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Research on the Influence Mechanism of Artificial Intelligence Application on Enterprise Innovation Efficiency

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Abstract. Based on the data of Shanghai and Shenzhen A-share listed enterprises from 2012 to 2023, this paper empirically examines the impact of artificial intelligence (AI) application on enterprise innovation. The study finds that AI application can significantly improve enterprise innovation efficiency, and the transmission mechanism is mainly realized through the mediating effects of enterprise new-quality productivity, enterprise data factor utilization level, and enterprise ESG performance. Meanwhile, market segmentation, fiscal support intensity, and human capital structure exert moderating effects on the above benchmark relationship. In addition, heterogeneity analysis shows that the impact of AI application on enterprise innovation efficiency is stronger in central and western state-owned enterprises that are asset-intensive and labor-intensive.

Keywords: Artificial Intelligence Application, Enterprise Innovation Efficiency, Mediating Effect, Moderating Effect, Heterogeneity Analysis

1. Introduction

With the deepening of the digital technology revolution, artificial intelligence is accelerating the reshaping of enterprise innovation ecology and has become a key engine driving high-quality economic development. Enterprises' active exploration of AI application is not only an inevitable choice to cope with market competition, but also a strategic path to obtain sustainable competitive advantages. However, although most enterprises have deployed AI applications, they have failed to clearly grasp its transformation path, making it difficult to effectively convert technology application into improved innovation efficiency. Therefore, clarifying whether and how AI application affects enterprise innovation and the internal logic of efficiency improvement has important practical significance.

This also raises a series of questions to be considered: First, what impact does AI application have on enterprise innovation efficiency? Second, if relevant effects exist, through which intermediary channels does AI application function, and what factors moderate its impact? Third, will such effects vary significantly due to the region where the enterprise is located, the type of enterprise production factors, and the nature of enterprise property rights? Based on this, this study aims to comprehensively reveal the causal relationship, action paths, boundary conditions, and heterogeneous manifestations between AI application and enterprise innovation efficiency. Theoretically, it helps to make up for the deficiencies of existing literature in the research on digital

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technology and enterprise innovation efficiency. Practically, the research results can provide a basis for enterprises to rationally deploy artificial intelligence and optimize innovation strategies.

The marginal contributions of this study are mainly in the following three aspects: First, by identifying specific mechanisms such as enterprise new-quality productivity, enterprise data factor utilization level, and enterprise ESG performance, it clarifies the transmission paths. Second, by identifying specific factors such as market segmentation, fiscal support intensity, and human capital structure, it reveals the boundary conditions. Third, it reveals the heterogeneous impacts in dimensions such as the region where the enterprise is located, the type of enterprise production factors, and the nature of enterprise property rights, and refines the differentiated logic of AI empowering enterprise innovation.

2. Literature review

Existing studies generally confirm that artificial intelligence application has a significant impact on enterprise innovation capability, but the direction of its effect shows divergent characteristics. In terms of innovation resilience, Liao Xiaoyu and He Xiaoming [1] found that the application of AI technology can significantly improve the innovation chain resilience of high-tech node enterprises. However, Xue Ximeng et al. [2] revealed the "double-edged sword" effect of AI on enterprise innovation resilience: it "empowers" innovation resilience by promoting executives' innovation awareness, but also exerts an "inhibiting" effect by increasing digital technology distance. In terms of breakthrough innovation, based on the socio-technical system theory, Lin Chunpei et al. [3] found a U-shaped relationship between AI application and breakthrough innovation of high-tech enterprises, which first declines and then rises. In terms of green innovation, Chen Minling et al. [4] confirmed that AI can significantly promote green innovation in manufacturing enterprises, with knowledge base playing a partial mediating role in their relationship.

At the mechanism level, existing studies have revealed the action paths of AI affecting enterprise innovation from two dimensions: mediating mechanism and moderating mechanism. First, regarding the mediating mechanism, Liao Xiaoyu and He Xiaoming [1] found that the application of AI technology enhances the innovation chain resilience of enterprises by improving factor collaboration efficiency and digital knowledge management capabilities. Chen Minling et al. [4] verified that knowledge base plays a partial mediating role in the process of AI promoting green innovation in manufacturing enterprises. Tian Haifeng and Li Jin [5] pointed out that AI application strengthens enterprise innovation resilience through resource effect, governance effect and learning effect.

