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Artificial Intelligence Application and Enterprise Competitive Advantage

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Abstract. Significant differences have been observed in the application effects of Artificial Intelligence technology across industries, which has widened the "Digital divide" among enterprises. Using data from A-share listed companies spanning 2008 to 2023, this study employs the Two-way fixed effects model to examine how AI applications influence Enterprise competitive advantage and to investigate the moderating role of Enterprise attributes (specifically high-tech and technology-intensive industries). The results indicate that AI applications significantly boost Enterprise competitive advantage, with a more pronounced positive impact observed for High-tech enterprises and Technology-intensive enterprises. In terms of mechanism, AI exerts its effects through three channels: enhancing Operational efficiency, driving innovation, and strengthening Market response ability.This study offers a theoretical foundation for enterprises with different attributes to develop tailored AI strategy, which helps reduce the Gap in the distribution of technological dividends.

Keywords: Artificial Intelligence, Enterprise competitive advantage, Enterprise attributes, Moderating effect, Mechanism analysis

1. Introduction

Against the backdrop of the fast-growing Digital economy, Artificial Intelligence technology is widely recognized as a key driver behind Industrial transformation and Economic growth [1]. Yet, the outcomes of AI technology applications vary greatly across industries. As noted in a report by the McKinsey Global Institute, AI projects in the high-tech sector achieve a return on investment of 15% to 20%, whereas this rate drops to approximately 5% in the Traditional manufacturing industry [2].The uneven distribution of such technological dividends has not only widened the "Digital divide" between companies but also left many traditional industries stuck in the situation where "they adopt new technologies but fail to boost their competitiveness effectively". For example, while the AI production scheduling system could theoretically cut the Delivery cycle in manufacturing down to 36 hours, most Small and medium-sized enterprises find it hard to integrate the technology well because of their poor Data foundation and inflexible Organizational processes [3]. As a result, figuring out how AI can work differently for businesses with various characteristics has become an important and pressing problem to solve in today's Digital economy age.

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Enterprise competitiveness serves as the key driver behind High-quality economic development, and its strength has a direct impact on a nation's Industrial structure upgrading and Long-term growth quality [4]. In today's environment of growing Global competition, the ability of businesses to build Sustainable competitive advantage through Technological innovation has become especially critical. Yet the widespread "AI productivity paradox" in real-world settings is perplexing: despite heavy investments by many companies in AI technology, they have not seen the expected gains in efficiency or profits [5]. According to the World Bank, the key issue behind this paradox is whether enterprises have the right Organizational capabilities and Resource endowment to match their AI technologies [4]. Therefore, gaining a deeper understanding of how AI technology impacts Enterprise competitiveness will be theoretically and practically valuable for overcoming the Transformation dilemma characterized by "high input but low output".Most existing studies have focused on examining how AI technology directly affects business efficiency, productivity, or innovation. However, they have generally overlooked the important role that Enterprise attributes might play in regulating the AI empowerment process. Without considering this angle, AI application strategies lack clear direction, which in turn makes the distribution of technical resources across different types of companies more uneven. In reality, High-tech enterprises like Huawei usually have better Data infrastructure and stronger Technology absorption capacity, allowing them to fully implement Complex AI systems. On the other hand, Traditional enterprises face limitations from Process rigidity and Resource constraints, so they often depend more on Lightweight and scenario-based solutions.If enterprises ignore this fundamental difference and blindly adopt the High-end technology route, they will not only struggle to boost Enterprise competitiveness but also risk causing significant resource waste and Technology adaptation failure.

The research value of this paper is mainly reflected in two aspects:

Theoretical significance: By integrating the Resource-based view and Organizational fit theory, this paper develops a "Enterprise attributes - AI fit - Competitive advantage" Three-dimensional analysis framework. This framework systematically reveals how enterprise attributes influence the acquisition and maintenance of competitive advantage by affecting the degree of adaptation of AI technology. It addresses the research gaps in existing literature regarding organizational adaptability and broadens the theoretical meaning of Enterprise competitive advantage in the AI era.Practical significance: The differentiated paths of AI application among enterprises with different attributes are identified in this paper, which provides a basis for enterprises to formulate precise AI implementation strategies. This helps ease the Resource misallocation issue arising from Technology differentiation, promotes deep integration between Traditional industries and Digital technologies, and ultimately achieves High-quality economic development.

