise INQ is not only of great significance for theoretical research, but also provides guidance for enterprise practice.

In recent years, research on the impact of AI on businesses has increased, but the majority of the literature focuses on short-term benefits such as improved production efficiency and cost control[8], [9], often neglecting how AI fundamentally transforms business innovation capabilities and influences long-term development. While a few studies have begun to explore the influence of AI on corporate innovation, their conclusions are not yet consistent. More importantly, the theoretical black box of how AI drives improvements in INQ remains understudied. Furthermore, existing literature lacks an examination of the differential adoption of AI among firms with different characteristics, making it difficult to fully reveal the deep- seated mechanisms through which AI technologies affect INQ. To address these gaps, this study uses panel data from Chinese-listed companies between 2010 and 2021 and employs empirical analysis methods to explore the impact and pathways of AI adoption on INQ. The aim is to provide a new perspective for the academic and offer scientific guidance for business managers crafting relevant strategies.

The innovation contributions of this study are highlighted in several aspects: Firstly, the study employs quantitative research methods to systematically evaluate the impact of AI adoption on the corporate INQ. This approach advances the understanding of the factors influencing corporate INQ. Secondly, the study validates the pathway through which AI adoption influences corporate innovation quality. Specifically, it demonstrates that adopting AI technology can facilitate firm innovation collaboration, thereby creating favorable conditions for enhancing INQ. Lastly, recognizing that different firm characteristics and geographical environments may affect the outcomes of AI adoption, the study conducts subgroup analyses based on ownership structure, regional distribution, and intellectual property protection, which provides more targeted strategic recommendations for firms with different characteristics.

2. Theoretical hypothesis

2.1 Direct impact of AI adoption on INQ

First, the adoption of AI technologies by enterprises can enhance their data processing and analyzing capabilities[10]. By utilizing efficient data mining and pattern recognition, enterprises can more accurately capture information related to market demand, which provides strong support for product innovation and service improvement, leading to more precise market positioning and product optimization, which will undoubtedly enhance the quality of innovation. Second, AI helps optimize the decision-making process within an enterprise. Advanced machine learning algorithms and digital technology tools enable enterprises to scientifically allocate internal resources, reduce resource mismatches, and ensure that innovation efforts are more targeted and efficient[11]. Therefore, this article proposes the first hypothesis:

H1: Enterprise AI applications can positively promote the enterprise's INQ.

2.2 The Impact Path of AI Adoption on INQ

In the digital age, high-quality innovation by enterprises cannot rely solely on their own efforts, but also on broader open innovation. The adoption of AI will be an important means to promote innovation cooperation and thus improve the quality of enterprise innovation. First, AI can help enterprises cross physical boundaries and build a more open and efficient platform for information exchange and cooperation. On this platform, communication and collaboration between different departments and teams within the enterprise, as well as between the enterprise and external partners, will become more convenient. This convenience not only accelerates the flow of information and reduces delays and distortions in the transmission of information, but also promotes in-depth cooperation between multiple parties and makes the innovative products or patents developed more valuable[12]. Second, AI technology can accurately match potential partners and resources for enterprises through intelligent analysis and prediction. Enterprises can more effectively manage and track the progress of innovation cooperation, and adjust cooperation strategies and directions in a timely manner, making innovation cooperation more targeted and effective[13]. High-quality cooperation can make the enterprise's innovative products more in line with market dynamics and technological trends, thus improving the INQ. Therefore, this article proposes the second hypothesis:

H2: The adoption of AI by enterprises can enhance INQ by promoting innovation cooperation.

