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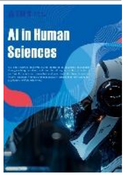

The Impact of Artificial Intelligence on Firm Performance: Disruptive Threat or Strategic Enhancement?

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Abstract: As artificial intelligence (AI) technology is increasingly integrated into business operations, its impact on firm performance has garnered significant attention from the academic community. This study reviews 37 peer-reviewed articles, following the PRISMA 2020 guidelines, to explore the effects of AI on firm performance, with a particular focus on identifying performance dimensions and industry heterogeneity. These articles are sourced from leading Chinese and English academic databases, including Web of Science, Scopus, and CNKI. The review categorizes performance outcomes into three main dimensions: financial performance (78.4%), innovation performance (16.2%), and productivity (5.4%). Most studies indicate a significant positive correlation between the adoption of AI and improvements in firm performance. However, the results also highlight significant heterogeneity across different industries, with manufacturing and technology-intensive sectors showing more consistent benefits, while service and traditional industries exhibit mixed performances. Overall, AI can enhance performance but may also exacerbate disparities, depending on factors such as industry characteristics, firm size, and digital maturity. Based on these insights, this study recommends policies such as subsidies for SMEs, talent development, and regional infrastructure to support broader AI adoption. It also offers practical strategies for enterprise transformation and highlights the need for future empirical and longitudinal research.

Keywords: firm performance, artificial intelligence, financial performance, innovation performance, productivity, and industry heterogeneity

1. INTRODUCTION

The rapid development of AI technology is changing all enterprises' operating model, revenue generation strategy and performance elevation in recent years. Many areas have been influenced, including manufacturer, finance, retails, logistics and medical industries, AI is gradually penetrating into every step of enterprise operation. Through algorithm-driven intelligent analysis, prediction and decision-making, AI helps enterprises achieve significant results in improving efficiency, reducing costs and improving customer satisfactions(Cheng et al., 2025; Khan et al., 2024; Sun, 2021; Yang et al., 2020).Especially in the context of gradual maturity of underlying technologies, such as big data and cloud computing, AI technology has become an important tool for enterprises transformation and improve their performance(Ma et al., 2025; X. Xu et al., 2025).AI-driven companies are using technology to achieve more efficient resource allocation. For example, machine learning algorithms can help enterprises achieve precision marketing, intelligent scheduling and inventory management, which significantly improve operational efficiency (Sun & Jiao, 2024; Ying & Yijuan, 2024). Natural language processing technology can help enterprises optimize the processes of customer service and document processing, which can reduce labor costs. In intelligent manufacturing and predictive maintenance, AI systems enable enterprises to identify potential risks in advance and make active adjustments, thus reducing disruptions and waste in the production process(Yang et al., 2020).These changes have contributed to the continuous optimization of productivity, innovation performance and financial performance(Ma et al., 2025; Q. Xu & Xu, 2022; Zhu et al., 2024).AI has created a large number of new jobs and improved enterprise productivity. At the same time, AI automation technology is also replacing traditional jobs and reshaping traditional industries. However, AI is not “stealing people’s jobs”, but “upgrading their jobs”.

However, the dividends brought by AI are not evenly distributed among enterprises, and its effect is affected by multiple factors such as enterprise resources, technical capabilities and organizational management level. In practice, those enterprises with advantages in capital, talent, data and technological foundation(such as technology platform enterprises and large manufacturing enterprises) are more likely to take the lead in deploying AI systems to improve their performance(Zhai & Liu, 2023; Y. Zhang et al., 2023).However, traditional industries, private enterprises and enterprises with scarce resources face many obstacles in the process of technology adoption, which makes it difficult to effectively transform technology into firm performance, and even marginalized by the rapid development of new technologies. This trend not only exacerbates the competitive imbalance between enterprises, but also leads to a wide discussion about the performance differences between enterprises intensified by AI technology(Huang & Xiao, 2021)。Globally, tech giants such as OpenAI and Meta have effectively formed an “oligopoly” over the AI industry chain by controlling core AI technologies, algorithm infrastructure and high-quality data resources. This further amplifies the technology gap between large companies, and presents a “winner-takes-all” feature(Sekmokas et al., 2020).On the one hand, these tech giants are using AI to accelerate innovation, expand market share and attract more capital and talent(J. Wang et al., 2024).On the other hand, many small and medium-sized enterprises are unable to form effective competitiveness in the process of “digital transformation” and “AI empowerment” due to limited funds, lack of technical capabilities or lagging management mechanisms(Huang & Xiao, 2021).

