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PAPER

The Mediating Role of Resource Allocation Optimization in AI-Enhanced Corporate Performance: An Integrated Framework

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ABSTRACT

The application of artificial intelligence (AI) is a key factor to promote the sustainable development of the global economy. Based on the panel data of A-share listed companies from 2001 to 2022, this study explores the promoting effect and influence mechanism of AI on the business performance of high-tech enterprises. The study found that the development of AI technology effectively improves the business performance of high-tech enterprises. Mechanism analysis shows that AI technology can improve the overall operating performance of enterprises by improving the mechanism of enterprise factor structure. Further analysis shows that there are significant regional differences in the business performance of enterprises, with the strongest positive impact on high-tech enterprises in the eastern region. This study enriches the research on the influencing factors of the business performance of high-tech enterprises and provides reference for improving the business performance of high-tech enterprises, strengthening the data-driven policy, and building a perfect AI system.

KEYWORDS

artificial intelligence (AI) application, high-tech enterprise, business performance, factor structure optimization

1 INTRODUCTION

As the application of technological achievements under the background of the development of new information technology, artificial intelligence (AI) has significantly promoted society's high-quality development and enterprise business performance improvement. The scientific and technological revolution accelerates information technology application in global production and promotes countries around the world to pay continuous attention to AI policy formulation and technology research and development. The cooperation and collaboration between human beings and AI has become a new research paradigm for human intelligence

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cooperation in the future. How to give full play to AI, a resource of huge commercial interests, is not only related to the global application field of technical cooperation but also provides an important guarantee for enterprises to improve management efficiency. Based on this, on the theoretical basis of combing the literature related to AI and enterprise performance, this paper selects the panel data of A-share listed companies from 2001 to 2022 as sample data to carry out empirical exploration on the above research issues. This study enriches the quantitative research on enterprise performance under the background of AI. The research conclusions provide theoretical support and experience reference for the development of AI in China and the promotion effect of the performance of high-tech enterprises and provide reference for promoting the intelligence and "going out" of China's high-tech enterprises.

2 LITERATURE REVIEW

The academic community remains divided on AI's conceptualization, with some scholars emphasizing its technical integration (e.g., AI as a fusion of IoT, big data, and cloud computing) (Halbusi and Sulaiti, 2024) [1], while others highlight its strategic role in mimicking human cognition through machine learning (Gupta and Lakhera, 2024) [2]. Economically, AI's impact is debated: one camp argues it exacerbates skill-based income inequality (Amran and Syahid, 2024; Ali & Khan, 2024) [3, 4], whereas another posits stage-dependent effects, where automation's maturity dictates labor market outcomes (Hémous and Olsen, 2015) [5]. Strategic management research underscores how technology strategies—spanning R&D investment, intellectual property protection, and external collaboration—shape high-tech startups' performance (Zahra and Bogner, 2000) [6], with policy interventions (Spatola, 2024) [7] and fuzzy evaluation methods (Mughari, 2024) [8] further influencing industrial upgrading and resource allocation.

3 THEORETICAL HYPOTHESIS

3.1 Direct influence

The application of AI in high-tech enterprises reduces the communication cost of enterprises, accelerates the rapid flow of information within enterprises, promotes the realization of unmanned management in enterprises, builds a flat management framework, and reduces redundant supervision links (Autor, 2017) [12]. The theory of intelligent manufacturing points out that intelligent manufacturing is a technology that uses AI, big data, the Internet of things and other new technologies and new methods to carry out manufacturing production management and decision support. From the perspective of display, intelligent manufacturing is not only reflected in the intelligent production process but also in the organizational management to achieve the improvement of enterprise business performance (Bob, 2023) [13].

Based on this, the following hypothesis is proposed:

- H1: The development of AI technology has effectively improved the business performance of high-tech enterprises.
- H1a: The development of AI technology has effectively improved the operating productivity of high-tech enterprises.
- H1b: The development of AI technology has effectively improved the operational output efficiency of high-tech enterprises.