3. Research design

3.1 Quantitative modeling

$$INQ_{k,i,t} = \alpha_0 + \alpha_1 AI_{k,i,t} + \sum \varphi CVs + FI + YE + \varepsilon_0$$

Where, INQ_{kit} stands for the innovation quality of the k firm in year t, AI_{kit} represents the degree of artificial intelligence adoption, *a1* is the estimated coefficient of the explanatory variable, *f1* refers to the control variables.

$$INQ_{k,i,t} = \alpha_0 + \alpha_1 AI_{k,i,t} + \alpha_2 AI_{k,i,t} * M_{k,i,t} + \sum \varphi CVs + FI + YE + \varepsilon_0$$

Where, model (2) is used to examine the path of AI adoption on INQ. M_{kit} stands for the mechanism variables, 2 is the estimated coefficient of the mechanism variables.

3.2 Variable selection

The explanatory variable in this study is the degree to which a company adopts artificial intelligence, which is measured as the ratio of the book value of machinery relative to AI to the number of employees[14]. The dependent variable is the INQ of the enterprise, represented by the knowledge breadth of enterprises' invention patents. Control variables include the natural logarithm of the largest shareholder's equity concentration (lnlargest), debt-to-assets ratio (Lev), industry structure (Indus), state ownership (SOE), return on assets (ROA) as a measure of profitability and foreign investment (Foin).

To illustrate the relationships among these variables more clearly, Figure 1 presents a conceptual framework showing how AI adoption influences enterprise innovation quality through direct and indirect mechanisms, while controlling for financial and structural characteristics.

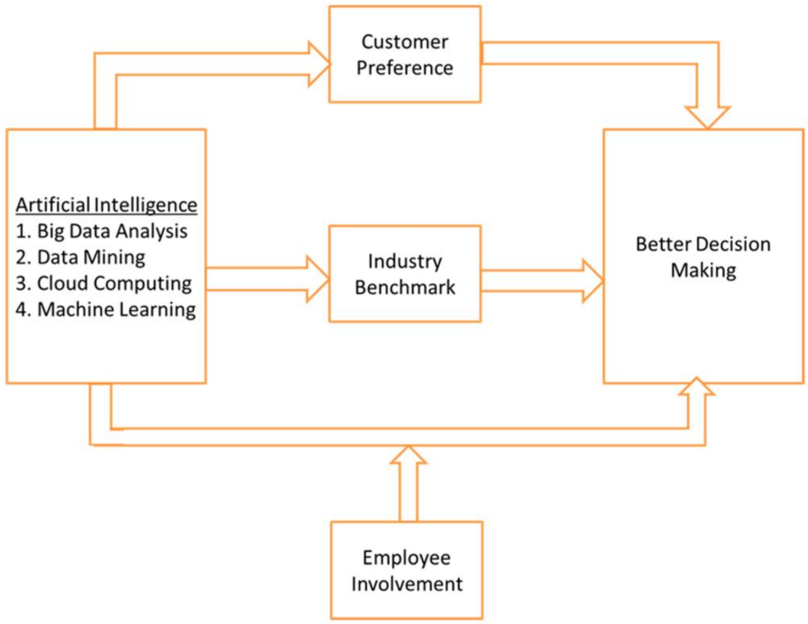

Figure 1. Conceptual framework of variable relationships in the AI-innovation model.

3.3 Sample Selection

This article selects Shanghai and Shenzhen A-shares listed enterprises from 2010 to 2021 as the main research samples. The sample of firms with debt ratios greater than 1 is excluded. Enterprises with special treatment (ST), and special transfer (PT) are excluded.

4. Regression analysis

4.1 Descriptive statistics

The mean AI adoption level is 13.012, with a standard deviation of 1.027, indicating a relatively consistent level of AI adoption across firms. The mean of INQ is 0.321, with a standard deviation of 0.266, suggesting considerable variability in INQ among the firms. The VIF values are all around 1, indicating that there is no covariance between the variables, see Table 1.