2. Literature review

2.1. Definition and influencing factors of enterprise competitiveness

Enterprise competitiveness refers to the core capability of enterprises to gain and maintain competitive advantage in the market. Existing studies mainly define it from two perspectives: Resource-based view and dynamic capability theory. pointed out that in the digital era, the connotation of Enterprise competitiveness has shifted from static resource advantage to dynamic capability construction, emphasizing rapid response to market changes and efficient integration of digital resources [3]. Through empirical research, Li Jinchang et al. showed that enterprises need to reconstruct value chains through Technological innovation to form differentiated competitive advantage [6]. These studies provide important perspectives for understanding competitiveness in

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the digital era, but they have not systematically explored how emerging technologies such as Artificial Intelligence reshape enterprises' dynamic capabilities, especially neglecting the specific boundary conditions and adaptation mechanisms required for AI to enhance the competitiveness of traditional industries. This also partially explains the productivity paradox of "high AI investment but low output" in practice .

2.2. Research status of artificial intelligence technology

Current research on Artificial Intelligence technology mainly focuses on two levels: technical principles and industry applications. At the technical level, Acemoglu & Restrepo emphasize that AI improves production efficiency through automation and enhanced decision-making, but its effectiveness varies depending on the industry Data foundation and technological maturity [7]; at the application level, Brynjolfsson & McAfee have verified the efficiency-enhancing potential of AI in scenarios such as predictive maintenance in the manufacturing industry [8]. However, these studies generally imply the "technology universality" assumption, that is, they assume that AI technology has the same mechanism of action in different types of enterprises, ignoring the moderating effect of Enterprise attributes such as industry type and digital foundation on the application effect of AI.Practical evidence shows that High-tech enterprises can quickly deploy full-process AI systems by virtue of their well-developed Data infrastructure and talent reserves, while Small and medium-sized enterprises in the Traditional manufacturing industry are more dependent on lightweight tools due to rigid processes and resource constraints. This difference clearly indicates that the enabling effect of AI is highly dependent on the attribute characteristics of the enterprises themselves, rather than a one-size-fits-all approach.

2.3. Research review and limitations

Although existing literature provides an important foundation for understanding the relationship between AI technology and Enterprise competitiveness, there are still the following two major limitations:

First, excessive focus on technology itself while neglecting organizational adaptability. Most studies start from the perspective of technological determinism, assuming that the introduction of AI technology can naturally enhance Enterprise competitiveness, but fail to deeply explore whether enterprise organizational structure, culture, processes, etc. match AI technology [9].This perspective leads to misjudgment of the actual effectiveness of AI. For instance, some enterprises face the dilemma of "high AI investment but low output" due to insufficient organizational adaptation.

Second, There is a lack of systematic research on the moderating effect of Enterprise attributes [10]. Existing literature rarely compares the differences in AI application between high-tech enterprises and Traditional enterprises, resulting in fragmented research on the AI empowerment mechanism. For example, High-tech enterprises achieve full-process intelligence through AI, while Traditional enterprises can only pilot applications in specific links. Such differences have not been fully incorporated into theoretical frameworks.

Therefore, by revealing the moderating effect of Enterprise attributes on AI technology's empowerment of Enterprise competitiveness, this paper fills the gap in existing research regarding the interactive relationship among "technology-organization-attributes" and provides a more complete theoretical perspective for understanding competitive advantage in the digital era.III. Mechanism analysis

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3. Research hypotheses

Existing studies have extensively explored the impact of Technological innovation on corporate performance and competitive advantage. At the macro level, scholars focus on how technological development laws, industrial policies, and infrastructure upgrades shape the corporate competitive environment; at the micro level, studies concentrate on the role of internal corporate factors in technological absorption and application capabilities, which ultimately affect enterprises' market position and profitability. These "macro-micro" perspective studies provide an important foundation for understanding the sources of Enterprise competitive advantage.