3.2 Regional heterogeneity

Artificial intelligence development in China shows regional differences. The eastern region has advantages in the digital economy and infrastructure. The impact of AI on high-tech enterprise business performance also varies regionally. In developed regions, high education levels and infrastructure can meet high-tech enterprise needs, boosting performance. In contrast, central and western regions face limitations. Based on this, this paper proposes the following assumptions:

H2: The development of AI technology affects the business performance of high-tech enterprises with regional heterogeneity; that is, it has a more obvious effect on the promotion of enterprises in eastern China.

3.3 Elements intermediary mechanism

The introduction of AI will promote high-tech enterprises to invest more human resources to adapt to the market demand and technological changes so as to optimize the allocation structure of human resources, improve the production efficiency of enterprises, and promote the development of business performance of high-tech enterprises. Under the combined action of capital and optimal allocation of human resources, the introduction of AI promotes high-tech enterprises to invest more knowledge capital, human capital, and other capital factors and reduces the relative input in ordinary labor factors (Stefan et al., 2023) [14], so as to accelerate the process of capital replacing labor in high-tech enterprises.

H3: Factor structure optimization has all (part) intermediary effects in the process of AI affecting the business performance of high-tech enterprises.

4 RESEARCH DESIGN

4.1 Model design

In order to investigate the influence of AI on high-tech enterprises, that is, whether the test hypothesis 1 is valid, in this paper, the two-way fixed effect model of each enterprise and each year is constructed as the benchmark model. The specific setting is as follows:

$$ROA_{\mathrm{it}} = \varphi + \alpha_1 AI_{\mathrm{it}} + \alpha_2 \mathrm{Controls}_{\mathrm{it}} + \mathrm{year}_{\mathrm{i}} + \mathrm{individual}_{\mathrm{t}} + \varepsilon_{\mathrm{it}} \tag{1}$$

$$TFP\_GMM_{\mathrm{it}} = \varphi + \alpha_1 AI_{\mathrm{it}} + \alpha_2 \mathrm{Controls}_{\mathrm{it}} + \mathrm{year}_{\mathrm{i}} + \mathrm{individual}_{\mathrm{t}} + \varepsilon_{\mathrm{it}} \tag{2}$$

ROA represents the return on assets (ROA) of the high-tech enterprise at year t, Measure how much net profit generated per unit of asset; TFP_GMM_{it} represents the total factor productivity of high-tech enterprise at t year, is a measure of economic productivity, and represents the amount of output produced by a unit of production; AI represents the AI-application scale of high-tech enterprise at year t, to measure the degree of AI in high-tech enterprises, controls it is the control variable, φ is a constant term, α_1, α_2 are the parameters to be estimated, $\varepsilon_{\mathrm{it}}$ is the random disturbance term, The year, and individual represent years and fixed effects for various high-tech enterprises respectively.

Building on the methodology proposed by Lee et al. (2020) [15], this study employs a mediation model to examine the underlying mechanism through which AI adoption enhances business performance in high-tech enterprises. Specifically, we test the hypothesized causal chain: 'AI capability level → factor structure optimization → enterprise performance' to verify Hypothesis 2. Accordingly, we extend the baseline model (1) by constructing two additional measurement models:

$$M_{it} = \varphi + \beta_1 AI_{it} + \beta_2 X_{it} + \eta_t + \mu_i + \varepsilon_{it} \tag{3}$$

$$ROA_{it} = \varphi + \gamma_1 AI_{it} + \gamma_2 M_{it} + \gamma_3 X_{it} + \eta_t + \mu_i + \varepsilon_{it} \tag{4}$$

$$TFP\_GMM_{it} = \varphi + \lambda_1 AI_{it} + \lambda_2 M_{it} + \lambda_3 X_{it} + \eta_t + \mu_i + \varepsilon_{it} \tag{5}$$

Among them, M_{it} is the intermediary variable, β and γ_2, λ_2 is the new parameter to be estimated, and the other settings are the same as models (1) and (2). If both β and γ_2, λ_2 are significantly positive, it means that the mechanism of AI to promote the development level of business performance of high-tech enterprises through the optimization of factor structure exists; otherwise, if both β and γ_2, λ_2 are significantly negative, it means that AI hinders the development of business performance of high-tech enterprises through the optimization of structural elements.

