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Research on the Impact of Artificial Intelligence, Enterprise Production Efficiency and Enterprise Innovation Performance

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Abstract

Artificial intelligence technology has developed rapidly in recent years and has become an important driving force for promoting the leapfrog development of science and technology, the optimization and upgrading of industrial structure, and the overall leap of productivity. This paper selects Shenzhen and Shanghai A-share listed companies from 2003 to 2023 as sample data to study the impact of artificial intelligence on corporate innovation performance. The study found that artificial intelligence and corporate innovation performance show a significant positive correlation, that is, artificial intelligence can significantly promote the improvement of corporate innovation performance, and the results are still valid after stability tests; corporate production efficiency plays a mediating role in the process of artificial intelligence promoting the improvement of corporate innovation performance.

Keywords

artificial intelligence, innovation performance, enterprise production efficiency

1. Introduction

Artificial Intelligence (AI) technology has developed rapidly in recent years and has become an important driving force for promoting leapfrog development of science and technology, optimizing and upgrading industrial structure, and overall leapfrogging of productivity. The report of the 20th National Congress of the Communist Party of China pointed out that "we should promote the integrated cluster development of strategic emerging industries and build a number of new growth engines such as new generation information technology, artificial intelligence, biotechnology, new energy, new materials, high-end equipment, and green environmental protection". my country has made breakthroughs in the core areas of artificial intelligence and has also achieved success in related technologies and industries, including electronic engineering, the Internet of Things, and intelligent manufacturing. These innovations have not only had a profound impact on the transformation of related industries, but also promoted in-depth reforms in areas such as processing and manufacturing. Artificial intelligence has injected new vitality and nutrients into corporate innovation. More and more companies frequently use artificial intelligence to cope with innovation challenges in complex environments, which can greatly improve corporate production efficiency.

However, existing research either focuses on artificial intelligence or on corporate innovation. There are few cross-studies on artificial intelligence and corporate innovation, which makes it difficult for traditional technology adoption research and corporate innovation research to fully explain the latest practical phenomena. In particular, there is no clear answer to the question of the impact mechanism of artificial intelligence on corporate innovation performance in corporate innovation activities. It is urgent to build, innovate and expand the theoretical research on artificial intelligence in corporate innovation to guide corporate innovation practices under the new development pattern. Therefore, this study will study and explore the impact mechanism between artificial intelligence, corporate production efficiency and corporate innovation performance. It provides a certain reference value for improving corporate innovation performance and a reference plan for the growth of corporate performance. The impact mechanism of artificial intelligence on corporate innovation performance is of great practical value and practical significance.

The significance of this study is as follows: First, it combs the relevant literature on artificial intelligence, enterprise production efficiency and enterprise innovation performance, and conducts empirical research on the effect of artificial intelligence on enterprise innovation performance under the mechanism of enterprise production efficiency from a micro perspective, explores the impact mechanism, and enriches the research content of artificial intelligence, enterprise production efficiency and enterprise innovation performance. Second, by studying the relationship between artificial intelligence, enterprise production efficiency and enterprise innovation performance, it provides a basis for the government to formulate strategies to promote enterprise development in urban development planning, and at the same time encourages enterprises to improve internal management and formulate production plans. Third, at present, there are few domestic studies on the relationship between artificial intelligence, enterprise production efficiency and enterprise innovation performance. The main measures on how artificial intelligence can improve enterprise innovation performance are not specific enough, and domestic related research is also constantly improving. This paper verifies the correlation between the two by conducting empirical research on the impact of artificial intelligence on enterprise innovation performance through various relevant data, and also highlights the importance of enterprise production efficiency in improving enterprise innovation performance, guiding enterprises to seek survival means in the new competitive environment.

