Research on the Impact of Artificial Intelligence Development on the Innovation Efficiency of Enterprises

Jia Liu [1, a], Jingyao Li [1, b], Shuwei Wang [2, *]

[1]University of Business Studies, Qingdao University of Technology, Qingdao, Shandong, China
[2]Faculty of Economics and Management, Shandong University of Science and Technology, Qingdao, Shandong, China

[a]e-mail: liujias@qut.edu.cn, [b]e-mail: 17861129687@163.com
[*] Corresponding author: skd996371@sdust.edu.cn

Abstract. As a universal technology, artificial intelligence has a strong technology spillover effect, which can improve production efficiency, promote enterprise innovation and optimize factor allocation. Drawing upon the data pertaining to A-share listed companies in China from the period of 2017 to 2023, this research empirically examines the impact of artificial intelligence development on enterprise innovation efficiency by utilizing a double fixed-effects model. The results indicate that the progress of AI acts as a driving force in boosting enterprise innovation efficiency. Remarkably, this conclusion maintains its validity even after undergoing a comprehensive series of robustness checks and endogeneity tests. This study delves into the function of AI in enhancing enterprise innovation efficiency from a micro-level perspective, thereby enriching our comprehension and insight into AI at the enterprise level, and offering practical recommendations for enterprises to elevate their innovation efficiency.

Keywords: artificial intelligence; innovation efficiency; high quality development

1 Introduction

The 2024 government work report emphasized the imperative to intensify research, development, and application of big data and artificial intelligence, while also launching the “Artificial Intelligence +” initiative. Artificial intelligence, as a revolutionary general technology, it has emerged as a crucial element in driving the innovation and growth of enterprises, finding widespread application in sectors such as healthcare, finance, education, transportation, and beyond [1]. Innovation as the first driving force to lead development, and adherence to innovation is the formation of an innovation-driven connotative economic growth model, which is an inevitable requirement for promoting robust economic development. At present, China's economy is at a critical stage of transformation and upgrading, and the pursuit of high-quality development has become the core objective of national strategy. From the domestic level, the traditional

W. Zang and C. Xia (eds.), *Proceedings of the 2025 3rd International Conference on Digital Economy and Management Science (CDEMS 2025)*, Advances in Economics, Business and Management Research 336,
https://doi.org/10.2991/978-94-6463-770-0_9

economic growth model is facing many problems such as tightening resource and environmental constraints, rising labor costs, etc., and the driving force of economic development urgently needs to change from factor-driven and investment-driven to innovation-driven. As the main body of the market economy, enterprises play an important role in promoting the construction of the national innovation system. In this context, enterprises have become an important force in promoting innovation and development. From the viewpoint of the internal logic of innovation, enterprises are at the forefront of the market, and are able to keenly perceive the changes in market demand, technological development trends and competitive dynamics of the industry. This makes enterprises more capable of precisely grasping the direction of innovation and efficiently allocating innovation resources to the most promising areas. Therefore, strengthening the innovation ability of enterprises is not only a need for enterprises to improve their own competitiveness, but also a critical component of national economic advancement framework. Currently, artificial intelligence technology is profoundly changing the operation mode and development trajectory of enterprises with its powerful functions and unlimited potential, becoming the core force driving enterprise innovation and change. In the traditional mode, enterprise development often relies on cumbersome market surveys, academic exchanges and limited information collection channels, which not only consumes a lot of time and labor costs, but also acquires data that may be lagging and limited. However, AI technology can accurately capture and deliver the current status of market development as well as advanced management experience, enabling enterprises to grasp the latest industry dynamics and trends in a timely manner, providing solid knowledge support for the innovative development of enterprises. At the same time, artificial intelligence can also be machine learning and algorithm optimization, the production, operation, management and other aspects of the intelligent transformation of enterprises. Enterprises are able to respond more flexibly to market changes and improve operational efficiency and market competitiveness by breaking the constraints of traditional operation modes. In addition, the development of artificial intelligence also deepens the traditional business processes of enterprises through intelligent means, so that employees are liberated from repetitive work and can devote more time and energy to more creative tasks [2]. This not only improves the job satisfaction and sense of achievement of employees, but also stimulates their innovative vitality and injects new momentum into the innovative development of enterprises. In summary, AI development has become an important factor in enhancing the innovation efficiency of enterprises by virtue of its significant advantages in data collection, operation mode innovation, market trend identification and business process optimization.

