“Impact of artificial intelligence applications on enterprise market value: Evidence from Chinese enterprises”

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IMPACT OF ARTIFICIAL INTELLIGENCE APPLICATIONS ON ENTERPRISE MARKET VALUE: EVIDENCE FROM CHINESE ENTERPRISES

Abstract

The application of artificial intelligence (AI) in enterprises presents new opportunities for growth in their market value. This study aims to evaluate the impact of AI applications in enterprises on the growth of enterprise market value and the transmission mechanism of these impacts. Using an enterprise AI application level as the independent variable, a regression model is constructed to analyze the long-term and short-term market value of the enterprise. This study uses relevant data from Chinese listed companies from 2014 to 2023 for analysis. Findings show that for every 1% increase in AI application level, the enterprise market value increases by 0.03% and the enterprise value multiple increases by 0.44%. Increasing the level of AI application in enterprises will enhance their ability to implement low-carbon measures and investors' expectations of corporate profits, thereby increasing the market value of enterprises. High-quality talent within the enterprise and market share can enhance the impact of these two mechanisms. The application of AI in enterprises has different impacts on different industries and companies of different sizes. This study provides new empirical evidence for enterprise market valuation.

Keywords artificial intelligence, enterprise, market value, low-carbon, expectation, investment, market share

JEL Classification O12, O14, M10

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INTRODUCTION

Artificial intelligence (AI) is a digital intelligence technology that has penetrated various departments of enterprises due to its universality and is used to promote the economic development of enterprises. AI applications can enhance the information processing capabilities and value creation mechanisms of enterprises (Haefner et al., 2021; Huang & Rust, 2021). AI is gradually transforming from an edge tool to a core element of enterprises. The advantage of AI over traditional information technology lies in its ability to learn and reason, which can reshape the value creation process of enterprises. AI applications are an important investment in the development process of enterprises. However, the key issue in theoretical research is to what extent AI applications are recognized by the capital market as the market value of enterprises.

Previous studies have provided scattered evidence on the impact of AI on businesses. For example, AI improves production efficiency, technological empowerment, process collaboration, work efficiency, resource allocation, environmental protection, and innovation capabilities (Xiao & Xiao, 2025; Hu et al., 2024; Lin et al., 2024; Wang et al.,

2023; Zhang et al., 2024; Li et al., 2025; Han & Mao, 2023; Wang & Liu, 2025). These studies indicate that AI can influence the expectations of capital markets for business development through multiple pathways (Mishra et al., 2022). The existing study mainly focuses on the relevant impact of AI applications within enterprises and lacks research on the external evaluation of enterprises after the AI application. There is little discussion on the impact of enterprise AI application level on its market value. Therefore, whether the application of AI will affect the market value of enterprises and, through what mechanisms, it will affect the market value of enterprises is an urgent issue that needs to be addressed. Based on data from Chinese listed companies, this article constructs an indicator of the level of AI application in enterprises, analyzes the impact of AI application on the long-term and short-term market value of enterprises, and supplements the research on the dimensions of the capital market.

1. LITERATURE REVIEW

AI applications are increasingly integrated into various aspects of enterprise operations (Xue et al., 2025), not only bringing efficiency improvements but also posing new challenges to the structural transformation of enterprises. More and more companies are using AI to analyze their development status (Orazgaliyeva et al., 2023). AI applications are gradually becoming the key to enhancing the market value of enterprises. Research has shown that AI utilizes product innovation to enhance enterprise valuation (Babina et al., 2024) and can also have a positive impact on market valuation in terms of financial sustainability and controlling operating costs (Moro-Visconti et al., 2023). Empirical research has shown that AI applications significantly optimize corporate performance, enhance productivity, strengthen financial forecasting and management capabilities, reduce environmental compliance costs, stimulate innovation, and systematically drive market value growth for enterprises (Zheng, 2022; Chen et al., 2023; Wang & Li, 2023; Huang & Lin, 2025; Li et al., 2025). The above research confirms that AI applications can be transformed into market value for enterprises.

AI applications are an important driving force for enterprises' green and low-carbon transformation. AI applications can significantly improve green total factor productivity and generate significant economic benefits (Gao et al., 2025). The intelligent advantages of AI applications can further improve production processes and reduce corporate carbon emissions by increasing energy efficiency (Zhu et al., 2024). The green business strategy empowered by AI can enhance the environmental performance and low-carbon development capabilities of the manufacturing industry (Chotia et al., 2024). AI applications can significantly reduce the energy intensity per unit product of manufacturing enterprises (Li et al., 2024). The application of AI has significantly improved the carbon emission performance of enterprises (Wang et al., 2024). The improvement in carbon emission performance has led to a reduction in energy intensity per unit product, thereby enhancing their profitability. The profitability of a company is a key factor driving its value, stock price, and stock returns (Novy-Marx, 2013; Fama & French, 2015). AI applications promote the transformation of low-carbon behavior into a company's profitability, which is reflected in its long-term market valuation, such as through Tobin's Q value.