However, in the digital era, the key to enterprises' ability to Continued maintain competitive advantage lies in their "dynamic capabilities".As one of the most transformative technologies, Artificial Intelligence does not have a universal impact on Enterprise competitive advantage; instead, it is highly dependent on the enterprise's own attribute characteristics. These attributes not only constitute the specific environment for the implementation of Artificial Intelligence technology but also determine the depth, breadth, and form of technology application. Studies have shown that the successful empowerment of enterprises by Artificial Intelligence technology is highly dependent on its degree of matching with existing production processes, Data foundation, and organizational management capabilities.

Combined with the actual situation of Chinese enterprises, the promotion effect of Artificial Intelligence technology is significantly constrained by the enterprises' own conditions: there are huge differences in technology maturity and data availability across different industries; enterprises of different scales have vastly different capabilities in bearing transformation costs and cultivating talents; the investment enterprises have made in information system construction and data management in the past directly determines whether Artificial Intelligence can be effectively integrated into the existing operational system.Therefore, the technology adaptability, resource conditions, and organizational management capabilities determined by Enterprise attributes are the key factors determining whether Artificial Intelligence can effectively improve enterprise efficiency, drive innovation, and enhance Market response ability.

Based on the above analysis, this paper focuses on the moderating effect of Enterprise attributes to explore how it affects the effect and mechanism of Artificial Intelligence technology in enhancing Enterprise competitive advantage. Specifically, Enterprise attributes further influences its enabling effects in the three dimensions of efficiency, innovation, and market by determining the adaptability of Artificial Intelligence technology:

3.1. Efficiency improvement mechanism

The effective application of Artificial Intelligence technology can significantly optimize production processes and supply chains management, reduce operational costs, and form cost advantages. The empirical study by Yao Jiaquan et al. shows that manufacturing enterprises' application of AI predictive maintenance can reduce downtime losses by 15% [3]. The theoretical logic lies in that AI improves overall Operational efficiency by compressing auxiliary activity costs such as equipment maintenance and inventory management. This improvement in efficiency is one of the most direct manifestations of Enterprise competitive advantage.

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3.2. Innovation-driven mechanism

Artificial Intelligence helps enterprises create unique and differentiated value propositions by empowering R&D activities and new product/service innovation.For example, medical AI diagnostic systems not only improve diagnostic accuracy but also create entirely new service models [11]. The core mechanism lies in the fact that AI, as a strategic resource, can enhance enterprises' intensity of innovation investment and R&D efficiency, thereby forming inimitable innovation advantages [12].

3.3. Market response mechanism

Artificial Intelligence technology can enhance enterprises' insight into market dynamics and rapid response capabilities. By analyzing massive amounts of market data, Artificial Intelligence can help enterprises more accurately predict consumer demand, optimize inventory management, and achieve more agile supply chains operations. For instance, real-time replenishment systems can significantly increase inventory turnover rates [13]. Kong Dongmin et al. pointed out that the essence of this mechanism is data-driven decision-making to optimize response efficiency, enabling enterprises to more accurately predict demand and quickly adjust strategies, thereby seizing the initiative in competition within the rapidly changing market environment [14].Based on the above analysis, this paper proposes the following research hypotheses:

H1:The application of Artificial Intelligence has a significant positive impact on Enterprise competitive advantage.

H2:Artificial Intelligence has a significant positive impact on Enterprise competitive advantage by improving Operational efficiency.

H3:Artificial Intelligence has a significant positive impact on Enterprise competitive advantage by driving innovation.

H4:Artificial Intelligence has a significant positive impact on Enterprise competitive advantage by enhancing Market response ability.

4. Methodology/ empirical framework

4.1. Data description

We use data obtained from online sources and select Chinese A-share listed companies from 2008 to 2023 as our research samples. The samples are screened in the following ways: excluding samples from the financial industry (given the significant heterogeneity in their business models and financial characteristics compared with non-financial companies); excluding firms whose transaction status is special treatment (ST), *special treatment (*ST), or particular transfer (PT); and excluding samples with missing key variable data. Finally, 41,268 sample observations are obtained.