Table 1. Descriptive statistics

variables	Obs.	Mean	SD	Min	P50	Max	VIF
AI	15,193.00	13.012	1.027	10.345	12.998	15.957	--
INQ	15,193.00	0.321	0.266	0	0.426	0.816	1.01
lnlargest	15,193.00	3.433	0.458	2.212	3.466	4.3	1.09
Lev	15,193.00	0.415	0.199	0.057	0.407	0.893	1.82

Indus	15,193.00	1.622	1.115	0.721	1.226	5.244	1.38
SOE	15,193.00	0.337	0.473	0	0	1	1.27
ROA	15,193.00	0.041	0.063	-0.276	0.041	0.198	1.22
CR	15,193.00	2.505	2.479	0.335	1.695	16.105	1.82
Foin	15,193.00	15.799	1.786	9.113	15.887	17.891	1.38
IC	15,193.00	0.844	1.207	0	0	5.13	1.14
IPR	15,193.00	6.964	2.257	0	7.296	10.739	1.7

4.2 Baseline regression

Table 2 presents the baseline regression results. Column (1) includes only the explanatory and explanatory variables without controlling for fixed effects. Column (2) builds upon column (1) by incorporating firm-fixed and time-fixed effects. Column (3) adds regional-level control variables, and column (4) includes firm-level control variables. Across all four columns, the coefficient of the AI variable remains significantly positive at the 1% level, indicating a robust positive relationship between a firm's level of AI adoption and its INQ. The first hypothesis of this article is verified.

Table 2. Baseline regression results

Variables	-1	-2	-3	-4
	INQ	INQ	INQ	INQ
AI	0.026***	0.018***	0.018***	0.018***
	-0.002	-0.006	-0.006	-0.006
Indus	_	_	0.002	0.001
	_	_	-0.012	-0.012
Foin	_	_	0.014	0.014*
	_	_	-0.008	-0.008
lnlargest	_	_	_	-0.005
	_	_	_	-0.014
Lev	_	_	_	-0.022
	_	_	_	-0.024
ROA	_	_	_	-0.058
	_	_	_	-0.046
Constants	-0.019	0.09	-0.131	-0.103
	-0.027	-0.079	-0.152	-0.158
Enterprise fixed effect	NO	YES	YES	YES
Year fixed effect	NO	YES	YES	YES
R^2	0.01	0.323	0.323	0.323

Obs.	15193	15193	15193	15193

4.3 Robustness check

Columns (1) to (4) of Table 3 present the robustness check results for the relationship between AI adoption and INQ. To address the issue of omitted variables, this article incorporates the firm's current ratio to test for robustness. In column (1), the coefficient for AI remains significantly positive at 0.018 ($p<0.01$), indicating a robust positive association between AI adoption and INQ even after adding additional control variables. In addition, the industry-fixed effect is included in column (2) and the city-fixed effect is included in column (3). The coefficient for AI remains significant in both specifications, suggesting that the initial finding is robust. In column (4), this article further addresses the potential issues of heteroskedasticity and serial correlation by clustering standard errors at the city level. Despite these adjustments, the coefficient on AI remains statistically significant, reinforcing the robustness of benchmark regression finding that AI has a positive and significant impact on INQ.

Table 3. Robustness check results

Variables	-1	-2	-3	-4
	Add missing variables	Increased fixed effects		City clustering
	INQ	INQ	INQ	INQ
AI	0.018***	0.018***	0.017***	0.018***
	-0.006	-0.006	-0.006	-0.006
Indus	0.002	0.001	0.009	0.001
	-0.012	-0.012	-0.017	-0.016
Foin	0.014*	0.013	0.024**	0.014*
	-0.008	-0.008	-0.01	-0.008
lnlargest	-0.006	-0.007	-0.009	-0.005
	-0.014	-0.014	-0.014	-0.018
Lev	0	-0.025	-0.019	-0.022
	-0.028	-0.024	-0.024	-0.023
ROA	-0.051	-0.054	-0.063	-0.058
	-0.046	-0.045	-0.046	-0.058
CR	0.003	_	_	_
	-0.002	_	_	_
Constants	-0.126	-0.088	-0.251	-0.103