Second, in terms of moderating mechanism, studies have revealed the situational conditions that affect the strength of the main effect. Liao Xiaoyu and He Xiaoming [1] found that public data openness and managers' cognitive flexibility positively moderate the relationship between AI application and innovation chain resilience. From the perspective of technological capability adaptability, Li Bin et al. [6] found that technological niche width strengthens the promoting effect of AI on enterprise innovation resilience, while technological lock-in and technological environment turbulence weaken this effect. Chen Minling et al. [4] showed that government subsidies positively moderate the impact of AI on green innovation.

In summary, few existing literature directly study the impact of AI application on enterprise innovation efficiency, and the research on mechanism and heterogeneity is still insufficient. Accordingly, this paper systematically examines the impact of AI application on enterprise innovation from the perspective of innovation efficiency, further reveals the mediating paths of new-quality productivity, data factor utilization level and ESG performance, as well as the moderating effects of market segmentation, fiscal support intensity and human capital structure. It also conducts

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heterogeneity analysis according to the type of production factors, region and property right nature of enterprises, so as to provide a new theoretical perspective and empirical evidence for analyzing the internal relationship between AI application and enterprise innovation efficiency.

3. Research design

3.1. Sample selection and data sources

This paper selects Shanghai and Shenzhen A-share listed enterprises from 2012 to 2023 as research samples, with the following screening procedures: First, enterprises labeled ST, *ST, PT and firms in the financial industry are excluded. Second, samples with extensive missing data are eliminated. Third, data of all variables are matched and integrated. For data sources: enterprise innovation efficiency data are obtained from the China Center for Economic Research (CCER) database; AI application level and enterprise data factor utilization data are extracted from annual reports of listed companies; market segmentation index data are derived from the *China Provincial Marketization Index Report*; other firm-level data are collected from the China Stock Market & Accounting Research Database (CSMAR); and macro-level data are from the Wind database.

3.2. Variable definition

Regarding the dependent variable, this study adopts the number of patent applications per unit of R&D investment as a comprehensive indicator of innovation efficiency, calculated as Patent1 / ln(1 + R&D expenditure). Patent1 is the natural logarithm of one plus the total number of applications for invention patents, utility model patents and design patents.

Regarding the core independent variable, following the practice of Li Yuhua et al. [7], this study uses machine learning methods to generate an artificial intelligence dictionary and measures the level of artificial intelligence application through textual analysis of annual reports of listed companies.

Regarding mediating variables: first, enterprise new-quality productivity (NQPF). Following Li Xinru et al. [8], this study constructs an evaluation index system for enterprise new-quality productivity from three dimensions: new-quality laborers, new-quality objects of labor and new-quality means of labor, and obtains the new-quality productivity index using the entropy method. Second, enterprise data factor utilization level (Data). Following Dai Kuizao [9], this study retrieves and matches keywords related to data factors in the annual reports of listed companies, excludes keywords with negative meanings, and sums the total frequency of valid keywords. Third, enterprise ESG performance (ESG). This study adopts the enterprise ESG index issued by Shanghai Huazheng Index Information Service Co., Ltd.

Regarding moderating variables: first, market segmentation index (Seg). Following Yuan Jingbo et al. [10], it is measured by the deviation of the marketization index between the province where the enterprise is located and other provinces. Second, fiscal support intensity (GOV), measured by government subsidies. Third, human capital structure (Human), measured by the proportion of employees with a bachelor's degree or above.

Regarding control variables, this study selects a series of control variables at the enterprise level and macro level, including: (1) Enterprise-level variables: enterprise size (Size), enterprise profitability (ROA), enterprise solvency (Leverage), enterprise liquidity level (Liquidity), enterprise age (Age), board size (Board), executive compensation (Salary), ownership concentration (Top5), price-earnings ratio (PE); (2) Macro-level variables: regional economic development level (GDP),

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regional industrial structure (Industry), regional financial development level (Finance). Detailed variable definitions are shown in Table 1.