Investor expectations are a key factor in the valuation of a company's market. The increase in corporate profit expectations will increase investor demand, and investor expectations will override fundamental risks (Lakonishok et al., 1994). The application of AI in enterprises can effectively enhance the positive sentiment of the market towards enterprises, thereby promoting the growth of the market value of listed companies (Fredström et al., 2022). The AI patent assets of enterprises can serve as an important technological strength to support their market value growth (Poege et al., 2019). These AI patents will enhance investors' confidence in the company's innovation capabilities and future profits, thereby promoting market value growth (Shu et al., 2021). Higher profitability quality is correlated with higher P/E ratios (Dechow & Sloan, 1997). When AI applications improve the profitability quality of enterprises, they increase valuation multiples, such as enterprise value multiples (EVM). Based on this logic, AI applications will affect the short-term market value of companies through market expectations.

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The resource-based view and competitive advantage theory indicate that a high market share typically implies greater market influence. Enterprises with high market influence are conducive to transforming the application of AI in their own enterprises into enterprise value (Bhattacharya et al., 2022). Enterprises with high Tobin's Q values are better at utilizing existing advantages to create corporate value, which is not solely dependent on new investments (Coluccia et al., 2020). The growth dividends brought by AI applications are mainly concentrated in enterprises with high market share (Babina et al., 2024). These types of enterprises have stronger organizational capabilities and can leverage the advantages of AI applications (Hötte, 2023). High market share is believed to enhance the value enhancement effect of AI (Wang & Liu, 2025), play a regulatory role, and amplify the potential of enterprise AI applications (Lee et al., 2024).

The absorptive capacity theory emphasizes that human capital is a key factor in leveraging AI applications. Research has shown that highly educated employees can significantly enhance a company's ability to apply new technologies, with a higher rate of AI adoption (Brey & van der Marel, 2024). The education level of business owners is positively correlated with the application rate of AI (McElheran et al., 2024). Enterprises with a high proportion of highly educated talent are more capable of leveraging the advantages of AI applications, and their valuations are higher (Soto, 2025). High-skilled talents are the key for enterprises to transform AI applications into competitive advantages (Kim et al., 2022). Therefore, the proportion of highly educated talents will amplify the impact of AI applications on the value of enterprises.

Based on the above description, AI applications can improve enterprise market value, enhance low-carbon capabilities, and influence investor expectations. Existing literature lacks analysis of AI applications at the enterprise level: How can AI applications enhance enterprise market value from two dimensions? What factors influence the enhancement of enterprise value through AI applications?

This study aims to evaluate the impact of AI applications in enterprises on the growth of enterprise market value and the transmission mechanism of these impacts.

This study proposes the following hypotheses:

H1: The application of AI in enterprises can drive the growth of corporate market value.

H2a: AI applications enhance a company's low-carbon capabilities, thereby increasing its long-term market value.

H2b: AI applications enhance investors' expectations of the company's future profits, thereby increasing its short-term market value.

H3a: Market share has a positive moderating effect on the long-term market value enhancement of enterprises through AI applications.

H3b: The proportion of highly educated employees has a positive moderating effect on the impact of AI applications on the short-term market value of enterprises.

2. METHOD

2.1. Data and sample

This study focuses on A-share listed companies in China (China Stock Market & Accounting Research Database, CSMAR). The AI patent data of listed companies come from Chinese Research Data Services (CNRDS). The selected sample time interval is from 2014 to 2023. The data were analyzed using Stata/MP 17.0 software. The preliminary data processing is as follows: retain data of companies in normal listing status, delete data of financial companies, clean up missing values, and clean up extreme values (Li et al., 2024).

2.2. Variable settings

This article constructs two explanatory variables to measure the enterprise market value, one explanatory variable to measure the enterprise AI application, two mediating variables representing the value transfer mechanism, two moderating variables, and a set of control variables commonly used in corporate finance and governance.

Model 1 uses Tobin's Q value to measure the long-term market value of a company. Tobin's Q value is calculated as the ratio of total market value to

total assets. The higher the Tobin's Q value, the higher the capital market's valuation of the company relative to its asset replacement cost.

Model 2 uses Enterprise Value Multiple (EVM) to measure the short-term market value of a company. EVM is the total market value divided by Earnings before Interest, Tax, Depreciation, and Amortization. This indicator is sensitive to changes in current business performance and is suitable for reflecting a company's short-term valuation.