Although some studies have analyzed the impact of AI on labor market, industrial structure and social income distribution from a macro level, there is still a lack of systematic review and hierarchical discussion at the enterprise level, especially about the micro impact mechanism of AI application on enterprise performance. Specifically, the current literature focuses on individual industries or case studies, and lacks a systematic analysis of the specific effects of AI on different types of enterprises from the perspective of multi-dimensional performance (such as operational efficiency, financial return, innovation performance). In terms of methodology, the existing research also has problems such as insufficient theoretical integration, large heterogeneity of research indicators and lack of longitudinal tracking. More importantly, there is still a significant controversy over whether AI will narrow or widen the performance gap between enterprises, and the theoretical support and empirical evidence have not yet formed a unified consensus.

Especially in China, an emerging economy with rapid transformation, the degree of digitalization of enterprises is different, and the breadth and depth of AI technology adoption show significant heterogeneity (Li et al., 2021; Y. Wang & Su, 2022). On the one hand, the government continues to promote “intelligent manufacturing”, “digital economy” and “high-quality development” policies, which provide policy support for the implementation of AI technology in enterprises. On the other hand, the differences in technology absorption ability, talent structure and management practice among different types of enterprises make the effect of AI technology on improving enterprise performance show complex and diverse forms(J. Liu et al., 2020; Wu & Huang, 2022; Zhai & Liu, 2023).In this context, it is necessary to focus on Chinese listed enterprises to deeply explore the practical application of AI technology in enterprises and its impact path on performance.

The PRISMA method (Preferred Reporting Items for Systematic Reviews and Meta-Analysis) helps to identify and comprehensively analyze the dual impact of AI technology application on enterprise performance (Page et al., 2021). It includes identifying, selecting, collecting and synthesizing data from relevant studies. Therefore, this study will use PRISMA method to explore the impact of AI technology on enterprise performance. In the past five years, there has been a significant lack of literature reviews using the PRISMA method in relevant studies, which also highlights the need for a structured and systematic review of existing research.

Based on this, this research aims to categorize, summarize, and compare the relevant literature from multiple dimensions, including AI technology types (such as data intelligence, automation, algorithmic decision-making, etc.), enterprise performance metrics (such as operational efficiency, financial indicators, innovation performance, etc.), and enterprise characteristics (such as industry attributes, scale, level of digitalization). This analysis is intended to reveal the specific mechanisms and impact effects of AI technology on enterprise performance in various scenarios. Furthermore, this research will integrate the main theoretical foundations of current research, including Resource-Based View (RBV), Dynamic Capability Theory (Dynamic Capability), Technology-Organization-Environment (TOE) framework, and Diffusion of Innovation Theory, to explore how AI technology can be transformed into firm performance within organizational systems. It will also identify the shortcomings in existing literature and suggest areas for future research.

This study aims to comprehensively understand the impact of AI technology on enterprise performance, whether there are differences in the performance of AI application in different industries and enterprises, and discuss whether AI technology can help narrow the performance gap or exacerbate the technology gap. This research will provide a more comprehensive and critical analysis perspective for the academic research to understand the enterprise performance driven by AI, and at the same time provide feasible technical application suggestions and performance improvement strategies for policy makers and enterprise managers, so as to promote the construction of a more fair and sustainable technology transformation path. In the next section, the study describes the methodology. Then, the study introduces and discusses the results and their implications for future related research.

2. METHOD

In order to achieve the above research objectives, this study adopted systematic literature review method, which followed the PRISMA 2020 guidelines (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) to ensure transparency, repeatability and scientific rigor (Mohsin et al., 2025; Page et al., 2021). Therefore, this study created a specific protocol for retrieval strategy, selection criteria, data extraction and final data analysis.

2.1. Information Sources and Search Strategy

The systematic literature review consists of articles drawn from three online databases, Scopus, the Web of Science (WOS) and China National Knowledge Infrastructure （CNKI）. The selection of these databases was made due to their international recognition and their extensive and remarkable collection of articles concerning many different scientific subjects and fields.

The search was performed using the “advanced search” feature of these databases, using keywords (“Artificial Intelligence” OR “AI” OR “Digital Transformation”, AND “Firm Performance” OR “Financial Performance”, AND “China”). No specific date frame was set for the age of the articles.