Table 1. Variable definition

Variable Type	Variable Symbol	Variable Definition
Dependent Variable	InnoEff1	Firm Innovation Efficiency
Explanatory Variable	AI	Artificial Intelligence Application
Mediating Variables	NQPF	New Quality Productive Forces
	Data	Level of Data Factor Utilization
	ESG	Corporate ESG Performance
Moderating Variables	Seg	Market Segmentation Index
	GOV	Fiscal Support Intensity
	Human	Human Capital Structure
Control Variables	Size	Firm Size
	ROA	Firm Profitability
	Leverage	Firm Solvency
	Liquidity	Firm Liquidity Level
	Age	Firm Age
	Board	Board Size
	Salary	Executive Compensation
	Top5	Ownership Concentration
	PE	Price-to-Earnings Ratio
	GDP	Regional Economic Development Level
	Industry	Regional Industrial Structure
	Finance	Regional Financial Development Level

3.3. Model specification

3.3.1. Benchmark regression model

To examine the intrinsic relationship between AI application and enterprise innovation efficiency, a two-way fixed-effects model is constructed as follows:

$$InnoEff1_{it} = \alpha_0 + \beta_0 AI_{it} + \sum \gamma_k Control_{it} + \lambda_t + \eta_i + \varepsilon_{it} \tag{1}$$

where $Control_{it}$ represents all control variables. Time fixed effects λ_t and firm individual fixed effects η_i are included to control for unobservable time-varying and individual heterogeneity. ε_{it} is the random error term. If α_0 is significantly positive, AI application has a positive promoting effect on enterprise innovation efficiency.

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3.3.2. Mediating effect model

To test the mediating effects of new-quality productivity, data factor utilization level and ESG performance, the following models are established:

$$NQPF_{it} = \alpha_1 + \beta_1 AI_{it} + \sum \gamma_k Control_{it} + \lambda_t + \eta_i + \varepsilon_{it} \tag{2}$$

$$InnoEff1_{it} = \alpha_2 + \beta_2 AI_{it} + \theta_2 NQPF_{it} + \sum \gamma_k Control_{it} + \lambda_t + \eta_i + \varepsilon_{it} \tag{3}$$

$$Data_{it} = \alpha_3 + \beta_3 AI_{it} + \sum \gamma_k Control_{it} + \lambda_t + \eta_i + \varepsilon_{it} \tag{4}$$

$$InnoEff1_{it} = \alpha_4 + \beta_4 AI_{it} + \theta_4 Data_{it} + \sum \gamma_k Control_{it} + \lambda_t + \eta_i + \varepsilon_{it} \tag{5}$$

$$ESG_{it} = \alpha_5 + \beta_5 AI_{it} + \sum \gamma_k Control_{it} + \lambda_t + \eta_i + \varepsilon_{it} \tag{6}$$

$$InnoEff1_{it} = \alpha_6 + \beta_6 AI_{it} + \theta_6 ESG_{it} + \sum \gamma_k Control_{it} + \lambda_t + \eta_i + \varepsilon_{it} \tag{7}$$

On the premise that β_0 is significantly positive, if $\beta_1$and θ_2 , $\beta_3$and θ_4 , β_5 andθ_6 are all significantly positive, then new-quality productivity, data factor utilization level and ESG performance exert mediating effects respectively.

3.3.3. Moderating effect model

To test the moderating effects of market segmentation, fiscal support intensity and human capital structure, the following models are constructed:

$$InnoEff1_{it} = \alpha_7 + \beta_7 AI_{it} + \theta_7 Seg_{it} + \mu_7 Seg_{it} \times AI_{it} + \sum \gamma_k Control_{it} + \lambda_t + \eta_i + \varepsilon_{it} \tag{8}$$

$$InnoEff1_{it} = \alpha_8 + \beta_8 AI_{it} + \theta_8 GOV_{it} + \mu_8 GOV_{it} \times AI_{it} + \sum \gamma_k Control_{it} + \lambda_t + \eta_i + \varepsilon_{it} \tag{9}$$

$$\begin{aligned} InnoEff1_{it} &= \alpha_9 + \beta_9 AI_{it} + \theta_9 Human_{it} \\ &+ \mu_9 Human_{it} \times AI_{it} + \sum \gamma_k Control_{it} + \lambda_t + \eta_i + \varepsilon_{it} \end{aligned} \tag{10}$$

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On the premise that □0 is significantly positive: If □7 is significantly negative, market segmentation weakens the positive effect of AI application on innovation efficiency. If □8 and □9 are significantly positive, fiscal support intensity and human capital structure strengthen the positive effect of AI application on innovation efficiency.

4. Empirical analysis

4.1. Descriptive statistics

Table 2 presents the descriptive statistics of the variables. The standard deviation of AI application (AI) is 1.231, indicating large disparities in the level and intensity of AI adoption across enterprises. The minimum value of enterprise innovation efficiency (InnoEff1) is 0 and the maximum is 0.441, reflecting noticeable differences in innovation performance among firms.