The central explanatory variable is the AI application level (AIAL) of each enterprise. This research draws on existing literature to construct the foundation of AIAL based on the number of AI patents owned by enterprises (Giczy et al., 2022; Parteka & Kordalska, 2023; Damioli, 2021). It incorporates the patent contribution algorithm proposed in the Chinese recommended standard "Guidelines for Patent Evaluation" released on August 6, 2023, and further integrates the relative indicator of "the proportion of total patent contribution value to total enterprise revenue" (Lee & Oh, 2020; Hoffmann & Kleimeier, 2019) to eliminate differences in enterprise size. The calculation process for AIAL is as follows:

$$PVD_{it} = \left(\alpha \cdot LVD_{it} + \beta \cdot TVD_{it} + \gamma \cdot EVD_{it}\right) + PVD_{Eit}, \quad (1)$$

where *PVD* represents the value of the patent. *LVD* represents legal value, *TVD* represents technological value, *EVD* represents economic value, and PVD_E represents the additional score of patent value. α, β, and γ are coefficients, and the total sum is 1.

$$AIAL_{it} = \frac{PVD_{Tit}}{OTR_{it}}, \quad (2)$$

where PVD_T represents the total patent value, and OTR represents the total revenue of the enterprise. $ALAL_{it}$ represents the level of AI applications that company i has in year t. The higher the AIAL value, the more economically significant it is.

To identify the impact of AIAL on company value, control variables of enterprise characteristics and corporate governance were examined, the details of which are summarized in Tables 1 and 2. The control variables for Model 1 are shown in Table 1, and the control variables for Model 2 are shown in Table 2.

Table 1. Mode 1 control variable

Variable type	Variable name	Variable symbol
Control variable	Asset-liability ratio	Lev
	Accounts receivable ratio	REC
	Inventory ratio	INV
	Increase rate of business revenue	RGROW
	Total net profit margin of assets	ROA
	Return on equity	ROE
	Number of directors	Board
	Shareholding ratio of the top ten shareholders	Top10
	Degree of equity balance	Balance
	Age of the company	FirmAge
	Management shareholding ratio	Mshare

Table 2. Mode 2 control variable

Variable type	Variable name	Variable symbol
Control variable	Asset-liability ratio	Lev
	Increase rate of business revenue	RGROW
	Total asset growth rate	TGROW
	Operating profit growth rate	RFGROW
	Capital preservation and appreciation rate	INGROW
	Total net profit margin of assets	ROA
	Number of directors	Board
	Shareholding ratio of the top 10 shareholders	Top10
	Shareholding ratio of institutional investors	INST

This study reveals the transmission relationship between AIAL and company market value through the value transmission mechanism, with the following intermediary channels:

Model 1 uses the Corporate Carbon Emission Index provided by CSMAR to measure a company's Green Low Carbon Efficiency (GCE). From the perspective of value creation analysis, a higher GCE indicates that the company has stronger low-carbon capabilities, which can improve operational efficiency, reduce regulatory risks, and convey positive ESG signals to investors.

Model 2 uses the price-to-earnings ratio (PER) provided by CSMAR to measure the extent of investors' profit expectations. A higher PER

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has raised market expectations for future profit growth of enterprises, and investors are more willing to give higher valuation multiples.

Model 1 uses market share (MSR) as a moderating variable to measure the proportion of a company's operating revenue to its total revenue in the industry. A larger market share enables enterprises AIAL to obtain larger profits, further enhancing market value. Model 2 uses the proportion of employees with a bachelor's degree or higher (BDPR) as the moderating variable. Enterprises with higher BDPR have stronger absorption capacity, the ability to integrate AI into business processes, and translate it into performance and value. In regression analysis, mean centrality is applied to the moderating variables and AIAL to reduce multicollinearity.

2.3. Regression model

Model 1. This study chooses a fixed effects model for regression, and the specific model settings are as follows

$$Tobin'sQ_{i,t} = \alpha_0 + \alpha_1 AIAL_{i,t} + \alpha' V_{i,t} + \lambda_i + year_t + {}_{i,t}. \quad (3)$$

In the formula, $Tobin'sQ_{i,t}$ is the dependent variable. α_0 is the intercept, V is the control variable, λ_i is the individual fixed effect, $year_t$ is the time fixed effect, and i, t is the random disturbance term. i and t are the data of the i-th enterprise in the t-th year.

Model 2. This study chooses a fixed effect model for regression, and the specific model setting is as follows

$$EVM_{i,t} = \gamma_0 + \gamma_1 AIAL_{i,t} + \gamma' V_{i,t} + \lambda_i + year_t + \mu_{i,t}. \quad (4)$$

In the formula, $EVM_{i,t}$ is the enterprise Value Multiplier. γ_0 is the intercept, V is the control variable, λ_i is the individual fixed effect, $year_t$ is the time fixed effect, and $\mu_{i,t}$ is the random disturbance term. i and t are the data of the i-th enterprise in the t-th year.