2.2. Inclusion and Exclusion Criteria

To select articles that contribute to the research purpose, the following screening criteria were set and applied (Table 1).

Table 1. Inclusion and exclusion criteria

Order number	Inclusion Criteria (IC)	Exclusion Criteria (EC)
1	The article must be a journal article.	Chapter in a book, dissertations and all literature reviews.
2	The article must not be a duplicate (exist in another database).	Duplicate records
3	Related to the application of AI at the enterprise level	The literature is based on individual consumers or regions and the macro national level as the

Order number	Inclusion Criteria (IC)	Exclusion Criteria (EC)
		analysis unit
4	Focus on the impact of AI on enterprise performance	Technical literature that only involves the principles of AI technology or is not related to enterprise performance

The systematic literature review was conducted in four stages, following the PRISMA 2020 guidelines.

The first stage consisted of the initial search of the literature included in the WOS (n = 101), Scopus (n = 196) and CNKI (n=181). Based on the first inclusion and exclusion criteria, a total of 48 articles were deemed ineligible due to type of article.

In the second stage, the third inclusion and exclusion criteria were applied by reviewing the title, the abstract and keywords, resulting in the exclusion of 256 articles. These articles focused on individual consumers, regions, or macro-national levels as the unit of analysis rather than enterprise-level.

In the third stage, applying the fourth inclusion and exclusion criteria, a total of 51 were carefully screened for eligibility based on the full text, resulting in the exclusion of 23 papers which only involved AI technology and has nothing related with business performance.

In the fourth and last stage, regarding duplicates (IC4), 7 articles were excluded.

So, the remaining 37 articles were reviewed thoroughly in this study. The above process is illustrated in a PRISMA flow diagram (Figure 1), while the corresponding Table 2 listing all included papers in the systematic literature review.

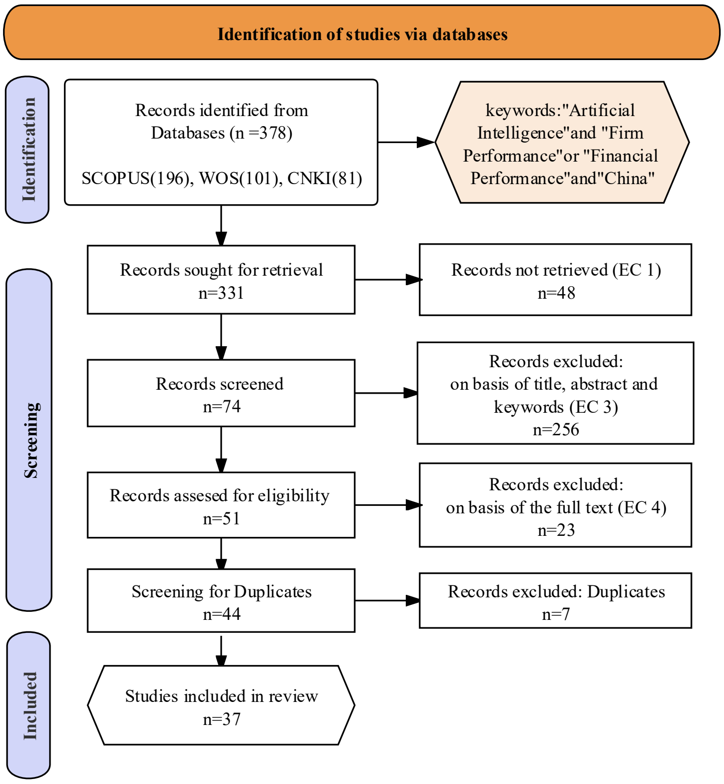

Figure 1. PRISMA flow diagram

Table 2. Papers included in the systematic literature review

Code	Title	Authors	Journal/Conference/Book	Year
1	Navigating financial performance of the organisations through artificial intelligence and financial decision-making process: Moderation of risks	Chen, J.	International Journal of Information Systems and Change Management	2025
2	Investigating the determinants of performance of artificial intelligence adoption in hospitality industry during COVID-19	Chen, Y., Hu, Y., Zhou, S., & Yang, S.	International Journal of Contemporary Hospitality Management	2022
3	The impact of digital transformation on firm's financial performance: Evidence from China	Chen, Y., & Zhang, Y.	Industrial Management & Data Systems	2024
4	Internal business process governance and external regulation: How does AI technology empower financial performance?	Cheng, X., Du, A. M., Yan, C., & Goodell, J. W.	International Review of Financial Analysis	2025
5	Research on financial performance evaluation on artificial intelligence listed companies in China based on DEA method	Hu, J., Nian, Z., & Wang, X.	2019 Portland International Conference on Management of Engineering and Technology (PICMET)	2019
6	The impact of information technology investment on enterprise financial performance in China	Ji, P., Yan, X., & Yu, G.	Chinese Management Studies	2019