The core variable "Enterprise AI Application Level" data comes from the MD&A (Management Discussion and Analysis) text of annual reports of listed companies. Referring to the approach of Yao Jiaquan in "Management World," the AI level of listed companies is calculated by statistically analyzing the frequency of 73 AI-related terms (including precise and extended vocabulary) through text analysis [3].

The dependent variable “product market competitive advantage” follows the approach of Yang Xingquan et al. and is measured using the growth rate of main business revenue adjusted by annual

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and industry medians, reflecting changes in the firm's market share relative to industry competitors [11].

Data for the control variables are primarily sourced from the CSMAR database's corporate governance and financial data. To eliminate the influence of extreme values, all continuous variables in this study are winsorized at the 1% level. Data processing and text analysis are performed using Python and Stata 18.0.

4.2. Variable definitions and assessment

4.2.1. Corporate competitive advantage

This paper uses product market competitive advantage as a measure of corporate competitiveness. The calculation formula is:

$$\text{Compet}_{\,i,t} = \frac{\text{Operating Revenue Growth Rate}_{i,t}}{\text{Annual Median Industry Operating Revenue Growth Rate}_{\,i,t}}$$

This indicator reflects the relative competitive position of an enterprise within its industry. A higher value indicates a stronger competitive advantage, and it effectively eliminates industry cyclical fluctuations, providing a more accurate measure of market performance. To control for firm heterogeneity, four control variables are introduced in the robustness tests: Return on Equity, Total Asset Turnover, Firm Age, and Tobin's Q, to more comprehensively control for the potential impact of firm characteristics.

Furthermore, to test the sensitivity of the conclusions to the measurement of the dependent variable, the original dependent variable is replaced with the Stock Lerner Index. This indicator reflects competitive advantage from the perspective of pricing power and monopoly power, thereby verifying the robustness of the results under different measurement standards.

4.2.2. Artificial intelligence level

Referring to the measurement method of Yao Jiaquan in "Management World," this paper calculates the enterprise AI application level through text analysis [3]:

AI Word Frequency Statistics: Based on the MD&A text of listed companies' annual reports, count the frequency of 73 AI-related vocabulary items, including precise vocabulary (e.g., "artificial intelligence," "machine learning") and extended vocabulary (e.g., "algorithm," "big data," "intelligent decision-making").

AI Level Calculation: Standardize the word frequency data to construct a listed company-artificial intelligence level index ($AI_{i,t}$), reflecting the enterprise's investment and application intensity in AI technology.

4.2.3. Control variables

To comprehensively control for other influencing factors, the model introduces the following control variables:

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Table 1. Controlled variables table

Variable Name	Code	Measurement Criterion
Firm Size	Size	The natural logarithm of total assets, reflecting the overall strength and resource base of the enterprise.
Asset-Liability Ratio	Lev	Total liabilities / total assets, measuring financial risk and solvency.
Return on Assets	Roa	Net profit / total assets, reflecting basic competitiveness.
Board Size	Board2	The natural logarithm of the number of board directors, reflecting the complexity of the corporate governance structure and decision-making efficiency. A larger board may bring more expertise but could also lead to reduced decision-making efficiency [15].
Shareholding Proportion of the Largest Shareholder	Top12	Number of shares held by the largest shareholder / total shares, reflecting ownership concentration. High ownership concentration may enhance the supervision of technological decisions by major shareholders but may also inhibit innovation due to a lack of checks and balances [16]

Additionally, the model controls for industry fixed effects (Industry) and time fixed effects (Year) to capture differences in industry characteristics and macroeconomic fluctuations.