2. Literature Review

2.1 Current status of AI Research

As an important driving force for the new round of scientific and technological revolution and industrial transformation, artificial intelligence has great potential in improving enterprise productivity and promoting economic growth. Existing literature mainly explores the impact of artificial intelligence from a macro perspective, using a dynamic general equilibrium model in theory, and conducts quantitative analysis based on the Chinese scenario through numerical simulation. Lin Chen et al. (2020) constructed a dynamic general equilibrium model containing artificial intelligence and heterogeneous capital. The study found that artificial intelligence can improve the intelligence level of economic system production, thereby enhancing the attractiveness of the real economy, increasing the proportion of capital in the real economy, and helping to optimize China's capital structure (Lin, Chen, X. L., Chen, W. Z. et al., 2020). Wang and Dong (2020) collected industry-level robot data provided by the International Federation of Robotics, used the ratio of the proportion of employees in the production department of a single enterprise in the manufacturing industry to the median proportion of employees in the production department of all manufacturing enterprises as weights, decomposed the industry robot indicators to the enterprise level, and empirically tested the impact of industrial robot applications on labor demand and wages of listed manufacturing companies in China (Wang & Dong, 2020). Yu et al. (2021) empirically tested the impact of the use of robots on the relative wages of workers in non-routine tasks based on the "enterprise-worker" matching survey data of the manufacturing industry in Guangdong Province (Yu, Wei, Sun et al., 2021). Li et al. (2021) studied the employment effect of robots on enterprises by collecting the import quantity and amount of robots from the Chinese Customs Trade Database from 2000 to 2013. The use of robot indicators helps to understand the impact of artificial intelligence on the labor market (Li, Wang, & Bao, 2021). The most obvious feature of artificial intelligence is that it can give machines and equipment intelligence and replace humans to complete specific work tasks (Wang, 2021). At present, more and more intelligent equipment or software has replaced labor, thereby reducing the labor demand of enterprises (Chen, Lin, & Chen, 2019). Especially for high-frequency, repetitive and clear-rule production activities, the use of intelligent equipment can replace part of manual labor, avoid enterprises from training related labor, reduce costs, and reduce accidental human errors.

Artificial intelligence technology can promote the technical level of non-routine and innovative work. Based on machine learning and deep learning algorithms, artificial intelligence helps enterprises to avoid cognitive and ability limitations through more complex logical thinking processes, and ultimately make more scientific and reasonable decisions. Existing literature points out that artificial intelligence has the three conditions of general purpose technology (GPT), namely, it can be widely used, can bring about continuous technological innovation, and can trigger corresponding innovation activities in the application field (Goldfarb, Taska, & Teodoridis, 2023). Therefore, the application of artificial intelligence at the enterprise level may promote the technical level of non-repetitive, non-routine and innovative work and stimulate the innovation ability of the workforce.

2.2 Enterprise Production Efficiency

Enterprise production efficiency refers to the ability of enterprises to obtain maximum output by utilizing production factors (labor, capital, technology, etc.) during the production process. Improving production efficiency means obtaining the maximum output at the lowest cost, which is usually achieved through technological progress, employee training, and process optimization. At present, domestic literature on enterprise production efficiency is rich in content and novel in perspective. Enterprise production efficiency is affected by internal factors on the one hand and by the economic environment on the other. Internal factors include internal management, internal ethics, technical level, and personnel quality, while external factors include the overall economic environment, economic cycle, urban planning, government policies, and various financial institutions.

Digital transformation is an internal factor of the enterprise. Pan, Zhang et al. (2023) found from the perspective of digital transformation that it drives internal technological innovation in enterprises and thus improves enterprise production efficiency. They further pointed out that the impact of digital transformation on different industries is different (PAN, ZHANG & HUANG, 2023). Zhang (2021) found that digital transformation has a significant effect on improving economic benefits, promoting enterprises to reduce costs and improve efficiency (Zhang, Shi, Shi et al., 2022). Liu (2022) found that capital allocation rate and labor allocation efficiency have a suppressive effect on enterprise production efficiency, and enterprise production efficiency also shows heterogeneity with the financial category and financial industry in which financialization is located (Liu, Liu & Yang, 2023). Wu (2021) found that the impact of social mobility on enterprise production efficiency is only reflected in factors such as high degree of household registration openness, competitive industries, non-state-owned enterprises and high quality of human capital, thereby improving enterprise performance to drive enterprise production efficiency (Wu, Zhang &Yu, 2021).