7	Navigating innovation in the age of AI: How generative AI and innovation influence organizational performance in the manufacturing sector	Khan, S., Mehmood, S., & Khan, S. U.	Journal of Manufacturing Technology Management	2024
8	The application of AI and product innovation efficiency: The role of knowledge innovation under SECI model	Liu, C.	Aslib Journal of Information Management	2024
9	Influence of artificial intelligence on technological innovation: Evidence from the panel data of China's manufacturing sectors	Liu, J., Chang, H., Forrest, J. Y.-L., & Yang, B.	Technological Forecasting and Social Change	2020
10	Green entrepreneurial leadership and AI-driven green process innovation: Advancing environmental sustainability in the traditional Chinese medicine industry	Liu, Y., Ho, T. C., Omar, R., & Ning, B.	Journal of Environmental Management	2025
11	Digital transformation, artificial intelligence and enterprise innovation performance	Ma, J., Shang, Y., & Liang, Z.	Finance Research Letters	2025
12	Emerging IT investments and firm performance: A perspective of the digital options	Sun, J., & Jiao, H.	Chinese Management Studies	2024
13	The moderating effect of proprietary assets on international performance in the context of digital economy	Tan, H., & Wei, S.-Y.	2022 International Conference on Artificial Intelligence, Internet and Digital Economy (ICAID 2022)	2022
14	Driving factors of digital transformation for manufacturing enterprises: A multi-case study from China	Wang, Y., & Su, X.	International Journal of Technology Management	2022

15	The effects of digital finance and financial constraint on financial performance: Firm-level evidence from China's new energy enterprises	Wu, Y., & Huang, S.	Energy Economics	2022
16	The impact of artificial intelligence strategy on corporate financial performance--An empirical analysis based on listed companies panel data	Xu, Q., & Xu, C.	2022 International Conference on Artificial Intelligence, Internet and Digital Economy (ICAID 2022)	2022
17	Digital transformation and export duration: Implications for firm financial performance	Xu, X., Chen, X., Yang, J., & Li, Q.	Pacific-Basin Finance Journal	2025
18	The influence of intelligent manufacturing on financial performance and innovation performance: The case of China	Yang, J., Ying, L., & Gao, M.	Enterprise Information Systems	2020
19	The impact of digital technology application on tourist enterprise performance: The moderating role of ownership balance degree	Ying, D., & Yijuan, B.	2024 IEEE 24th International Conference on Software Quality, Reliability, and Security Companion (QRS-C)	2024
20	The financial effect of firm digitalization: Evidence from China	Zeng, H., Ran, H., Zhou, Q., Jin, Y., & Cheng, X.	Technological Forecasting and Social Change	2022
21	Artificial intelligence technology innovation and firm productivity: Evidence from China	Zhai, S., & Liu, Z.	Finance Research Letters	2023
22	Determinants of financial performance in China's intelligent manufacturing industry: Innovation and liquidity	Zhang, G., & Lee, Y.	International Journal of Financial Studies	2021

23	How does digital inclusive finance promote the financial performance of Chinese cultural enterprises?	Zhang, W., Chen, F., Liu, E., Zhang, Y., & Li, F.	Pacific-Basin Finance Journal	2023
24	The role of internal control and digital transformation between political connections and financial performance: Evidence from China	Zhang, Y., Pan, C., Meng, S., & Wang, K.	Asia Pacific Business Review	2023
25	The impact of intelligent manufacturing on labor productivity: An empirical analysis of Chinese listed manufacturing companies	Zhu, M., Liang, C., Yeung, A. C., & Zhou, H.	International Journal of Production Economics	2024
26	Economic Benefits Analysis of Enterprise Digital Transformation Under the Digital Economy (In Chinese)	Liu Jianing	Science Technology and Economic Market	2023
27	The Impact of Artificial Intelligence on Retail Enterprise Performance: Empirical Evidence from A-Share Listed Companies (In Chinese)	Lu Huan	Commercial Economy Research	2024
28	Application of AI Technology in Financial Management and Economic Benefits Analysis (In Chinese)	Tang Lijuan	Time-honored Brand Marketing	2024
29	R&D Investment, Innovation Strategies, and firm performance in the AI Industry: Empirical Research Based on 112 Listed Enterprises (In Chinese)	Kong Xu, Hao Feiyan, Liu Peipei, & Zhang Lianbiao	Science and Technology Management Research	2021
30	Application of AI Systems in Enterprise Performance Evaluation (In Chinese)	Meng Yuan	Shanxi Electronic Technology	2024