4.3. Model

To test our hypotheses, we apply a model.

$$\mathrm{Compet}_{i,t} = \beta_0 + \beta_1 \mathrm{AI}_{\ i,t} + \sum \beta_k \mathrm{Controls}_{\ i,t} + \lambda_t + \mu_i + \varepsilon_{i,t} \tag{1}$$

To clarify the variables in the model, the definitions and explanations are as follows:

$\mathrm{Compet}_{i,t}$ denotes corporate competitive advantage, which is measured by the "ratio of the growth rate of main business revenue to the industry annual median" and reflects the enterprise's relative competitive position within the industry. $\mathrm{AI}_{\ i,t}$ represents the enterprise's AI application level; it is calculated through text analysis of the Management's Discussion and Analysis (MD&A) section in annual reports and reflects the enterprise's investment and application intensity in AI technology. $\mathrm{Controls}_{\ i,t}$ stands for a series of control variables . The subscript i denotes company i, and t refers to year t. λ_t represents time fixed effects, which are used to control for macroeconomic fluctuations; μ_p denotes industry fixed effects, which controls for industry-level characteristics that do not change over time. $\varepsilon_{i,t}$ refers to the random disturbance term.i denotes the individual firm, t represents the year, k stands for the number of control variables, and p refers to the industry

5. Empirical analysis

5.1. Descriptive statistic analysis

Table 2 reports the main descriptive statistics of dependent variable, independent variable and control variables.Descriptive statistics show that the mean value of enterprise AI application level is 0.866, with a standard deviation of 1.228 and a median of 0, indicating that more than half of the enterprises have a low level of AI application, but some enterprises have a high level of application (maximum value is 6.497). The mean value of corporate competitiveness is 0.052, the median is 0, mainly concentrated near zero, while showing polarization.

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The mean value of firm size is 22.190, showing a right-skewed distribution. The mean leverage ratio is 0.421, with a range of 1.825, indicating significant differences in capital structure among enterprises. The mean profitability is 0.037, with a minimum value of -0.942, indicating that some enterprises face significant loss risks.

The mean ownership concentration is 0.337, and the 75th percentile is 0.434, reflecting relatively high ownership concentration in some enterprises. The median and 75th percentile of board size are both 2.197, with a minimum value of 0, suggesting possible anomalies in governance structure.

Table 2. Descriptive statistic

VarName	Obs	Mean	SD	Median	P25	P75	Min	Max
AI	41264	0.866	1.228	0.000	0.000	1.386	0.000	6.497
Compet	41268	0.052	0.387	0.000	-0.126	0.144	-1.019	4.882
Size2	40370	22.190	1.267	22.005	21.289	22.899	18.761	26.452
Lev2	40370	0.421	0.201	0.415	0.262	0.570	-0.268	1.557
ROA2	40370	0.037	0.067	0.037	0.012	0.070	-0.942	0.881
Top12	40370	0.337	0.147	0.313	0.222	0.434	0.017	0.789
Board2	40370	2.121	0.200	2.197	1.946	2.197	0.000	2.732

5.2. Baseline estimate

The main results of the panel regression are shown in Table 3.

Column (1) does not include control variables and only controls for time fixed effects. The results show that the estimated coefficient of AI application degree (AI) is significantly positive at the 1% level, indicating that for every 1% increase in the enterprise AI adoption level, its Lerner index ranking increases by 0.0038%, and the industry-adjusted Lerner index increases by 0.0038%.

After adding control variables such as firm size, asset-liability ratio, return on assets, shareholding proportion of the largest shareholder, and board size in columns (2), (3), and (4), the estimated coefficient of AI application degree (AI) remains significantly positive at the 1% level. This indicates that for every 1% increase in the enterprise AI adoption level, its Lerner index ranking increases by 0.0044%, and the industry-adjusted Lerner index increases by 0.0044%. Therefore, overall, the application of AI has a significantly positive impact on corporate competitive advantage, and Hypothesis 1 is supported.

Furthermore, after adding control variables, the estimated coefficient of firm size is significantly negative at the 10% level, indicating that the larger the firm size, the lower its Lerner index ranking. A possible reason is that larger enterprises face more intense market competition and require stronger innovation capabilities to maintain their competitive advantage. The estimated coefficient of the asset-liability ratio is significantly positive at the 1% level, indicating that the higher the financial leverage, the higher the Lerner index ranking. A possible reason is that highly leveraged enterprises can obtain more funds through borrowing, thereby conducting more R&D investment and innovation activities. The estimated coefficient of return on assets is significantly positive at the 1% level, indicating that the stronger the profitability, the higher the Lerner index ranking. A possible reason is that enterprises with strong profitability have more resources available for R&D and innovation.