Table 2. Descriptive statistics of variables

Variable Name	Observations	Mean	Std. Dev.	Min	Max
InnoEff1	22297	0.168	0.082	0.000	0.441
AI	25701	0.972	1.231	0.000	6.497
NQPF	23339	12.813	7.174	1.220	36.991
Data	25701	89.872	138.662	0.000	1938.000
ESG	23882	4.178	0.941	1.000	7.250
Seg	25691	10.467	5.502	3.218	80.334
GOV	25691	0.191	0.097	0.105	1.354
Human	21616	0.293	0.234	0.000	5.961
Size	25486	3.093	0.061	2.848	3.357
ROA	25485	0.052	0.061	-0.163	0.171
Leverage	22908	1.172	0.564	0.630	4.947
Liquidity	25457	0.780	2.047	-5.723	8.204
Board	17692	8.331	1.646	0.000	17.000
Salary	17644	0.312	0.376	0.005	1.689
Age	25483	9.213	8.380	0.000	27.000
PE	21658	58.711	86.751	6.843	550.452
Top5	25241	0.483	0.187	0.200	0.991
Industry	25691	55.495	10.550	34.500	84.800
GDP	25691	10.775	0.748	6.565	11.818
Finance	25691	1.702	0.440	0.701	2.998

4.2. Correlation analysis

Before formal regression, correlation analysis is conducted to verify the rationality of variable design and the relationships among variables. The results generally support the hypotheses of this paper. AI application (AI) is significantly positively correlated with enterprise innovation efficiency (InnoEff1) at the 1% level, providing preliminary evidence that AI application improves innovation

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efficiency. The variance inflation factors (VIF) of all variables in regression are less than 2, suggesting no serious multicollinearity in the model.

4.3. Benchmark regression analysis

Table 3 reports the benchmark regression results. Columns (1) to (4) show the regression results of AI application on enterprise innovation efficiency with stepwise inclusion of control variables: no controls, firm financial controls, corporate governance controls, and macroeconomic controls. In all four specifications, the coefficients of AI application are significantly positive at the 5% level, indicating that AI application significantly improves enterprise innovation efficiency.

Table 3. Regression results of AI application on enterprise innovation efficiency

	(1)	(2)	(3)	(4)
VARIABLES	InnoEff1	InnoEff1	InnoEff1	InnoEff1
AI	0.0033***	0.0019***	0.0018**	0.0018**
	(5.31)	(2.90)	(2.48)	(2.52)
Size		0.4616***	0.4169***	0.4241***
		(18.32)	(13.37)	(13.58)
ROA		-0.0233*	-0.0153	-0.0169
		(-1.67)	(-0.89)	(-0.98)
Leverage		-0.0017**	-0.0030***	-0.0031***
		(-1.96)	(-2.59)	(-2.64)
Liquidity		-0.0004*	-0.0006**	-0.0006**
		(-1.82)	(-2.37)	(-2.32)
Board			-0.0001	-0.0002
			(-0.23)	(-0.36)
Salary			-0.0060*	-0.0059*
			(-1.86)	(-1.82)
Age			-0.0021	-0.0016
			(-1.03)	(-0.80)
PE			0.0000	0.0000
			(1.56)	(1.59)
Top5			-0.0006	-0.0000
			(-0.11)	(-0.01)
Industry				0.0005
				(1.63)
GDP				-0.0115
				(-1.40)
Finance				-0.0151***
				(-3.55)
Constant	0.1266***	-1.2806***	-1.1292***	-1.0392***
	(52.86)	(-16.68)	(-11.81)	(-8.14)

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Table 3. (continued)

Year	YES	YES	YES	YES
Individual	YES	YES	YES	YES
Observations	22,297	19,942	13,690	13,684
R-squared	0.089	0.135	0.139	0.140

(Note: t-statistics in parentheses; *** p<0.01, ** p<0.05, * p<0.1, the same below)

4.4. Mediating effect analysis

Table 4 shows the test results of the mediating effects. Columns (1), (3), and (5) indicate that the regression coefficients of AI application on new-quality productivity, data factor utilization level, and ESG performance are all significantly positive, meaning that AI application promotes the improvement of the three mediators. Columns (2), (4), and (6) introduce the three mediators respectively, and all of them are significantly positive at the 5% level. This demonstrates that new-quality productivity, data factor utilization level, and ESG performance play significant mediating roles in the process through which AI application enhances enterprise innovation efficiency.