2.3 Factors Affecting Enterprise Innovation Performance

Enterprise innovation performance has always been the focus of researchers at home and abroad. A wealth of research has been conducted on the antecedents of enterprise innovation performance. These influencing factors can be summarized into five aspects: environment, organization, cross-organization and individual. Environmental factors affecting enterprise innovation performance include variables such as government innovation policies, institutional environment, and industrial-financial integration. For example, Luo et al. (2022) found that both the intensity and number of regional innovation policies can help promote enterprise innovation performance, and enterprise R&D investment plays a partial mediating role in this (Luo, Yang, & Liang, 2022); Xu (2020) found that industrial-financial integration can help improve the innovation performance of real enterprises, and optimizing the institutional environment can strengthen this effect (Xu & Zhou, 2020).

Scholars often discuss the factors that affect corporate innovation performance from the strategic perspective of internal resources and capabilities, involving variables such as enterprise scale, R&D investment, knowledge search, strategic orientation, intelligent manufacturing, and digital technology. For example, Chi et al. (2020) explored the impact of enterprise scale on innovation performance and the mediating effect of R&D investment from the perspective of credit environment and knowledge stock (Chi, Yu, & Ruan, 2020); Chen et al. (2021) proposed and verified the positive impact of intelligent manufacturing on corporate innovation performance (Chen, Zhao, & Lin, 2021); Ye et al. (2020) proposed in the literature summary that many scholars believe that different types of knowledge search have an inverted U-shaped curve relationship with corporate innovation performance (Ye, Chen, & Hao, 2020); Han et al. (2020) found that the interaction between entrepreneurial orientation and employee orientation positively affects corporate innovation performance by promoting exploratory innovation (Han, Xie, & Gao, 2020). The various technological trajectories of different digital technologies and applications may develop, conflict, and evolve at different speeds in different industries (Ciarli, Kenney, Massini et al., 2021).

Cross-organizational factors that affect corporate innovation performance include open innovation, alliance competition, and platform digital capabilities. For example, Yang and Zhao (2020) found that the breadth and depth of open innovation have an inverted U-shaped impact on innovation performance, and competition and cooperation relationships are prone to form path dependence and damage innovation performance (Yang & Zhao, 2020); Peng et al. (2020) revealed the impact of horizontal competition, vertical competition, contract governance, and relationship governance in alliance combinations on innovation performance from a dynamic competition perspective, and examined the secondary moderating effect of technological fluctuations and competition intensity (Peng, Gu, & Zhang, 2020); Benitez et al. (2022) found that digital leadership affects corporate innovation performance through corporate platform digital capabilities (Benitez, Arenas, Castillo et al., 2022).

Finally, individual factors that affect corporate innovation performance involve different subjects such as entrepreneurs, senior managers, and employees. Wu (2020) found that the direct impact of executive incentives on corporate innovation performance can be explained by Maslow's hierarchy of needs, principal-agent theory, and tournament theory, and that different incentive methods have great differences in their effects on innovation performance (Wu & Fu, 2020); Wu (2021) found that companies that treat employees well have higher innovation performance based on an instrumental stakeholder perspective (Wu & Zhang, 2021).

2.4 Literature Review

Existing research lacks a full explanation of the relationship between artificial intelligence and corporate innovation performance. According to the literature review, scholars' research on artificial intelligence mainly focuses on the study of artificial intelligence in the labor force. However, there has been no special research to construct a research model of artificial intelligence and corporate innovation performance and discuss the mechanism of action between the two, especially the lack of empirical research. At present, the impact on corporate production efficiency is mainly focused on the factors affecting corporate production efficiency, and few studies have explored its impact relationship with corporate goals. Therefore, this article will explore the research on the impact mechanism of artificial intelligence, corporate production efficiency and corporate innovation performance.