Digital innovation is a decisive factor and an important source of enterprise core competitiveness and competitive advantage, from general technological innovation to a new generation of general purpose technology represented by artificial intelligence, how to empower enterprise competitiveness through technological innovation has been a topic of common concern in both the academic and business communities [3]. A comprehensive review of the existing literature indicates that prior studies have predominantly centered on the implications of artificial intelligence on various dimensions, including total factor productivity, economic growth, industrial structure, and the labor force [4]-[7]. Furthermore, certain scholars have utilized industrial robots as a proxy for

AI to investigate its innovation effects[8], with a particular emphasis on the correlation between AI and the quality of innovation [9]-[10]. However, these studies have overlooked the ramifications of AI concerning the efficiency of corporate innovation. As AI continues to advance, enterprises can leverage data analysis to strategically plan, optimize resource allocation, and enhance their competitiveness in a more scientific manner. Moreover, the integration of artificial intelligence dismantles the conventional organizational structure's boundaries and information silos, leading to a reduction in enterprise research and development costs. This, in turn, presents a greater opportunity to bolster the technological innovation efficiency of enterprises. Consequently, examining the influence of AI on enterprises' innovation capabilities not only enriches the relevant theoretical framework surrounding AI but also elevates enterprises' awareness of AI technology. Additionally, it provides empirical evidence that enterprises can leverage to enhance their innovation efficiency. Drawing on the aforementioned analysis, this study selects A-share listed companies from 2017 to 2023 as the research sample. It formulates Hypothesis H: The evolution of AI technology bolsters enterprises capacity for innovative productivity. Furthermore, it empirically scrutinizes the dynamic relationship between artificial intelligence and enterprise innovation efficiency.

2 Research Design

2.1 Selection of Samples and Sources of Data

In order to seize the major strategic opportunity for the development of artificial intelligence, China introduced the New Generation Artificial Intelligence Development Plan in 2017. From the perspective of the international environment, the world's major economies have taken the development of artificial intelligence as a national strategy, and the competition for the technological commanding heights is becoming increasingly heated; from the perspective of domestic development needs, China's economy is in a critical period of digital transformation, and there is an urgent need to realize industrial transformation and upgrading through disruptive technological breakthroughs such as artificial intelligence. However, the conduction mechanism of the development of artificial intelligence to empower enterprise innovation efficiency is characterized by a significant time lag. According to data from the National Bureau of Statistics, the R&D investment intensity of industrial enterprises above designated size in China has increased from 1.06% in 2017 before the implementation of the policy to 1.44% in 2021, but the peak year-on-year growth rate of invention patent authorizations appeared in the third year after the implementation of the policy. Therefore, it is important to expand the observation window period of the sample subjects to accurately measure the impact of AI development on enterprise innovation efficiency.

For this study, the initial research sample encompasses data from A-share listed companies covering the period from 2017 to 2023. The dataset includes the number of enterprise patent applications sourced from the State Intellectual Property Office, information regarding the list of cities designated as part of the National New Generation of Artificial Intelligence Innovation Development Pilot Zone along with their approval dates, which was obtained from the Chinese government website and the authorized platform of the Ministry of Science and Technology. The remaining data were collected from the CSMAR database. To ensure the reliability and validity of the empirical results, this paper implements a series of sample procedures. Specifically, it excludes companies operating in the financial industry, those classified as ST companies, and entities with missing financial data. Additionally, the study winsorizes the upper and lower 1% of the continuous variables to reduce the effect of aberrant data points on the empirical findings.

2.2 Model Design

In this paper, a double fixed effects model is constructed to test hypothesis H:

$$InnoEff = \beta_0 + \beta_1 AIarea + \beta_2 Controls + \Sigma Year + \Sigma Industry + \varepsilon$$

The consequences of AI development on firms' innovation efficiency is determined by observing the significance of coefficient β_1. If β_1 is significantly positive, hypothesis H is valid.

2.3 Definition of Variables

1) Explained variable.