The estimated coefficient of the shareholding proportion of the largest shareholder is significantly negative at the 1% level, indicating that the higher the ownership concentration, the lower the Lerner

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index ranking. A possible reason is that enterprises with high ownership concentration are more prone to insider control problems, thereby affecting the innovation capability and competitiveness of the enterprise.

The estimated coefficient of board size is significantly negative at the 1% level, indicating that the larger the board size, the lower the Lerner index ranking. A possible reason is that an excessively large board size may lead to low decision-making efficiency, thereby affecting the innovation capability and competitiveness of the enterprise.

Table 3. Basic results: the effect of AI on enterprise competitive advantage

	(1)	(2)	(3)	(4)
	Compet	Compet	Compet	Compet
AI	0.0038**	0.0067***	0.0072***	0.0044**
	(0.00)	(0.00)	(0.00)	(0.00)
Size2		-0.0030*	-0.0048***	-0.0047**
		(0.00)	(0.00)	(0.00)
Lev2		0.2730***	0.2824***	0.2967***
		(0.01)	(0.01)	(0.01)
ROA2		1.6843***	1.6912***	1.7209***
		(0.03)	(0.03)	(0.03)
Top12		-0.0758***	-0.0717***	-0.0558***
		(0.01)	(0.01)	(0.01)
Board2		-0.0455***	-0.0409***	-0.0342***
		(0.01)	(0.01)	(0.01)
_cons	0.0301***	0.0569	0.0527	0.0387
	(0.01)	(0.04)	(0.04)	(0.05)
N	41264	40366	40366	40366
R^2	0.007	0.077	0.082	0.089
adj. R^2	0.007	0.076	0.081	0.086
year	Yes	No	Yes	Yes
Industry	No	No	No	Yes

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

5.3. Robustness tests

To control for firm heterogeneity, the robustness checks introduce four control variables: return on equity (ROE), total asset turnover, firm age, and Tobin's Q, so as to more comprehensively account for the influence of firm characteristics. Additionally, to test the sensitivity of the conclusions to variable measurement, the original explanatory variable is replaced with the firm-level Lerner index, which reflects competitive advantage from the perspective of pricing power and monopoly position, thereby verifying the robustness of the results under different measures.

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The core purpose of robustness checks is to ensure that the baseline regression results are not driven by contingency in model specification or variable measurement, thus enhancing the credibility of the empirical findings. The results show that after controlling for more firm characteristics, the degree of competition still has a significant positive effect on growth rate; consistent conclusions are also drawn using the Lerner index, confirming the robustness of the research findings. This process effectively mitigates endogeneity issues arising from omitted variables or measurement errors, strengthening the reliability of the causal inference that artificial intelligence enhances firms'competitive advantage.

Table 4. Robust tests results

	(1)	(2)	(3)	(4)	(5)
	Compet	Compet	Compet	IndustryLernerIndex	StockLernerIndex
AI	0.0070***	0.0069***	0.0052***	-0.0097**	0.0025**
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Size2	-0.0059***	-0.0037**	-0.0040**	0.0027	0.0153***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Lev2	0.2741***	0.2389***	0.3031***	-0.0587**	-0.0592***
	(0.01)	(0.01)	(0.01)	(0.03)	(0.01)
ROA2	1.3295***	1.5769***	1.7297***	-0.2916	1.3936***
	(0.06)	(0.03)	(0.03)	(0.19)	(0.05)
Top12	-0.0722***	-0.0815***	-0.0891***	-0.1291***	-0.0030
	(0.01)	(0.01)	(0.01)	(0.03)	(0.01)
Board2	-0.0406***	-0.0379***	-0.0327***	0.0201	-0.0078
	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)
ROE2	0.1962***			0.0991	-0.0088
	(0.03)			(0.07)	(0.02)
ATO2		0.0629***		-0.0359***	-0.0661***
		(0.00)		(0.01)	(0.00)
FirmAge			-0.0664***	-0.0004	-0.0126***
			(0.01)	(0.04)	(0.00)
_cons	0.0826**	0.0008	0.1820***	0.0930	-0.1597***
	(0.04)	(0.04)	(0.04)	(0.15)	(0.03)
N	40366	40366	39811	297	15734
R^2	0.083	0.086	0.088	0.285	0.287
adj. R^2	0.082	0.086	0.088	0.222	0.285
year	Yes	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes	Yes