4.2 Selection of indicators and data description

This study utilizes panel data from A-share listed high-tech enterprises spanning 2001 to 2022, sourced from the CSMAR database. After excluding ST/*ST companies and those with abnormal or missing data, our final sample comprises 536 listed companies yielding 20,696 observations. The dependent variables measuring business performance include: (1) ROA, calculated as net profit divided by average total assets, and (2) TFP_GMM (Total Factor Productivity) estimated using the Levinsohn-Petrin method (Lu, 2018; Sun, 2017) [16, 17]. Our core independent variable, AI adoption, is operationalized through patent analysis, specifically counting each firm's patents containing 'automatic' or 'artificial intelligence' in their titles (Badghish, 2024) [11]. The mediating variable, factor structure optimization (STRU), is measured by the capital-to-labor ratio, reflecting the shift toward knowledge-intensive production (Harandi et al., 2025) [18]. We control for nine firm-level characteristics: Size (natural log of total assets), Lev (leverage ratio), Liquid (liquidity ratio), cash flow (operating cash flow ratio), INV (inventory ratio), FIXED (fixed assets ratio), Intangible (intangible assets ratio), Invest1 (long-term investment ratio), and TOP5 (ownership concentration ratio). All financial and accounting data are obtained from the CSMAR database, ensuring consistency and reliability in our measurements. This comprehensive research design enables us to rigorously examine the relationship between AI adoption and business performance while accounting for key firm characteristics and production factor dynamics.

Descriptive statistics of the data are shown in Table 1. From the specific value, we can find that the average value of AI is 2.228, the standard deviation is 15.076, the minimum value is 0, and the maximum value is 902, reflecting that the overall level of AI of high-tech enterprises is at a high level, but there are obvious differences in the level of AI among enterprises.

Table 1. Descriptive statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
AI1	20,695	2.228	15.076	0	902
Size	20,695	21.929	1.168	19.178	28.273
Lev	20,695	.381	.185	.008	.99
Liquid	20,695	2.911	3.87	.106	190.869
INV	20,596	.134	.088	0	.821
FIXED	20,695	.205	.134	0	.838
Intangible	20,683	.039	.034	0	.453
Invest1	20,692	.069	.079	0	3.713
TOP5	20,227	52.879	14.694	6.908	99.23

5 EMPIRICAL ANALYSIS

In order to consider the influence of AI on the operation performance of high-tech enterprises, this paper first estimates the two-way fixed effect model, then tests the stability of changing the mathematical model, changing the sample interval, and eliminating the outlier in the model and tests the sample heterogeneity. Finally, the influence of AI on the operation performance of high-tech enterprises is tested from the optimization of factor structure.

5.1 Benchmark regression

Table 2 reports the benchmark regression results of the impact of AI on business, performance and productivity of high-tech enterprises. In the absence of TNE and TY, the positive effect of in AI on ROA and TFP_GMM was significant at 5%; see columns (1) and (3). The results show that the development of AI significantly promotes the business performance and production efficiency of high-tech enterprises.

Further, the positive effect of in AI on ROA and TFP_GMM, with the introduction of control variables, is still significant in columns (2) and (4), thus testing hypothesis 1. In terms of the control variables, In terms of economic efficiency, The correlation coefficients of the enterprise size (size), cash flow ratio (cash flow), INV (Invest1) of fixed assets, intangible assets and other long-term assets to the total assets at the beginning of the period, the ratio of the number of shares held by the top five shareholders of the enterprise (TOP5) are 0.0120, 0.369, 0.0878, 0.0132, 0.000726, respectively, Both are positive numbers, The results show that these variables have a positive effect on the business performance of enterprises; the correlation coefficients of asset-liability ratio (Lev), current ratio (Liquid), proportion of fixed assets (FIXED) and proportion of intangible assets (Intangible) are –0.147, –0.00103, –0.0828, –0.150, respectively. Both are negative numbers, The results show that these variables have negative effects on business performance; from the perspective of enterprise production efficiency, The enterprise size (Size), asset-liability ratio (Lev), cash flow ratio (cash flow), INV, and the ratio of the number of shares held by the top five shareholders to the total number of shares (TOP5) all have a positive effect; The current ratio (Liquid), the ratio of fixed assets (FIXED), the ratio of intangible assets (Intangible), and the ratio of cash paid by other long-term assets to the total assets at the beginning (Invest1) all have a negative effect.