Enterprise innovation efficiency ($InnoEff$). The sensitivity of enterprise R&D inputs and outputs can better portray the enterprise innovation efficiency, drawing on existing research[11]-[12], this paper employs the natural logarithm of the ratio between the cumulative volume of patent filings and R&D inputs for the enterprise in the given year as a metric to quantify enterprise innovation efficiency.

2) Explanatory variables.

Artificial intelligence development ($AIarea$). Drawing on existing research[13], if the city where the listed company is registered in the sample period is approved to build a pilot zone, it takes the value of 1 in the year of approval and the following years, otherwise it takes the value of 0. If the city where the listed company is registered in the sample period is not approved to build a pilot zone, $AIarea$ takes the value of 0 in all.

3) Control variables.

In this study, other factors that have the potential to influence enterprise innovation efficiency are identified and integrated into the model as confounding factors, including company size ($Size$), gearing ratio (Lev), total assets profitability (ROA), operating income growth rate ($Growth$), net cash flow per share (EPS), proportion of shares owned by the lead shareholder ($TOP1$), year of establishment of the enterprise (Age), and number of directors ($Board$). In addition, the model fixes the effects of industry ($Industry$) and year ($Year$). The variable definitions are presented in Table 1.

Table 1. Explanation of parameters

Variable Category	Variable Name	Variable Symbol	Variable Definition
Explained variable	Enterprise innovation efficiency	*InnoEff*	Cumulative number of patent applications/ *Ln* (R&D investment)
Explanatory variable	Artificial intelligence development	*AIarea*	If the city where the listed company is registered is approved to build a pilot zone during the sample period, the year of approval and subsequent years *AIarea* =1, otherwise *AIarea* = 0.
Control variables	Company Size	*Size*	*Ln* (Year-end total assets)
	Gearing Ratio	*Lev*	Total liabilities / Total assets
	Total Assets Profitability	*ROA*	Year-end net profit / average total assets
	Operating Income Growth Rate	*Growth*	(Current year's amount of total operating revenue - previous year's amount of total operating revenue) / previous year's amount of total operating revenue
	Net cash flow per share	*EPS*	Net increase in cash and cash equivalents / closing value of paid in capital
	Proportion of shares owned by the lead shareholder	*TOP*1	Largest shareholder's equity holding
	Year of Establishment of the Enterprise	*Age*	Current year minus founding year
	Number of Directors	*Board*	*Ln* (Number of directors)

3 Experimental findings and analysis

3.1 Descriptive statistics

Table 2 illustrates the results of summary statistics for key variables presented. In particular, the mean (standard deviation) of the explanatory variable firm innovation efficiency (*InnoEff*) is 4.146 (8.811). The mean (standard deviation) of the independent variable AI Development (*AIarea*) is about 0.347 (0.476), with a minimum value of 0 and a maximum value of 1. The findings from the control variables are basically agreeing with the established literature and are contained within a acceptable range.

Table 2. Summary statistics

Variable Sample	Size	Mean	S.D.	Min	Max
InnoEff	25,553	4.146	8.811	0.000	64.871
AIarea	25,553	0.347	0.476	0.000	1.000
Size	25,553	22.236	1.295	19.951	26.366
Lev	25,553	0.401	0.200	0.055	0.922
ROA	25,553	0.039	0.075	-0.293	0.234
Growth	25,553	0.138	0.335	-0.547	1.844

EPS	25,553	0.302	1.439	-3.279	8.080
*TOP*1	25,553	32.718	14.422	8.240	72.220
Age	25,553	3.009	0.293	2.197	3.584
Board	25,553	2.209	0.172	1.792	2.639

3.2 Research hypothesis testing

Table 3 presents the findings from the standard regression analysis. In Column (1), the regression results regarding the association between AI development and enterprise innovation efficiency are displayed, revealing a coefficient of 1.268. This coefficient is strongly significant at the 1% threshold, suggesting a positive impact of AI development on enterprise innovation efficiency. Moving to Column (2), the regression results are presented after including a comprehensive set of control variables that may potentially influence enterprise innovation efficiency. In this case, the coefficient is 0.814, which is also statistically significant at the 1% level. These results provide further robust evidence that AI development can enhance enterprise innovation efficiency, thereby supporting Hypothesis H put forward in this paper.