	-0.159	-0.159	-0.188	-0.171
Enterprise fixed effect	YES	YES	YES	YES
Year fixed effect	YES	YES	YES	YES
Industry fixed effect	NO	YES	NO	NO
City fixed effect	NO	NO	YES	NO
R^2	0.323	0.323	0.323	0.323
Obs.	15193	15193	15193	15193

Standard errors in parentheses

* p < 0.1, ** p < 0.05, *** p < 0.01

To test the robustness of the positive relationship between enterprise AI adoption and INQ, this article further conducts several analyses from the sample selection level. These results are reported in Table 4. In column (1), this article restricts the sample to observations from the year 2015 onwards, to focus on more recent trends and developments in AI technology. The coefficient for AI is 0.017, which remains significant at the 5% level, indicating that the positive impact of AI on INQ holds in the more contemporary period. In column (2), this article excludes provinces with fewer than 50 observations to mitigate potential biases arising from provinces with small samples. Despite this reduction in the sample size, the coefficient for AI remains statistically significant, supporting the robustness of the benchmark regression finding. In column (3), this article removes industries with fewer than 50 observations to ensure that the results are not driven by industries with limited data. Again, the coefficient for AI is still significant, which suggests a positive relationship between AI adoption and INQ. Finally, in column (4), this article excludes the information industry from the analysis, given its potentially higher propensity to adopt AI technologies. The exclusion of this industry does not change the significant positive relationship between AI adoption and INQ, providing further evidence for the robustness of the findings. Overall, these robustness checks provide strong support for the hypothesis that AI adoption positively influences INQ.

Table 4. Robustness check results

Variables	-1	-2	-3	-4
	Year>=2015	Deletion of provinces with a sample size of less than 50	Deletion of industries with a sample size of less than 50	Delete Information Industry
AI	INQ	INQ	INQ	INQ
	0.017**	0.017***	0.017***	0.016**
Indus	-0.008	-0.006	-0.006	-0.007
	0.012	0.001	0.001	0.003

Foin	-0.018	-0.012	-0.012	-0.013
	0.004	0.013	0.014*	0.007
lnlargest	-0.012	-0.008	-0.008	-0.009
	0.003	-0.006	-0.005	-0.002
Lev	-0.019	-0.014	-0.014	-0.015
	-0.034	-0.021	-0.022	-0.019
ROA	-0.032	-0.024	-0.024	-0.026
	-0.03	-0.056	-0.058	-0.051
Constants	-0.05	-0.046	-0.046	-0.05
	0.046	-0.079	-0.107	0.023
Enterprise fixed effect	-0.22	-0.159	-0.158	-0.171
	YES	YES	YES	YES
Year fixed effect	YES	YES	YES	YES
R^2	0.323	0.323	0.323	0.311
Obs.	12443	15121	15149	13297

Standard errors in parentheses

* p < 0.1, ** p < 0.05, *** p < 0.01

4.4 Endogeneity test

4.4.1 PSM Balance Test

To address the potential bias caused by sample self-selection, this study employs propensity score matching (PSM) to divide the sample into two groups based on the average level of enterprise AI adoption. Firms with lower AI adoption levels serve as the control group, while those with higher levels form the treatment group. A 1:1 nearest-neighbor matching is performed on the corresponding control variables to ensure that firms with higher and lower AI adoption levels are comparable in observable firm characteristics. As shown in Table 5, the absolute standard deviations of the matching variables after PSM are all within 10%, suggesting good matching quality. Furthermore, the t-tests conducted post-matching indicate that the p-values are no longer significant, supporting the hypothesis that the means of the matching variables are equal after matching. This confirms the effectiveness of the PSM approach. After matching, column (1) of Table 6 reveals that the coefficients of the explanatory variables remain statistically significant.