Table 4. Test results of mediating effects of new-quality productivity, data factor utilization level and ESG performance

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	NQPF	InnoEff1	Data	InnoEff1	ESG	InnoEff1
NQPF		0.0007***				
		(6.72)				
Data				0.0000**		
				(2.21)		
ESG						0.0026***
						(4.10)
AI	0.7426***	0.0013*	35.7626***	0.0012	0.0265**	0.0016**
	(11.13)	(1.73)	(44.18)	(1.52)	(2.48)	(2.11)
Size	20.5155***	0.4195***	429.7492***	0.4155***	3.2436***	0.4271***
	(7.40)	(13.04)	(13.03)	(13.20)	(7.45)	(13.51)
ROA	-1.5441	-0.0115	-69.5396***	-0.0156	0.1084	-0.0144
	(-0.99)	(-0.66)	(-3.65)	(-0.91)	(0.43)	(-0.83)
Leverage	-0.0831	-0.0029**	-1.1421	-0.0031***	-0.0826***	-0.0030**
	(-0.79)	(-2.46)	(-0.90)	(-2.63)	(-4.99)	(-2.54)
Liquidity	0.0052	-0.0005*	-0.0460	-0.0006**	-0.0026	-0.0004*
	(0.25)	(-1.92)	(-0.18)	(-2.31)	(-0.77)	(-1.82)

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Table 4. (continued)

Board	0.1151**	-0.0001	-0.1843	-0.0002	-0.0176**	-0.0001
	(2.32)	(-0.26)	(-0.31)	(-0.35)	(-2.23)	(-0.09)
Salary	-0.0966	-0.0064*	-11.0371***	-0.0057*	-0.0984**	-0.0058*
	(-0.35)	(-1.92)	(-3.35)	(-1.76)	(-2.24)	(-1.76)
Age	0.0609	-0.0017	4.2942**	-0.0016	-0.0742***	-0.0014
	(0.39)	(-0.85)	(2.23)	(-0.82)	(-2.96)	(-0.69)
PE	0.0005	0.0000	0.0036	0.0000	-0.0001	0.0000
	(0.77)	(1.42)	(0.42)	(1.57)	(-0.96)	(1.64)
Top5	0.0093	-0.0008	10.7753*	-0.0003	-0.3478***	0.0011
	(0.02)	(-0.13)	(1.78)	(-0.05)	(-4.37)	(0.19)
Industry	0.0525*	0.0005	0.8125**	0.0005	0.0102**	0.0006*
	(1.83)	(1.49)	(2.37)	(1.61)	(2.24)	(1.70)
GDP	-0.2632	-0.0211**	15.8118**	-0.0114	-0.2584**	-0.0132
	(-0.41)	(-2.48)	(2.13)	(-1.40)	(-2.56)	(-1.57)
Finance	-1.0932***	-0.0132***	-10.2229**	-0.0149***	-0.2719***	-0.0144***
	(-2.89)	(-3.09)	(-2.22)	(-3.51)	(-4.49)	(-3.37)
Constant	-52.6379***	-0.9341***	-1,492.0688***	-1.0133***	-2.3584	-1.0478***
	(-4.89)	(-7.06)	(-11.73)	(-7.90)	(-1.40)	(-8.09)
Year	YES	YES	YES	YES	YES	YES
Individual	YES	YES	YES	YES	YES	YES
Observations	14,450	13,162	15,106	13,684	14,701	13,332
R-squared	0.141	0.146	0.318	0.141	0.030	0.143

4.5. Moderating effect analysis

Table 5 presents the moderating effect test results. In Column (1), the coefficient of the interaction term between AI application and market segmentation is significantly negative. In Columns (2) and (3), the coefficients of the interaction terms between AI and fiscal support intensity, and between AI and human capital structure are both significantly positive. All three interaction terms are significant at the 5% level. This indicates that market segmentation weakens the positive effect of AI application on enterprise innovation efficiency, while fiscal support intensity and human capital structure strengthen such positive effect.