Table 2. Benchmark regression results

Variables	(1)	(2)	(3)	(4)
	ROA	ROA	TFP_GMM	TFP_GMM
lnAI1	0.00181**	0.00164**	0.0211***	0.0201***
	(0.000905)	(0.000780)	(0.00581)	(0.00471)
Size		0.0120***		0.355***
		(0.00107)		(0.00862)
Lev		–0.147***		0.167***
		(0.00681)		(0.0451)
Liquid		–0.00103***		–0.0137***
		(0.000258)		(0.00161)
Cashflow		0.369***		1.003***
		(0.0117)		(0.0697)
INV		0.0878***		0.584***
		(0.0118)		(0.0822)
FIXED		–0.0828***		–1.830***
		(0.00803)		(0.0579)
Intangible		–0.150***		–0.873***
		(0.0269)		(0.175)
Invest1		0.132***		–0.331***
		(0.0107)		(0.0688)
TOP5		0.000726***		0.00152***
		(6.91e-05)		(0.000526)
Constant	0.0572***	–0.213***	4.197***	–2.351***
	(0.00938)	(0.0232)	(0.0584)	(0.182)
Year&Ind	yes	yes	yes	yes
Observations	5,600	5,489	5,444	5,337
Number of id	1,739	1,730	1,687	1,678

Note: ***p < 0.01, **p < 0.05, *p < 0.1.

5.2 Robustness test

In order to test whether the promoting effect of AI on the business performance of high-tech enterprises is stable, this paper carries out a robustness analysis from the following aspects.

1. Change the mathematical model. Above the adopted measurement model for multiple panel OLS regression model, in order to eliminate the influence of AI on the performance of high-tech enterprises, this paper introduces a heteroscedastic

regression model to investigate the influence of AI on the high-tech enterprise business performance. The estimated results in Table 2 column (1) and (2), can be seen in the condition of replacement model of in AI on ROA and TFP_GMM direction and significance did not change significantly, this shows that the benchmark regression results have certain reliability.

2. Change of the explained variable. Since ROA and TFP_GMM may also affect the results of benchmark regression due to the measurement method of ROA and TFP_GMM, the ROA variable and TFP value based on LP method, and the estimated results are shown in Table 3 columns (3) and (4). It can be seen that the significance of the two new indicators is not affected, and the original benchmark results are reliable.
3. Eliminate the outliers. In order to minimize the potential impact of the end value on the regression results, 1% bilateral tail reduction of the explained variables ROA and TFP_GMM and the core explanatory variables in AI were presented in Table 3 (5) and (6). The results show that even with the bilateral tail reduction treatment, the positive impact of AI on business performance is still significant.
4. Endogeneity test. Although the benchmark regression results show that AI can promote the development of the business performance of high-tech enterprises, the development of the business performance of high-tech enterprises will promote the development of the whole society and economy and then increase the investment in AI, so the two have endogenous problems of mutual causality. To solve the endogenous problem, This paper refers to the practice of Huang Zhi (2021) [19] and Qu Xiaobo et al. (2024) [20], The in AI with lag phase was selected as the instrumental variable to examine the correlation condition between the instrumental variables, The estimated results are shown in columns (7) and (8) in Table 3, The positive effect of the lagging first phase of in AI on ROA and TFP_GMM was still significant at the statistical level of 10%, thus it can be seen, The benchmark regression model does not have serious problems of endogeneity testing, the results are reliable.

Table 3. Robustness test

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Heteroscedastic Regression		Change of the Explained Variable		Eliminate Outliers		Endurance Test	
	ROA	TFP_GMM	ROA	TFP_LP	ROA	TFP_GMM	ROA	TFP_GMM
lnAI1	0.00154*	0.0623***	0.00335**	0.0212***	0.00153*	0.0201***		
	(0.000864)	(0.00890)	(0.00163)	(0.00583)	(0.000787)	(0.00578)		
L.lnAI1							0.00148*	0.0172***
							(0.000850)	(0.00606)
Constant	0.0499***	5.401***	0.0666***	5.068***	0.0570***	4.247***	0.0474***	4.438***
	(0.00141)	(0.0146)	(0.0174)	(0.0588)	(0.00806)	(0.0573)	(0.00811)	(0.0568)
Controls	Control	Control	Control	Control	Control	Control	Control	Control
Year and Ind	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5,600	5,444	5,600	5,444	5,600	5,444	4,800	4,774
Number of id	1,739	1,739	1,739	1,687	1,739	1,687	1,509	1,502

Note: ***p < 0.01, **p < 0.05, *p < 0.1.