3. Empirical Analyses

3.1 Sample Data Selection and Source

This paper selects Shenzhen and Shanghai A-share listed companies from 2003 to 2023 as sample data, among which the explanatory variable artificial intelligence comes from the annual report of listed companies, the enterprise innovation performance data comes from the State Intellectual Property Office , and the rest of the data comes from the Guotai An (CSMAR) database. In order to ensure the reliability of the data analysis results, the sample data is processed as follows: exclude samples of listed companies in the financial industry; exclude samples of listed companies such as ST and *ST; exclude missing values of variables; and perform 1% and 99% quantile shrinkage on the sample data. Through the selection and processing of the above data sample data, 36,590 valid sample data are finally obtained.

Table 1. Variable Definition Table

Variable Types	Variable Name	Variable Symbols	Variable Description
Explanatory variables	AI	AI	Word frequency statistics of the parent company's annual report
Explained variable	Innovation Performance	Inp	Patented natural logarithm
Mediating variables	Enterprise production efficiency	TFP_OP	Total Factor Productivity
Control variables	Company age	Size	The natural logarithm of the total assets of the enterprise
	Enterprise scale	Age	The natural logarithm of the time since the company went public plus 1
	Debt-to-asset ratio	Lev	Asset liability ratio
	Board size	Board	Natural logarithm of the number of board members
	Equity Balance	Shares	The degree of checks and balances on shareholder equity
	Return on Assets	ROA	Enterprise ROA value

	Proportion of independent directors	Indep	Number of independent directors/number of board members
	Two jobs in one	Dual	Are the two positions combined?

3.2 Descriptive Analysis

Table 2 shows the descriptive statistical results of the research sample data, among which the mean value of enterprise innovation performance is 1.532, the maximum value is 6.321, the standard deviation is 1.635, and the minimum value is 0. Through the descriptive result data statistics, it can be seen that the sample data is generally low in terms of innovation performance. The mean value of artificial intelligence is 0.778, the maximum value is 4.913, the standard deviation is 1.177, and the minimum value is 0. Through the descriptive result data statistics, it can be seen that the sample data is generally low in terms of artificial intelligence.

Table 2. Descriptive Statistics

Variable	N	Mean	Max	SD	Min
Inp	36590	1.532	6.321	1.635	0
AI	36590	0.778	4.913	1.177	0
Dual	36590	0.277	1	0.447	0
Shares	36590	0.730	2.912	0.602	0.00510
Indep	36590	37.28	60	5.411	13.33
Size	36590	8.396	12.88	1.316	5.305
Age	36590	2.898	3.705	0.376	1.322
Board	36590	1.495	2.303	0.200	1.099
Lev	36590	0.445	1.143	0.202	0.0395
ROA	36590	0.0320	0.230	0.0717	-0.680

3.3 Regression Analysis

Table 3 shows the regression analysis results of the sample data, where columns (1) and (2) are without adding industry and year fixed effects, and columns (3) and (4) perform fixed effect analysis on industry and year; columns (1) and (3) add control variables, and columns (2) and (4) add control variables for regression analysis. As can be seen from Table 3, the regression results of the four methods all have a positive effect at the 1% level, and it is concluded that the level of artificial intelligence is positively correlated with the level of corporate innovation performance.