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Table 5. Test results of moderating effects of market segmentation, fiscal support intensity and human capital structure

	(1)	(2)	(3)
VARIABLES	InnoEff1	InnoEff1	InnoEff1
AI × Seg	-0.0004***		
	(-3.39)		
Seg	-0.0000		
	(-0.14)		
AI × GOV		0.0315***	
		(3.42)	
GOV		0.0060	
		(0.17)	
AI × Human			0.0054**
			(2.22)
Human			0.0044
			(0.93)
AI	0.0057***	-0.0038**	0.0001
	(4.22)	(-2.12)	(0.09)
Size	0.4234***	0.4246***	0.4286***
	(13.56)	(13.59)	(12.61)
ROA	-0.0176	-0.0189	-0.0259
	(-1.02)	(-1.10)	(-1.38)
Leverage	-0.0030**	-0.0030**	-0.0040***
	(-2.55)	(-2.54)	(-3.07)
Liquidity	-0.0005**	-0.0005**	-0.0005*
	(-2.30)	(-2.30)	(-1.86)
Board	-0.0003	-0.0002	-0.0002
	(-0.49)	(-0.36)	(-0.30)
Salary	-0.0059*	-0.0059*	-0.0088**
	(-1.82)	(-1.82)	(-2.49)
Age	-0.0017	-0.0014	-0.0006
	(-0.82)	(-0.71)	(-0.18)
PE	0.0000	0.0000	0.0000
	(1.59)	(1.50)	(1.46)
Top5	0.0002	0.0002	0.0068
	(0.03)	(0.04)	(1.08)
Industry	0.0005	0.0005	0.0007*
	(1.37)	(1.52)	(1.86)

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Table 5. (continued)

GDP	-0.0098	-0.0084	-0.0080
	(-1.19)	(-0.99)	(-0.86)
Finance	-0.0129***	-0.0151***	-0.0161***
	(-3.00)	(-3.34)	(-3.28)
Constant	-1.0523***	-1.0716***	-1.0983***
	(-8.24)	(-8.26)	(-7.78)
Year	YES	YES	YES
Individual	YES	YES	YES
R-squared	0.141	0.141	0.142

4.6. Robustness checks

4.6.1. Replacing the dependent variable

To ensure the robustness of the regression analysis, this paper adopts InnoEff2 as an alternative measure of innovation efficiency, calculated as Patent2/ln(1+R&D Expenditure), where Patent2 is the natural logarithm of one plus the weighted total patent applications (invention, utility model and design patents weighted at 3:2:1). Column (1) of Table 6 reports the benchmark regression result of AI application on InnoEff2, which is significantly positive at the 1% level, verifying the robustness of the benchmark conclusion.

4.6.2. Using lagged independent variable

Considering the possible time-lag effect of AI application on enterprise innovation efficiency, this paper re-estimates the benchmark model using the one-period lagged AI variable. As shown in Column (2) of Table 6, the coefficient of AI remains consistent in sign with the benchmark regression and is significant at the 1% level, indicating that the benchmark conclusion is not affected by the time dimension of variables and is highly robust.

4.6.3. Winsorization

This paper conducts a robustness test using 2% winsorization on all continuous variables to eliminate the interference of extreme values. As shown in Column (3) of Table 6, the sign and statistical significance of the AI coefficient remain largely unchanged compared with the benchmark regression, proving that the benchmark results are not affected by extreme outliers and are robust.

Table 6. Robustness checks

	(1)	(2)	(3)
VARIABLES	Replaced Dependent Variable	Lagged Independent Variable	Winsorization
AI	0.0022***		0.0019***
	(2.59)		(2.60)
lag_AI		0.0023***	
		(2.72)	

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Table 6. (continued)

Size	0.4407***	0.3951***	0.4144***
	(12.20)	(10.17)	(13.31)
ROA	-0.0266	-0.0126	-0.0176
	(-1.34)	(-0.63)	(-1.02)
Leverage	-0.0037***	-0.0023*	-0.0029*
	(-2.70)	(-1.71)	(-1.77)
Liquidity	-0.0006**	-0.0003	-0.0005**
	(-2.18)	(-1.00)	(-2.32)
Board	-0.0004	-0.0004	-0.0001
	(-0.58)	(-0.55)	(-0.23)
Salary	-0.0053	-0.0074*	-0.0064**
	(-1.41)	(-1.86)	(-1.98)
Age	-0.0020	-0.0028	-0.0020
	(-0.84)	(-1.28)	(-1.02)
PE	0.0000	0.0000	0.0000
	(1.11)	(1.25)	(1.17)
Top5	-0.0009	-0.0033	-0.0007
	(-0.14)	(-0.49)	(-0.12)
Industry	0.0006*	0.0005	0.0005
	(1.65)	(1.18)	(1.55)
GDP	-0.0134	-0.0292***	-0.0037
	(-1.41)	(-2.73)	(-0.51)
Finance	-0.0175***	-0.0112**	-0.0156***
	(-3.56)	(-2.16)	(-3.66)
Constant	-1.0302***	-0.7598***	-1.0858***
	(-6.98)	(-4.63)	(-9.04)
Year	YES	YES	YES
Individual	YES	YES	YES
R-squared	0.118	0.119	0.137