31	Economic Benefits Analysis of Energy Storage Technology and AI Integration in Power Systems (In Chinese)	Zhang Han	Construction Science and Technology	2024
32	The Impact of Artificial Intelligence on firm performance: Based on Managerial Myopia (In Chinese)	Li Tengfei	Modern Marketing (Late Decade)	2025
33	Application of AI in Computer Network Technology Innovation Development and Economic Efficiency Improvement (In Chinese)	Yang Jiyu	Modern Industrial Economy and Informatization	2024
34	Research on the Application of AI Technology in Digitalization of Enterprise Performance Management (In Chinese)	Wang Dacheng	Administrative Assets and Finance	2024
35	Government Subsidies, R&D Investment, and firm performance in the AI Industry: Empirical Study Based on 175 Listed Enterprises (In Chinese)	Qin Huimin & Qu Hongyue	Journal of Changchun University of Science and Technology (Social Sciences Edition)	2024
36	The Impact of AI Applications on Manufacturing Enterprise Performance: Mediating Role of Labor Structure and Moderating Role of Firm Size (In Chinese)	Chen Jin & Meng Yuanyuan	China Labor	2021
37	Construction of Performance Evaluation Index System for SMEs Under the Background of Big Data and AI (In Chinese)	Huang Chen & Xiao Dong	Modern Business	2021

3. RESULT

A total of 37 articles met all inclusion criteria， all articles were written from 2019, with the majority being published in 2024, as shown in Figure 2.

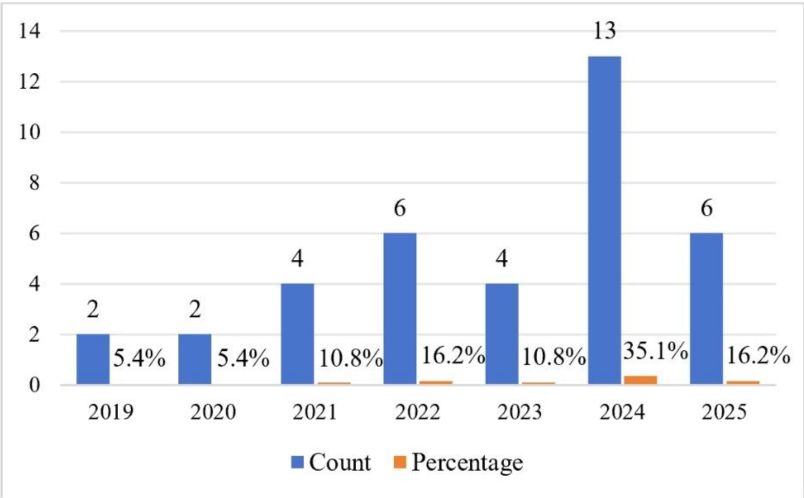

Figure 2. Selected articles' publications by year during the period 2019-2025

Of the 37 articles, most were quantitative studies (83.8%), followed by qualitative studies (13.5%) and mixed studies (2.7%)（Table 3）.

Table 3. Methodology of selected articles

Methodology	Quantitative	Qualitative	Both
Articles	[1] ,[2],[3],[4],[5],[6],[7],[8],[9],[10],[11],[12], [13] ,[15],[16],[17],[18],[19],[20],[21],[22],[23], [24],[25],[27],[29],[31],[32],[33],[35],[36]	[14],[26],[28],[30],[34]	[37]
Percentage	83.8%	13.5%	2.7%

3.1. The Impact of AI on Financial Performance

The 37 articles reveal the impact of AI technology on firm performance, which is subdivided in these studies: financial performance, innovation performance, and productivity. Financial performance was the most frequently mentioned and most affected by AI (78.4%), followed by innovation performance (16.2%), and productivity (5.4%) (Table 4).