5.3 Heterogeneity test

Table 4 shows the differential impact of AI on the business performance of high-tech enterprises after grouping according to different regions. In general, ROA and TFP_GMM are significantly different in the presence of AI in different regions. In terms of business performance, The AI coefficient in the western and central regions was not significant, The possible reason is that there is still a lag of economic development in the central and western regions, The technical effect brought by AI has not been effectively transformed into the business performance of enterprises; by comparison, ROA in the eastern region has benefited significantly from the use of AI, Its coefficient was significantly 0.00189, indicating that in this region, AI technology development, by improving the efficiency of information transmission, reduce labor intensity or optimize workflow, Promoted the business performance of high-tech enterprises by 0.189%, On the Enterprise TFP_GMM, A similar situation also exists, That is, the central and western regions are not significant, While the coefficient in the eastern region was significantly 0.0200, Verified that hypothesis 3, high-tech enterprises in the eastern region have relatively rich technical infrastructure and resources in the process of development. In particular, in terms of production efficiency, the application of AI has played an important role in influencing the growth of high-tech enterprises.

Table 4. Heterogeneity test

Variables	(1)	(2)	(3)	(4)	(5)	(6)
	East		West		Mid	
	ROA	TFP_GMM	ROA	TFP_GMM	ROA	TFP_GMM
lnAI1	0.00189*	0.0200***	0.000366	0.0217	0.00258	0.0248
	(0.000967)	(0.00695)	(0.00170)	(0.0132)	(0.00227)	(0.0165)
Constant	0.0669***	4.448***	0.0525***	4.237***	0.0186	3.523***
	(0.0119)	(0.0811)	(0.0129)	(0.101)	(0.0208)	(0.159)
Controls	Control	Control	Control	Control	Control	Control
Year&Ind	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4,014	3,884	972	955	613	604
Number of id	1,340	1,295	249	245	156	153

5.4 Mechanism test

According to the above analysis, AI can significantly promote the business performance and production efficiency of high-tech enterprises, and this role is robust. On this basis, this paper further analyzes the role mechanism behind the influence of AI on the business performance of high-tech enterprises. Referring to the research of Ihor et al. (2025) [21], this paper uses the mediation effect model to reveal the internal influence mechanism of this driving effect from the factor structure optimization (M1).

Table 5 reports the test results of the intermediary mechanism of ‘AI ---> factor structure optimization ---> business performance development of high-tech enterprises,' and the estimated results are shown in columns (1), (2), and (3). It can be seen that AI has a significant positive effect on M1. The result shows that AI can promote high-tech enterprises to use capital to replace the labor force and promote high-tech enterprises to develop in the capital-intensive direction so as to improve the capital-labor ratio of enterprises and optimize the structure of factor input. According to the estimated results of columns (2) and (3), M1 has a significant positive impact on ROA and TFP_GMM, indicating that the mechanism of AI application to promote the business performance development of high-tech enterprises through the improvement of capital-labor ratio (structural factor optimization) exists, which verifies hypothesis 3.

Table 5. Mechanistic testing

Variables	(1)	(2)	(3)
	Structure	TFP_GMM	ROA
structure		0.000948***	5.30e-05***
		(3.74e-05)	(5.59e-06)
lnAI1	11.50***	0.0267***	0.000330
	(2.967)	(0.00696)	(0.00103)
Constant	221.5***	5.221***	0.0389***
	(4.115)	(0.0127)	(0.00189)
Observations	5,599	5,444	5,599
R-squared	0.004	0.151	0.023
Number of id	1,738	1,687	1,738

Note: ***p < 0.01, **p < 0.05, *p < 0.1.

6 AUTHORSHIP

All authors contributed to the conception and design of the study.

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