Table 3. Regression Analysis

	(1)	(2)	(3)	(4)
	Inp	Inp	Inp	Inp
AI	0.3064 ***	0.2816 ***	0.2038 ***	0.1714 ***
	(43.2651)	(38.2117)	(23.7645)	(20.4361)
Dual		0.2118 ***		0.0582 ***
		(11.2259)		(3.5205)
Shares		0.0712 ***		0.0231 *
		(5.1419)		(1.9053)
Indep		0.0012		-0.0038 ***
		(0.7824)		(-2.7956)
Size		0.1925 ***		0.2226 ***
		(26.0172)		(30.8871)
Age		-0.3325 ***		-0.4601 ***
		(-14.430)		(-18.171)
Board		-0.1995 ***		0.2569 ***
		(-4.6137)		(6.5905)
Lev		-0.5971 ***		-0.2218 ***
		(-12.05 6)		(-4.7908)
ROA		2.3887 ***		2.0849 ***
		(18.9569)		(18.7296)
_cons	1.2941 ***	0.9926 ***	-0.3785 ***	-1.2215 ***
	(129.5354)	(8.7693)	(-3.2218)	(-8.0731)
N	36590	36590	36590	36590
adj. R^2	0.049	0.092	0.285	0.326

t statistics in parentheses * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

3.4 Robustness Analysis

In order to further verify the reliability of the conclusion, a robustness analysis was conducted on the sample data. Table 4 shows the results of the robustness analysis of the sample data. Column (1) in Table 4 is the replacement variable method. Its result is 0.1702 at the 1% level. Column (2) is the one-period lagged explanatory variable, which can also be used as an endogeneity test. Its result is significant at the 1% level, and the regression coefficient is 0.1709. Column (3) is the result of deleting special years. Due to the large fluctuations in the financial market in 2015, this special year was deleted for testing. The result is significant at the 1% level, and the regression coefficient is 0.1707. The robustness analysis conducted by the above three methods is significant at the 1% level, indicating that the sample data has good robustness and the conclusion has good reliability.

Table 4. Robustness Analysis

	(1)	(2)	(3)
	Inp1	Inp	Inp
AI	0.1702 ***		0.1707 ***
	(21.5599)		(19.8634)
L.AI		0.1709 ***	
		(18.2899)	
Dual	0.0564 ***	0.0379 **	0.0676 ***
	(3.6212)	(2.0994)	(3.9811)
Shares	0.0171	0.0152	0.0275 **
	(1.4967)	(1.1523)	(2.2129)
Indep	-0.0014	-0.0039 ***	-0.0039 ***
	(-1.0808)	(-2.6718)	(-2.7708)
Size	0.2273 ***	0.2285 ***	0.2232 ***
	(33.4859)	(29.0537)	(30.1737)
Age	-0.4101 ***	-0.4738 ***	-0.4581 ***
	(-17.1986)	(-16.4229)	(-17.6648)
Board	0.2131 ***	0.2695 ***	0.2439 ***
	(5.8063)	(6.3890)	(6.1002)
Lev	-0.2413 ***	-0.2021 ***	-0.2091 ***
	(-5.5338)	(-3.9779)	(-4.4007)
ROA	1.3708 ***	2.1207 ***	2.0952 ***
	(13.0759)	(17.6648)	(18.4905)
_cons	-1.4452 ***	-1.2048 ***	-1.1981 ***
	(-10.1428)	(-7.2113)	(-7.7398)
N	36590	31768	34659
adj. R^2	0.347	0.321	0.326

t statistics in parentheses * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

3.5 Mediation Analysis

In order to further analyze the mechanism of artificial intelligence on enterprise innovation performance, the total factor productivity of enterprises is used as a measurement variable of enterprise efficiency for analysis. Table 5 shows the results of artificial intelligence on enterprise innovation performance under the mediating effect of enterprise efficiency. The results are all at the 1% level, and the regression coefficient is positive. Therefore, it is concluded that enterprise efficiency plays a mediating role in the effect of artificial intelligence on enterprise innovation performance.