Table 4. Distribution of research results of selected articles

Variables	Indicators	Percentage	Articles	Result
Financial performance	ROA, ROE, Net profit margin, Tobin's Q	78.4%	[1],[3],[4],[5],[6],[7],[12],[13],[15],[16],[17],[18],[19],[20],[22],[23],[24],[26],[27],[28],[29],[30],[31],[32],[33],[34],[35],[36],[37]	Significant and positive （$p<0.05$；$\beta=0.18-0.35$）
Innovation performance	Number of patents, R&D investment intensity	16.2%	[2],[8],[9],[10],[11],[14]	Significant and positive （$p<0.1$；$\beta=0.12-0.25$）
Productivity	Total Factor Productivity (TFP)	5.4%	[21],[25]	Partially significant （$p<0.05$；[25]shows $\beta=0.15$）

Note: [21] found that AI had no significant impact on TFP ($p=0.12$), which may be related to industry characteristics.

Financial performance is the dominant category, representing 78.4% of the studies. Commonly used indicators include Return on Assets (ROA), Return on Equity (ROE), Net Profit Margin, and Tobin's Q, which capture firms' profitability, operational efficiency, and market valuation. All reviewed studies within this category report a significant and positive relationship between AI adoption and improved financial outcomes, suggesting that AI technologies contribute meaningfully to enhancing enterprises' economic value.

Innovation performance was analyzed in 16.2% of all reviewed articles, primarily using patent counts and R&D investment intensity as proxies. These studies consistently found that AI positively influences firms' technological innovation capabilities by supporting intelligent design, knowledge recombination, and R&D efficiency.

Productivity is particularly measured through Total Factor Productivity (TFP), accounted for 5.4% of all reviewed articles. Results were partially significant, while one study [25] showed a positive and statistically significant effect. Another [21] found no significant impact, which the authors attributed to possible industry-level heterogeneity, and indicates the impact of AI on productivity would be more pronounced in large-size enterprises, state-owned enterprises, and labor-intensive industries.

These results provide robust evidence that AI contributes positively to financial performance, innovation performance and productivity. However, its effects may vary across industries, this study further explore its differences on industries.

3.2. Heterogeneity Analysis by Industry, Enterprise, and Technical Characteristics

Empirical research in all reviewed articles analyzed the impact of AI on financial performance based on three dimensions of contextual heterogeneity: industry attributes, enterprise attributes, and technical characteristics (Table 5).

Table 5. Industry, enterprise, and technical distribution of reviewed articles

Industry Attributes	Count	Articles
Manufacturing sector	9	[7], [8], [9], [14], [16], [18], [22], [25], [36]

AI industry	3	[5], [29], [35]
Chinese medicine industry	1	[10]
Cultural industries	1	[23]
Financial industry	1	[4]
Hospitality industry	1	[2]
IT industry	1	[12]
New energy industries	1	[15]
Power sector	1	[31]
Retail industries	1	[27]
Tourist industries	1	[19]
Enterprise Attributes		
All listed enterprises	5	[1], [3], [6], [32], [33]
State-owned enterprises	3	[11], [20], [24]
Large firms, State-owned enterprises, and Labor-intensive industries	1	[21]
Small and medium enterprises	1	[37]
Technical Characteristics		
Large firms, State-owned enterprises, and Labor-intensive industries	1	[21]
Large firms, Technology-intensive industries	1	[17]
Strategic emerging industries	1	[13]

Notes：Industry classification follows the *National Economic Industry Classification (GB/T 4754-2017)

*. Article [21] is cross-listed under multiple categories due to its dual focus on enterprise attributes and technical characteristics.

The manufacturing sector accounted for the largest proportion of studies (n=9), indicating that AI research is predominantly concentrated in industries with well-structured operations and measurable performance outcomes. Other commonly studied industries include the AI industry itself (n=3) and state-regulated sectors such as Chinese medicine, power, and finance, each represented by a limited number of studies (n=1). Sectors like tourism, cultural industries, and retail remain underrepresented, highlighting a need for more diversified industry-focused research.

In terms of enterprise attributes, listed enterprises were the primary focus in five studies, followed by state-owned enterprises (n=3). One study each examined small and medium enterprises (SMEs) and large firms. This distribution suggests a bias toward firms with public financial disclosures and available performance data, while SMEs and private firms are less frequently examined due to potential data limitations.