Table 3. The Effect of AI Advancements on Corporate Innovation Efficiency

Variable	(1) *InnoEff*	(2) *InnoEff*	Variable	(1) *InnoEff*	(2) *InnoEff*
AIarea	1.268***	0.814***	*TOP*1		0.024***
	(10.075)	(7.625)			(7.222)
Size		4.003***	*Age*		-0.871***
		(88.918)			(-5.345)
Lev		-1.138***	*Board*		-0.429
		(-3.823)			(-1.567)
ROA		1.313*	*Constant*	2.975***	-79.939***
		(1.829)		(6.581)	(-72.111)
Growth		-0.599***	*Year / Industry*	Yes	Yes
		(-4.133)	*Observations*	25,553	25,553
EPS		-0.070**	$R-squared$	0.104	0.361
		(-2.209)			

Note: ***, ** and * indicate p-values below 0.01, 0.05, and 0.10, respectively.

3.3 Robustness Tests

To make certain the robustness of the prior regression findings, this investigation employs a series of testing methodologies. Firstly, the explanatory variables are lagged by one period. Specifically, all variables utilized in the constructed model are lagged by one period, with the findings reported in column (1) of Table 4. The regression results point to the development of AI enhances enterprise innovation efficiency, which aligns with the findings from the previous benchmark regression. This approach also helps to alleviate potential endogeneity concerns. To ensure the resilience of the prior regression findings, this study employs a string of testing methodologies. Second, to expedite mitigate the possible simultaneity issue, this manuscript then introduces the industry mean

(AI_ave) of AI development taking as an instrumental variable. As evident from columns (2) and (3) of the table, the multipliers of the explanatory variables are all statistically significant and positive at the 1% level, corroborating the findings from the preceding section. Lastly, by incorporating province fixed effects into the previous model, the regression coefficient for the variables is 0.395, which is also significantly positive at the 1% level. The concordance with earlier regression outcomes validates the sturdiness of the paper's conclusions.

Table 4. Robustness and endogeneity tests

Variable	(1) *InnoEff*	(2) *AIarea*	(3) *InnoEff*	(4) *InnoEff*
AIarea			2.697*** (7.462)	0.395*** (3.069)
L.AIarea	0.829*** (6.542)			
AI_ave		0.946*** (51.032)		
Control variable	Control	Control	Control	Control
Constant	-82.864*** (-64.088)	-0.566*** (-9.827)	-64.061*** (-61.297)	-80.489*** (-71.056)
Year / Industry	Yes	Yes	Yes	Yes
Province	No	No	No	Yes
Observations	20,519	25,553	25,553	25,553
$R-squared$	0.369	0.247	0.252	0.369

Note: ***, ** and * indicate p-values below 0.01, 0.05, and 0.10, respectively.

4 Conclusion

This research centers on Chinese A-share listed firms spanning 2017 to 2023 and employs a two-way fixed-effects model to examine how artificial intelligence influences corporate innovation productivity. The results demonstrate that AI advancements substantially elevate firms' innovation efficiency. Moreover, these outcomes retain their robustness across rigorous sensitivity analyses and after mitigating potential endogeneity concerns through instrumental variable approaches.

To harness the full potential of AI for enhancing innovation efficiency and foster high-quality enterprise development, this paper, drawing upon its research findings, offers the following recommendations from the micro-perspective of enterprises: first, build a gradient artificial intelligence support system. The government and other relevant departments can give priority to support the construction of tech-driven businesses artificial intelligence, the implementation of R & D costs plus deduction policy, the intelligent transformation of enterprises to give special subsidies; additionally, preferential policies have been implemented to provide refundable value-added tax incentives for enterprises purchasing intelligent equipment. These policies offer graduated support for the construction and development of artificial intelligence technology within enterprises, addressing the issue of inadequate innovation capabilities. Secondly, efforts should be made to foster the in-depth integration of artificial intelligence technology with enterprise innovation. Enterprises ought to leverage artificial intelligence technology judiciously to analyze market demands, promptly adjust product positioning, business strategies, and marketing channels, thereby bolstering their competitiveness. And, AI can help enterprises segment and accurately locate customer groups, improve the return on investment, and reduce the cost of trial and error; in addition, it can optimize the production process, rationally plan the allocation of production and human resources through data analysis, and improve the efficiency of production and operation. Additionally, there is a need to improve the alignment of talents with artificial intelligence technology. Given the prevalence of information asymmetry, enterprises and regions often find it challenging to accurately grasp the talent supply and demand dynamics. In such instances, the government can play a pivotal role by integrating resources from various stakeholders, breaking down information barriers, and implementing targeted tax incentives or settlement policies. These measures can attract high-end talent in the field of AI to regions and enterprises that possess innovative potential but currently exhibit relatively low economic benefits. By doing so, the contradiction between the rapid development of artificial intelligence and the mismatch of information technology talent can be alleviated. Through these suggestions, this paper endeavors to provide a comprehensive reference for amplifying the role of AI in bolstering enterprise innovation efficiency and fostering an innovative ecosystem in the digital economy era.