4.7. Heterogeneity analysis

According to factor intensity, property right nature and regional location, the sample is divided into subgroups: technology-intensive, capital-intensive and labor-intensive enterprises; state-owned enterprises (SOEs) and non-SOEs; and eastern, central and western enterprises. The grouped regression results are shown in Table 7.

In terms of factor intensity, the coefficient of AI application on innovation efficiency is 0.0046 and significantly positive at the 1% level for labor-intensive enterprises, 0.0042 and significant at the 10% level for capital-intensive enterprises, and 0.0004 and insignificant for technology-intensive enterprises. This indicates that AI application exerts a stronger boosting effect on innovation efficiency in labor-intensive and capital-intensive enterprises. A possible reason is that AI can

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automate repetitive production processes in labor-intensive firms, freeing up more capital for R&D and innovation. For capital-intensive enterprises, AI optimizes equipment maintenance and resource allocation, reducing fixed costs and operational risks in innovation, thus fully releasing innovation dividends enabled by technology.

In terms of property right nature, the coefficient of AI application is 0.0052 and significantly positive at the 1% level for SOEs, while it is 0.0011 and insignificant for non-SOEs. This suggests that AI promotes innovation efficiency more significantly in SOEs, possibly because SOEs enjoy advantages in R&D funding and policy support, which steadily support the full implementation of AI in the innovation process and achieve synchronized improvement in technological iteration and innovation efficiency.

In terms of regional location, the coefficient of AI application is 0.0068 and significant at the 5% level for western enterprises, 0.0044 and significant at the 10% level for central enterprises, and 0.0011 and insignificant for eastern enterprises. This reflects a stronger empowering effect of AI on innovation efficiency in central and western enterprises. A plausible explanation is that eastern enterprises already have a relatively mature innovation foundation, leaving limited room for marginal improvement from AI. In contrast, central and western enterprises can use AI to compensate for insufficient innovation endowments and achieve leapfrog improvement in innovation efficiency.

Table 7. Heterogeneity analysis

	Enterprise Factor Endowment Type			Ownership Type		Region		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	Technology-Intensive	Asset-Intensive	Labor-Intensive	State-Owned Enterprises	Non-State-Owned Enterprises	Eastern Region	Central Region	Western Region
AI	0.0004	0.0042*	0.0046***	0.0052***	0.0011	0.0011	0.0044*	0.0068**
	(0.44)	(1.87)	(3.08)	(3.43)	(1.24)	(1.42)	(1.87)	(2.40)
Size	0.4674***	0.3651***	0.3843***	0.4340***	0.3967***	0.3726***	0.6787***	0.3860***
	(11.62)	(4.13)	(5.76)	(5.52)	(10.41)	(10.58)	(7.54)	(3.67)
Constant	-1.2998***	-0.8668***	-1.1027***	-1.0240***	-1.1477***	-1.1613***	-0.8739**	-0.7554*
	(-7.61)	(-2.70)	(-4.51)	(-3.53)	(-7.65)	(-6.68)	(-2.28)	(-1.89)
Controls	YES	YES	YES	YES	YES	YES	YES	YES
Year	YES	YES	YES	YES	YES	YES	YES	YES
Individual	YES	YES	YES	YES	YES	YES	YES	YES
Observations	7,337	2,189	4,039	3,190	9,514	10,775	1,645	1,203
R-squared	0.129	0.189	0.146	0.199	0.122	0.133	0.202	0.165

5. Conclusion

The empirical results show that artificial intelligence application has a significant positive effect on enterprise innovation efficiency. This effect is mainly realized through three mediating channels:

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improving enterprise new-quality productivity, data factor utilization level, and ESG performance. Meanwhile, market segmentation negatively moderates the benchmark relationship, while fiscal support intensity and human capital structure positively moderate it. Further heterogeneity analysis reveals that the promoting effect of AI application on innovation efficiency is more pronounced for capital-intensive and labor-intensive state-owned enterprises in central and western regions.

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