With respect to technical characteristics, only one study each has investigated technology-intensive, labor-intensive, and strategically-oriented enterprises. Among the reviewed articles, only one study analyzed large technology-intensive companies, while another focused on state-owned, large, and labor-intensive enterprises. This limited scope indicates that, despite theoretical support from the resource-based view (RBV) and dynamic capabilities theory, which suggest that the strategic value of AI depends on a company's specific technological readiness and absorptive capacity, existing research has not fully addressed the impact of technological heterogeneity on the relationship between AI and performance.

While most studies confirm a significant positive relationship between AI and firm performance, the evidence also suggests considerable heterogeneity across different industry backgrounds. This difference suggests that the economic benefits of AI technology are not evenly distributed across industries, but are influenced by industry-specific characteristics.

Specifically, research focused on manufacturing consistently found significant improvements in financial, operational and innovation performance with the adoption of AI. With its standardized processes, high capital intensity, and strong data infrastructure, manufacturing enterprises can take full advantage of AI to automate, predictive maintenance, and supply chain optimization, resulting in measurable performance improvements.

In contrast, studies focusing on industries such as tourism, cultural industries, hotels, retail and traditional Chinese medicine have produced more mixed or less robust results. These industries are characterized by high service intensity, customer interaction dependence and low digital maturity, which may limit the scope and directness of AI performance impact. The relatively low representation of these industries in the literature further underscores the need for caution when generalizing the impact of AI across all industries. In addition, in strategic emerging industries and technology-intensive enterprises, there are different impacts, indicating that technological readiness and innovation orientation play a key role in the effectiveness of AI. Companies operating in highly dynamic, knowledge-driven industries can reap greater performance gains from AI by improving R&D efficiency and accelerating product innovation cycles.

Overall, industry attributes (such as digital infrastructure, operational complexity, innovation dependence, and service orientation) influence the relationship between AI and firm performance.

4. DISCUSSION

It This study systematically reviewed 37 empirical articles to assess the impact of artificial intelligence (AI) adoption on enterprise performance. The results clearly show that AI has a significant and positive impact on firm performance, especially financial performance, innovation performance, and productivity. However, the results also reveal that there is heterogeneity in the relationship between AI and firm performance.

4.1. The Impact of AI on Financial Performance

This study shows through a review that AI technology has a positive impact on corporate performance in multiple dimensions, including financial performance, innovation performance and productivity. Many studies have consistently confirmed the significant positive impact of AI applications on performance, especially on financial indicators such as ROA, ROE, net profit margin and Tobin's Q (Ma et al., 2025; X. Xu et al., 2025). Financial performance emerged as the most frequently examined dimension, representing 78.4% of the reviewed studies. Indicators such as Return on Assets (ROA), Return on Equity (ROE), net profit margin, and Tobin's Q consistently reflected improved profitability, operational efficiency, and market valuation following AI implementation. This highlights the key role of AI in enhancing the economic value creation of enterprises. 16.2% of the studies involved innovation performance, which also showed a consistent positive impact, indicating that AI promotes technological progress in companies by facilitating intelligent design, facilitating knowledge reorganization and improving R&D productivity (C. Liu, 2024; Zhai & Liu, 2023).

Performance is measured by total factor productivity (TFP), and the productivity is discussed in two articles and shows different results. While one study showed a positive relationship between AI and productivity [21], another found no significant effect [25], suggesting that industry attributes and enterprise attributes may influence the relationship between AI and productivity.

These findings provide robust empirical support that AI adoption contributes meaningfully to improving firms' financial, innovation, and productivity outcomes. Nevertheless, the evidence also indicates that the extent to which AI benefits varies by industry, company type and technology. Therefore, it is necessary to investigate in depth how industry structure, organizational size and technical capabilities affect the realization of AI-driven performance improvement. Future research should focus more on the heterogeneity to further deepen the understanding of the strategic value of AI in different enterprises.

4.2. Heterogeneity Analysis by Industry, Enterprise, and Technical Characteristics

In all reviewed articles, Effect size（Financial performance β= 0.18-0.35; Innovation performance β =0.12-0.25） shows that AI technology has made a significant contribution to improving the economic results of enterprises. However, there may be great heterogeneity in industry attributes, enterprise size and technology level. This heterogeneity is manifested in three main dimensions, including industry attributes, enterprise characteristics and technology level.

First, relevant research based on different industries highlights that manufacturing companies benefit the most from the use of AI technology because they have a structured operating environment, higher levels of digital maturity, and standardized processes that facilitate the effective integration of AI technology (G. Zhang & Lee, 2021). In contrast, the growth of firm performance in industries characterized by high service intensity and low levels of digital infrastructure (such as tourism, cultural industries, hotels and retail) has been more limited or inconsistent [23][27][31]. For firm performance, these findings suggest that the effectiveness of AI technology rely on factors such as process standardization, data availability and technology.