Table 5. PSM Balance Test Results

Variables	Sample	Mean		%Bias	t-test	
		Treatment	Control		t	P>|t|
Lnlargest	Unmatched	3.447	3.419	6.2	3.81	0
	Matched	3.447	3.441	1.4	0.84	0.4
Lev	Unmatched	0.444	0.387	28.5	17.59	0
	Matched	0.443	0.45	-3.1	-1.84	0.066
ROA	Unmatched	0.031	0.05	-30.7	-18.89	0
	Matched	0.031	0.031	0.7	0.38	0.707
Indus	Unmatched	1.604	1.641	-3.3	-2.06	0.039
	Matched	1.604	1.614	-1	-0.6	0.547
Foin	Unmatched	15.603	15.99	-21.8	-13.43	0
	Matched	15.605	15.656	-2.9	-1.66	0.097

4.4.2 Elimination of alternative explanations

Previous studies have proved that when enterprises are in the innovation city pilot, they will have strong innovation ability[15]. This finding may interfere with the results of this article. To ensure the rigor of the study, the pilot project located in the innovative city is represented as a control variable in the form of a dummy variable, and the regression is performed again, as shown in column (2) of Table 6. The explanatory variables are still positive and significant, and the estimated coefficients of the pilot variables are not significant, indicating that the improvement of enterprise INQ is not caused by the policy effect of the pilot. This result proves the credibility of the results.

Table 6. Endogeneity test results

Variables	-1	-2
	INQ	INQ
AI	0.027***	0.0176***
	-0.003	-0.0061
Lnlargest	0.002	-0.0053
	-0.007	-0.0139
Lev	-0.071***	-0.0221
	-0.017	-0.024
ROA	-0.045	-0.0577

Standard errors in parentheses

* p < 0.1, ** p < 0.05, *** p < 0.01

4.5 Heterogeneity test

To gain a deeper understanding of how the relationship between enterprise AI adoption and INQ varies across different contexts, this article conducts a series of heterogeneity tests. These tests focused on regional differences, ownership characteristics, and the level of intellectual property protection (IPP). By examining these dimensions, this article aims to explore how firms' environments and firm characteristics affect the impact of AI adoption on the quality of firms' innovations. Table 7 presents the results of the heterogeneity analysis, which examines the impact of enterprise AI adoption on INQ across different subgroups.

First, in columns (1)-(3) of Table 7, the samples are divided into three groups according to Eastern, Central, and Western regions. The results indicate that the coefficient for AI is 0.0147 and significant at the 5% level in the Eastern region, suggesting a positive and significant impact of AI adoption on INQ. In the Central region, the coefficient is 0.0119, but it is not statistically significant, indicating a weaker or less established relationship. In the Western region, the coefficient for AI is 0.0351 and significant at the 10% level, implying that these enterprises in eastern regions show a stronger positive impact of AI adoption on INQ compared to the other regions. These regional differences may be attributed to several factors. Eastern regions, often more economically developed and technologically advanced, have greater access to resources and infrastructure that facilitate the integration and utilization of AI, leading to a significant positive impact on INQ. In contrast, the Central area may be in a transitional phase of adopting and adapting to AI technology, which would explain the non-significant coefficient. Although the influence is considerable in the Western region, the coefficient is larger due to possibly fewer resources but a stronger motivation for innovation in response to unique local demands or situations, resulting in an evident increase in INQ when AI is used.

Next, considering that the nature of ownership is an important characteristic affecting enterprise innovation[16], [17], the article compares state-owned enterprises (SOEs) and Non- state owned enterprises (Non-SOEs) and reports the results in columns (4)-(5) of Table 7. The AI coefficient for SOEs is 0.0381, which is significant at the 1% level, indicating that the adoption of AI has a significant positive impact on INQ. On the contrary, in non-state-owned firms, the coefficient is 0.0105, which is not statistically significant, suggesting that the impact of adopting AI on INQ is not significant in non-state-owned firms. The reason for this difference may be that SOEs usually have more stable funding and government support, which facilitates the adoption and effective implementation of AI technologies[18]. On the other hand, non-SOEs may face more challenges in accessing resources and securing the investment and adoption efforts needed to adopt AI.