Standard errors in parentheses

* p < 0.1, ** p < 0.05, *** p < 0.01

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5.4. Heterogeneities analysis

To investigate whether the impact of AI application on corporate competitive advantage varies depending on firm attributes, this paper conducts grouped regressions based on whether the firm belongs to a high-tech industry (HighTech) or a technology-intensive industry (Tech). The results show that the coefficient of AI in the high-tech industry group is 0.0082, significant at the 1% level, while it is only 0.0031 (significant at the 10% level) in the non-high-tech group, indicating that AI has a stronger enhancing effect on high-tech enterprises, mainly due to their stronger technology absorption capacity, well-established digital infrastructure, and sufficient talent reserves. In technology-intensive industries, the AI coefficient is 0.0076 (significant at the 1% level), while it is 0.0029 (not significant) in the non-technology-intensive group, reflecting that AI brings more significant gains to technology-intensive enterprises, benefiting from their innovation capability and data integration advantages.

Integrating the above grouped regression results, the enhancing effect of AI on corporate competitive advantage is more significant in high-tech and technology-intensive industries, while it is relatively weak in non-high-tech and non-technology-intensive industries. This conclusion confirms the important moderating role of firm attributes in the AI empowerment process and also indicates that different types of enterprises should adopt differentiated technology application paths based on their own industry attributes and technological foundations when formulating AI strategies.

Table 5. Sub-sample results

	(1)	(2)	(3)	(4)
	Compet	Compet	Compet	Compet
AI	0.0018	0.0150^{***}	-0.0018	0.0243^{***}
	(0.00)	(0.01)	(0.00)	(0.01)
Size2	0.0030	0.0001	0.0069^{*}	-0.0061
	(0.00)	(0.00)	(0.00)	(0.01)
Lev2	0.3038^{***}	0.2679^{***}	0.2930^{***}	0.2634^{***}
	(0.03)	(0.03)	(0.02)	(0.03)
ROA2	1.7516^{***}	1.7546^{***}	1.7708^{***}	1.7136^{***}
	(0.07)	(0.07)	(0.06)	(0.09)
Top12	-0.0249	0.0121	0.0221	-0.0371
	(0.03)	(0.03)	(0.03)	(0.04)
Board2	-0.0469^{**}	-0.0331	-0.0578^{***}	-0.0157
	(0.02)	(0.02)	(0.02)	(0.03)
_cons	-0.1474	-0.0753	-0.1477	0.0367
	(0.10)	(0.12)	(0.09)	(0.14)
N	7132	8867	9708	6291
R^2	0.103	0.095	0.104	0.091
adj. R^2	0.099	0.087	0.101	0.080
year	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes

Standard errors in parentheses

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* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

5.5. Mediation analysis

This study explores the impact mechanism of artificial intelligence on corporate competitive advantage, focusing on the mediating role of R&D investment, agility responsiveness, and supply chain optimization.

In terms of mediating variable measurement, R&D investment is represented by the ratio of R&D expenses to operating revenue, reflecting the intensity of technological innovation. Agility responsiveness is measured by the number of board meetings, reflecting the efficiency of decision-making and market response. Supply chain optimization is measured by transaction costs , representing the level of supply chain management and cost control.