Second, Enterprise attributes will also mitigate the impact of AI. The study focused on listed companies and state-owned enterprises, which typically have stronger financial resources, stronger regulatory compliance, and higher levels of organizational digitization (Ma et al., 2025; Zeng et al., 2022; Zhai & Liu, 2023; Y. Zhang et al., 2023). In contrast, there is limited research on SMEs, which suggests that there may be a serious research gap. Based on the financial and technical resource constraints of SMEs, there would be differences in return of investment on AI between SMEs and large organizations (Huang & Xiao, 2021).

Third, the analysis based on the technical characteristics of enterprises shows that companies operating in technology-intensive or strategic emerging industries tend to achieve greater performance improvement through AI (Tan & Wei, 2022; X. Xu et al., 2025). This supports the theoretical expectations of the resource-based view (RBV) and dynamic capability (DC) theory, which holds that companies with strong absorptive learning ability and innovation orientation are more capable of capturing the strategic value of AI (Sun & Jiao, 2024; X. Xu et al., 2025).

Overall, these findings suggest that while AI can significantly improve corporate performance, the extent and path of its impact will largely depend on the environment. Industry attributes, enterprises size, technology maturity and strategic orientation play a key role in shaping the realized returns of AI investments. Large firms, State-owned enterprises and Technology-intensive industries use AI technology in the operating process, can more significantly improve firm performance and create higher economic value. However, for non-state-owned, private enterprises and enterprises with lower technology level, the economic value brought by AI may not cover their cost expenditure, AI application will bring more financial burden for them.

5. CONCLUSION AND IMPLICATIONS

This review demonstrates that artificial intelligence (AI) has a dual impact on the economic performance of Chinese enterprises. On the one hand, AI adoption enhances productivity by optimizing resource allocation, streamlining operational processes, and fostering innovation. On the other hand, the technological gap would widen performance disparities among enterprises. The results further reveal that industry, enterprise, and technical Characteristics are key factors affecting the effectiveness of AI applications. Companies with advanced digital infrastructure, larger scale and innovation-driven strategies are better able to leverage AI to create economic value.

There are several policy interventions are recommended to maximize the inclusive benefits of AI and mitigate emerging inequalities. The government can implement subsidy programs and provide technical support to reduce barriers for SMEs to adopt AI. Government should strengthen AI-related skills training programs to reduce the technical talent differences in different companies and regions. Investments in digital infrastructure development should give priority to landlocked and less developed regions to address regional differences in AI application readiness. In addition, companies should respond to AI-driven opportunities and challenges through strategic practices, encouraging traditional industries to prioritize investment in AI infrastructure and employee skills to adapt to the digital economy shift. Small and medium-sized enterprises can enhance their AI capabilities by partnering with tech giants, universities or research institutions to gain technical expertise and innovative resources.

6. LIMITATIONS

This study relies on the systematic literature review method, and the literature sources are mainly from WOS, Scopus and CNKI databases, covering the relevant studies from 2019 to 2025. Although these databases are broadly representative, they may miss out on the latest research in some non-academic publications. This study is mainly based on the theoretical and empirical results of existing literature, and does not directly carry out the original data analysis for Chinese listed enterprises. This may limit the in-depth discussion of the specific causal relationship between AI technology and enterprise performance, especially in terms of quantifying performance differences and long-term effects. Therefore, future research can combine the original data to carry out empirical research, focusing on AI application of unlisted enterprises or specific regions, and enhance the representativeness of samples.

This study mainly focuses on Chinese listed enterprises, but listed enterprises are usually better than non-listed enterprises in capital, technology and digitalization level, so they may not fully represent the AI application situation of Chinese enterprises as a whole. In particular, the performance of AI applications in small and medium-sized enterprises and unlisted companies in traditional industries may be underestimated. Although this study considers the heterogeneity of industries and enterprise sizes, the analysis of other dimensions, such as regional differences, types of enterprise ownership, and segmentation of AI technology types, is limited. This may lead to an incomplete understanding of the performance differences of AI applications. Future research can further explore the differences in regions, ownership or types of AI technologies to build a more refined analytical framework. This study provides a new perspective to understand the differences in enterprise performance driven by AI, and provides operational suggestions for policy makers.

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

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