Finally, the columns (6)-(7) of Table 7, this article investigates the heterogeneity based on the level of IPP, distinguishing between high and low IPP regions. The coefficient for AI in high IPP regions is 0.0257 and significant at the 1% level, indicating a strong positive impact of AI adoption on INQ in high IPP regions. In contrast, in low IPP regions, the coefficient is -0.0064 and not statistically significant, suggesting that the impact of AI adoption on INQ is negligible or even negative. The possible explanation is in regions with high levels of IPP, enterprises are incentivized by a favorable innovation environment and are more likely to invest in AI-driven innovation[19]. On the contrary, in regions with lower levels of IPP, firms' innovation patents are insufficiently protected, which leads to weaker incentives for firms to adopt AI to improve the quality of their firms' innovations, and thus results in a less significant, or even negative, impact of AI adoption on INQ.

Table 7. Heterogeneity test results

Variables	-1	-2	-3	-4	-5	-6	-7

	East	Central	West	State- owned enterprises	Non-state-owned enterprises	High IPP	Low IPP
AI	INQ	INQ	INQ	INQ	INQ	INQ	INQ
	0.027***	0.0176***	0.0351*	0.0381***	0.0105	0.0257***	-0.0064
Lnlargest	-0.003	-0.0061	-0.0184	-0.0111	-0.0074	-0.0086	-0.01
	0.002	-0.0053	0.0088	-0.0076	-0.0244	-0.0058	0.0106
Lev	-0.007	-0.0139	-0.0415	-0.0243	-0.0185	-0.023	-0.0207
	-0.071***	-0.0221	-0.0829	0.0349	-0.0316	-0.0382	-0.0064
ROA	-0.017	-0.024	-0.066	-0.0458	-0.0302	-0.0367	-0.0377
	-0.045	-0.0577	-0.1159	-0.0148	-0.0920*	-0.1144*	-0.0267
Indus	-0.05	-0.0455	-0.1445	-0.0991	-0.0531	-0.06	-0.0777
	-0.014***	0.0011	0.038	0.0098	0.0013	0.0242	-0.0113
Foin	-0.003	-0.0121	-0.0792	-0.0179	-0.0172	-0.0182	-0.051
	0.002	0.0141*	0.0164	0.0172	0.0053	0.0145	0.0094
Pilot	-0.002	-0.0084	-0.0164	-0.0125	-0.0125	-0.0236	-0.012
	-	-0.0031	-0.4005	-0.4794*	0.2079	-0.2603	0.2507
Constants	-	-0.019	-0.3767	-0.2562	-0.2215	-0.4122	-0.2431
	-0.008	-0.1016	0.4536	0.4613	0.4784	0.5238	0.5033
R^2	-0.057	-0.1584	1722	5120	10073	8420	6773
	0.077	0.467	0.0351*	0.0381***	0.0105	0.0257***	-0.0064
Obs.	7956	15193	-0.0184	-0.0111	-0.0074	-0.0086	-0.01

Standard errors in parentheses

* p < 0.1, ** p < 0.05, *** p < 0.01

4.6 Influence channel analysis

Table 8 presents the mechanism check results that investigate the pathway through which the adoption of AI by firms positively influences their INQ by enhancing their innovation cooperation (IC) capabilities. The regression model shows a statistically significant positive relationship between AI adoption and INQ, with a coefficient of 0.0173 ($p < 0.01$). This suggests that as firms increase their AI adoption, they experience a substantial improvement in their INQ. Moreover, the interaction term between AI adoption and INQ (AI*IC) is also positive and statistically significant at the 5% level (coefficient = 0.0005, $p < 0.05$). This finding indicates that the positive effect of AI on INQ is further amplified when firms engage in IC activities. In other words, the synergy between AI adoption and IC significantly enhances INQ. Therefore, the second hypothesis of this article is tested.