Acknowledgment

This work was supported by the Key Research and Development Program of Shandong Province (Soft Science Project) “Research on the Construction Strategy of Industrial Brain in Shandong Province” (2024RZB0202).

References

1. Bai C, Yao D, Xue Q. Does artificial intelligence suppress firms' greenwashing behavior? Evidence from robot adoption in China[J]. Energy Economics, 2025, 142: 108168. DOI: 10.1016/J.ENECO.2024. 108168
2. Wu Q, Qalati S A, Tajeddini K, et al. The impact of artificial intelligence adoption on Chinese manufacturing enterprises’ innovativeness: new insights from a labor structure perspective[J]. Industrial Management & Data Systems, 2025,125: 849-874. DOI: 10.1108/IMDS-06-2023-0378
3. Du Chuanzhong, Cao Xiaoxi, Liu Shutong. Artificial intelligence and the competitiveness of high-tech enterprises: mechanisms and effects[J]. Business Economics and Management, 2024, (02): 30-49. DOI:10.14134/j. cnki.cn33-1336/f.2024.02.003.
4. Daron A, Pascual R. The wrong kind of AI? Artificial intelligence and the future of labour demand [J]. Cambridge Journal of Regions, Economy and Society, 2020, 13 (1): 25-35.DOI:10.1093/cjres/rsz022
5. Zhang G, Shi Y, Huang N. Government Subsidies, Green Innovation, and Firm Total Factor Productivity of Listed Artificial Intelligence Firms in China[J]. Sustainability, 2024, 16(8): 3369. DOI:10.3390/SU16083369

6. PAN Shan, LI Jianpei, GU Naihua. Artificial intelligence, industrial integration and industrial structure transformation and upgrading[J]. China Industrial Economy, 2025, (02):23-41. DOI:10.19581/j.cnki.cie- journal.2025.02.002.
7. Wang S, Wang Y, Li C. AI-driven capital-skill complementarity: Implications for skill premiums and labor mobility[J]. Finance Research Letters, 2024, 68: 106044. DOI:10.1016/J.FRL.2024.106044
8. Han F, Mao X. Artificial intelligence empowers enterprise innovation: evidence from China's industrial enterprises[J]. Applied Economics, 2024,56(57):7971-7986.https://doi.org/10.1080/00036846.2023.2289916.
9. Li J, Wu T, Hu B, et al. Artificial intelligence and corporate ESG performance[J]. International Review of Financial Analysis, 2025: 104036. DOI:10.1016/J.IRFA.2025.104036
10. Li Mang, Li Han. The impact of artificial intelligence on the quality of science and technology innovation: evidence based on Chinese A-share listed companies[J]. Social Science, 2024, (11): 122-137. DOI:10.13644/j. cnki.cn31-1112.2024.11.013.
11. Wan H, Fu J, Zhong X. ESG performance and firms' innovation efficiency: the moderating role of state-owned firms and regional market development[J]. Business Process Management Journal, 2024, 30(1): 270-290. DOI:10.1108/BPMJ-08-2023-0612
12. Wang H, Liu F. Digital finance and enterprise innovation efficiency: Evidence from China [J]. Finance Research Letters, 2024, 59: 104709. DOI:10.1016/J.FRL.2023.104709
13. Zhenwei Lu, Ocean Xie. Artificial intelligence development empowers corporate innovation: theoretical analysis and empirical evidence[J]. Statistics and Decision Making, 2025, 41(03): 169-174. DOI:10.13546/j. cnki.tjyjc.2025.03.029.