The mediation effect test adopts the stepwise test method. First, AI has a significantly positive total effect on competitive advantage (coefficient 0.5612, significant at the 1% level). Second, AI significantly increases R&D investment (coefficient 0.2073), agility responsiveness (coefficient 0.0050), and reduces transaction costs (coefficient -0.0050), all significant at the 1% level. These variables, in turn, all have significant effects on competitive advantage, with coefficients of 0.0528, 0.7010, and -0.0121, respectively. Therefore, AI enhances corporate competitive advantage partly through promoting R&D investment, accelerating response speed, and optimizing the supply chain.

In summary, AI not only directly enhances competitive advantage but also indirectly acts by stimulating innovation, improving decision-making, and reducing operating costs, providing a mechanistic pathway basis for enterprises to effectively utilize AI technology.

Table 6. Mediation analysis results

	(1)	(2)	(3)
	Investment	Agility	Cost
AI	0.5612***	0.2073***	0.0050***
	(0.04)	(0.03)	(0.00)
Size2	0.0528	0.7010***	-0.0121***
	(0.04)	(0.03)	(0.00)
Lev2	-5.4581***	2.7688***	0.0616***
	(0.24)	(0.19)	(0.00)
ROA2	-6.6333***	-1.5098***	0.0801***
	(0.60)	(0.50)	(0.01)
Top12	-0.5230**	-0.6449***	0.0142***
	(0.26)	(0.21)	(0.00)
Board2	0.2515	-0.9405***	0.0107***
	(0.20)	(0.16)	(0.00)
_cons	4.1610***	-3.7367***	0.2877***
	(1.11)	(0.86)	(0.01)
N	13495	15068	15999
R^2	0.319	0.147	0.323
adj. R^2	0.314	0.142	0.319
year	Yes	Yes	Yes

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Table 6. (continued)

Industry	Yes	Yes	Yes

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

6. Conclusions and policy suggestions

Several conclusions can be drawn from this work:

1.AI applications significantly enhance corporate competitive advantage, serving as an important driving force for enterprises to gain competitiveness in the digital economy era. Different from existing studies that mostly focus on partial efficiency perspectives, this paper expands the research boundary of AI technology from the overall competitive strategy level.

2.Firm attributes play a significant moderating role in the AI empowerment process. AI has a stronger positive impact on high-tech and technology-intensive enterprises, while its impact on traditional enterprises is weaker. This indicates that the effect of AI technology is selective, and not all enterprises can benefit equally.

3.AI enhances corporate competitive advantage through three pathways: improving operational efficiency, driving innovation, and enhancing market responsiveness. AI not only optimizes production processes and reduces costs but also accelerates product development and increases market agility, bringing multi-dimensional competitiveness improvements to enterprises.

4.Latecomer enterprises and those with faster AI application speeds are more likely to achieve leaps in competitive advantage. Latecomers achieve catch-up through technology leapfrogging and cost advantages, while enterprises that apply AI rapidly build competitive barriers relying on technology integration capabilities, enriching the theoretical framework of the relationship between "AI application speed" and "competitive advantage."

Based on the research conclusions and mechanism analysis, the following three suggestions are proposed:

1.Formulate differentiated AI strategies: Enterprises with different attributes should formulate differentiated AI development paths based on their own characteristics. High-tech and technology-intensive enterprises can focus on developing complex AI systems to enhance the level of full-process intelligence; traditional enterprises should prioritize adopting lightweight, scenario-specific solutions, focusing on specific business pain points to achieve precise empowerment.

2.Strengthen internal capacity building: Enterprises should enhance technology absorption capacity, data infrastructure, and talent reserves to improve the effectiveness of AI applications. This specifically includes strengthening data governance, cultivating interdisciplinary AI talents, optimizing organizational structure, and promoting cross-departmental collaboration to enhance technology integration and application capabilities.

3.Promote government policy guidance: The government should introduce policies to guide the balanced development of AI technology across different industries, alleviating resource misallocation caused by technological differentiation. For example, support latecomer enterprises in introducing AI technology through the establishment of special funds, tax incentives, etc., increase support for the digital transformation of traditional industries, and provide technical training and consulting services to help enterprises achieve intelligent upgrading.

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