Table 8. Mechanism analysis results

Variables	-1
	INQ
AI	0.0173***
	-0.0061
AI*IC	0.0005**
	-0.0002
Lnlargest	-0.0059
	-0.0139
ROA	-0.0601
	-0.0455
Lev	-0.0222
	-0.024
Indus	0.0007
	-0.012
Foin	0.0142*
	-0.0084
Constants	-0.1028
	-0.158
R^2	0.4671
Obs.	15193

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

5. Conclusion and discussion

5.1 Conclusion

The article concludes that, firstly, the adoption of AI by enterprises can positively promote the quality of enterprise innovation. This relationship has passed a series of robustness tests. Secondly, the mechanism by which AI adoption promotes the enterprise INQ is to enhance IC among enterprises. Finally, the relationship that the adoption of AI by enterprises can positively promote the quality of enterprise innovation presents heterogeneity in enterprise characteristics and regional environments. Compared with non-state-owned enterprises, state- owned enterprises can benefit more from the adoption of AI. The INQ of enterprises in the eastern region and enterprises located in areas with higher IPP can benefit more from the adoption of AI.

5.2 Theoretical contribution

The theoretical contributions of this study are multiple. By exploring the impact of adopting AI on firms' INQ, this article deepens the understanding of how AI affects organizational innovation performance. Specifically, the main theoretical contributions focus on the following areas: First, it reveals the positive impact of AI adoption on INQ in organizations. The findings of this article provide empirical evidence that firms' adoption of AI technologies positively affects the quality of their innovation performance. This relationship is confirmed through rigorous statistical analysis including various robustness tests. Although previous research on the factors influencing the quality of innovation in firms has been prevalent in the literature, this article fills a gap in the literature by quantitatively demonstrating a positive relationship between the adoption of AI and the quality of innovation, thereby validating the theoretical proposition that AI can act as the driver for improving the quality of innovation within an organization. Second, this study further elucidates the intrinsic mechanism of using AI to improve INQ. The research results indicate that a key approach is to strengthen IC between enterprises. This discovery contributes to theoretical research on inter-organizational cooperation and innovation networks, indicating that AI can serve as a facilitating factor in the collaborative innovation process. It also extends previous research on the role of technology platforms in promoting cross-organizational knowledge sharing and collaborative problem- solving. These findings are meaningful for practitioners and decision-makers seeking to leverage AI technology to drive innovation and economic growth.

5.3 Policy implication

Based on the research conclusions, this article offers the following policy recommendations: First, as a major innovation country, China should attach great importance to the development of AI, actively promote the deep integration of the Internet, big data, AI, and the real economy, strengthen infrastructure construction, such as data centers, cloud computing platforms, and provide better technical support and services for all types of enterprises. In particular, enterprises should be encouraged to adopt AI to provide new momentum for high-quality innovation. Second, AI adoption and innovation development plans should be developed for enterprises according to their actual characteristics. The government should encourage enterprises in the East and West to continue to use the advantages of AI technology to promote innovation and development. For enterprises in central China, the government should build a platform for them to exchange and learn from enterprises in other regions, organize regular industry exchange meetings and seminars, and promote the spread of knowledge and technology. At the same time, obstacles to the application of AI in central enterprises should be identified, such as technical difficulties, insufficient funds, etc., and targeted solutions and support should be provided. For non-state-owned enterprises, policymakers can try to introduce a series of targeted incentives and support programs to reduce the cost of introducing AI for non-state-owned enterprises and optimize their innovation environment. In addition, given that businesses in regions with higher levels of IPP benefit more from AI applications, policymakers should focus on strengthening IPP laws and enforcement mechanisms. Third, it is certainly a wise choice to promote IC networks among companies. The government should actively set up special funds to support inter-enterprise AI cooperation projects, especially cross-industry and cross-field cooperation plans, promote resource sharing and technological complementarity between different enterprises, accelerate the transformation of innovation results, and then improve the overall INQ and competitiveness.

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