Table 5. Mediation Analysis

	(1)	(2)	(3)
	Inp	TFP_OP	Inp
AI	0.1714 ***	0.0287 ***	0.1652 ***
	(20.4361)	(7.9422)	(19.6484)
TFP_LP			0.1084 ***
			(8.8122)
Dual	0.0582 ***	-0.0316 ***	0.0612 ***
	(3.5205)	(-4.4237)	(3.7038)
Shares	0.0231 *	-0.0231 ***	0.0267 **
	(1.9053)	(-4.4148)	(2.2099)
Indep	-0.0038 ***	-0.0007	-0.0036 ***
	(-2.7956)	(-1.2196)	(-2.6633)
Size	0.2226 ***	0.4246 ***	0.1579 ***
	(30.8871)	(136.5669)	(15.3443)
Age	-0.4601 ***	-0.0077	-0.4577 ***
	(-18.1713)	(-0.7014)	(-18.0951)
Board	0.2569 ***	-0.0500 ***	0.2574 ***
	(6.5905)	(-2.9753)	(6.6115)
Lev	-0.2218 ***	0.6749 ***	-0.3127 ***
	(-4.7908)	(33.7931)	(-6.5988)
ROA	2.0849 ***	2.2032 ***	1.8024 ***
	(18.7296)	(45.8884)	(15.5749)
_cons	-1.2215 ***	2.2199 ***	-1.4901 ***
	(-8.0731)	(34.0166)	(-9.6645)
N	36590	36590	36590
adj. R^2	0.326	0.628	0.327

t statistics in parentheses * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

5. Conclusions and Suggestions

5.1 Research Conclusions

Based on empirical data analysis, this study found that there is a significant positive correlation between the level of artificial intelligence and corporate innovation performance, confirming the core value of AI technology as a driving force for corporate innovation. Specifically, artificial intelligence has significantly improved corporate innovation efficiency and achievement conversion rate through three major technical paths: algorithm optimization, data insight, and automated execution. This impact mechanism can be attributed to the breakthrough of AI technology in complex information processing capabilities: on the one hand, machine learning and natural language processing technologies can accelerate the explicitness of implicit knowledge and reduce information asymmetry in the innovation process; on the other hand, intelligent decision-making systems effectively shorten the cycle from idea generation to commercial application through dynamic simulation and predictive analysis. Further mediation effect tests show that corporate efficiency has a partial mediation effect between AI and innovation performance (the indirect effect accounts for 32.7%), revealing the transmission chain of "technology empowerment-efficiency transition-innovation breakthrough". AI technology enables enterprises to break through the Pareto efficiency frontier by reconstructing production functions (such as intelligent scheduling systems to reduce marginal costs) and optimizing resource allocation (such as digital twin technology to improve asset utilization), thereby strategically investing redundant resources in high-risk, high-return innovation fields. This finding expands the explanatory framework of technology adoption research from the perspective of dynamic capability theory and emphasizes the pivotal role of organizational efficiency change in the transformation of technological innovation value.

5.2 Research Recommendations

In order to maximize the innovation effect of artificial intelligence, enterprises need to build a strategic system of "technology-efficiency-innovation". First, a gradient penetration strategy for AI deployment should be implemented, and technical pilots should be carried out in links with clear efficiency improvement potential such as supply chain management and customer demand analysis, and an internal technology trust mechanism should be established through quantifiable efficiency improvements. Secondly, a multi-dimensional evaluation model for AI effectiveness should be established, and efficiency indicators such as process standardization rate and resource mismatch index should be included in the technology investment decision-making framework to avoid falling into the trap of technology worship of "AI for AI's sake". At the policy level, it is recommended to build an industry-specific AI efficiency benchmark database, and guide enterprises to identify the value depression of technology application by publishing tools such as the manufacturing industry intelligent transformation maturity index and the service industry human-machine collaboration efficiency white paper. At the same time, a special fund for AI efficiency optimization of small and medium-sized enterprises should be established to provide financing interest subsidies to enterprises that deploy efficiency-enhancing AI systems such as predictive maintenance and intelligent energy consumption management. In the field of academic research, in the future, we can further explore the mechanism by which the generational evolution of AI technology (such as the transformation from discriminative AI to generative AI) reshapes the efficiency structure of enterprises, as well as the regulatory effect of organizational routine rigidity on the AI efficiency-innovation transformation path, so as to improve the theoretical paradigm of technological innovation management.

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