This study uses a mediation model to examine whether AIAL affects firm value through GCE and PER. In equations 5 and 6, T represents GCE and PER, and ML represents Tobin's Q or EVM.

$$T_{i,t} = \delta_0 + \delta_1 AIAL_{i,t} + \delta' V_{i,t} + \lambda_i + year_t + \eta_{i,t}, \quad (5)$$

$$ML_{i,t} = \theta_0 + \theta_1 AIAL_{i,t} + \theta_2 T_{i,t} + \theta' V_{i,t} + \lambda_i + year_t + \kappa_{i,t}, \quad (6)$$

where $T_{i,t}$ is the mediating variable. $ML_{i,t}$ is the explained variable. δ_0 and θ_0 are the intercept. $\eta_{i,t}$ and $\kappa_{i,t}$ are the random disturbance terms.

H2a predicts that AIAL will improve GCE, further increasing Tobin's Q value; H2b predicts that AIAL will increase PER, further increasing EVM.

To explore how MSR and BDPR shape the value effect of AI, we augment the baseline models with interaction terms. For Model:

$$TobinQ_{i,t} = \varphi_0 + \varphi_1 AIAL_{i,t} + \varphi_2 MSR \cdot AIAL_{i,t} + \varphi_3 MSR_{i,t} + \varphi' V_{i,t} + \lambda_i + year_t + \rho_{i,t}, \quad (7)$$

$$EVM_{i,t} = \tau_0 + \tau_1 AIAL_{i,t} + \tau_2 BDPR \cdot AIAL_{i,t} + \tau_3 BDPR_{i,t} + \tau' V_{i,t} + \lambda_i + year_t + \omega_{i,t}. \quad (8)$$

As summarized in Equations (7) and (8). A significantly positive coefficient on the interaction term in Model 1 (φ_2) would support Hypothesis H3a (MSR amplifies the long-term value effect of AIAL), while a positive coefficient on the interaction term in Model 2 (τ_2) would support Hypothesis H3b (*BDPR* strengthens the short-term value effect of AIAL).

2.4. Robustness and endogeneity checks

To ensure the robustness of the research results, this study used robust standard errors, removed data from 2021, adjusted the sample data to 2014–2020 and added industry fixed effects to test the model.

This study employs two strategies to address the potential endogeneity problem in the model. First, using the lagged explanatory variable method, AIAL lagged by one period and two periods is used as an instrumental variable. Second, two-stage least squares (2SLS), using the R&D investment ratio (RDSSR) as an instrumental variable for AIAL.

3. RESULT

3.1. Benchmark regression

Table 3 reports the baseline fixed effects estimates for AIAL and Tobin Q values. In column (1), AIAL only regresses with Tobin's Q value, and its coefficient is positive and statistically significant. By sequentially adding control variables and fixed effects in columns (2) to (4), the estimated effect of AIAL remains positive, and the amplitude is more stable. The fourth column shows the coefficient of AIAL in the complete model regression, which is 0.0325 (t = 6.79), and the adjusted R^2 reaches 0.613. The regression results of Model 1 indicate that after considering observable company characteristics and unobservable heterogeneity, companies with higher AIAL enjoy higher long-term market valuations, which is consistent with hypothesis H1.

Table 4 reports the corresponding results of the Enterprise Value Multiple (EVM). The coefficients of AIAL are significantly positive in all columns and have statistical significance. The fourth column shows that in the complete model regression, the AIAL coefficient is 0.444 (t = 4.43), and the adjusted R^2 is 0.658.

The results in Tables 3 and 4 together indicate that enterprises with high levels of AI application will improve their Tobin's Q and EVM, which is consistent with the emphasis of the abstract and supports hypothesis H1.

3.2. Robustness tests

Tables 5 and 6 report the robustness test results of Model 1 and Model 2, respectively. The first column of Tables 5 and 6 shows robust standard error estimates, and the coefficients of AIAL remain positive in both Tobin's Q and EVM indicators and are significant at the 1% significance level, indicating that the baseline conclusion is not driven by heteroscedasticity. The second column shows that after excluding observations from 2021, the estimation effect of AIAL slightly increases, indicating that the core results are not sensitive to potential noise in the 2021 data. The third column shows that when the sample is limited to the period

Table 3. Model 1 benchmark regression results

Variable Name	(1)	(2)	(3)	(4)
	Tobin's Q	Tobin's Q	Tobin's Q	Tobin's Q
AIAL	0.0186***	0.0249***	0.0303***	0.0325***
	(3.92)	(5.19)	(6.32)	(6.79)
Control variable	No	40%	70%	100%
Firm	No	No	Yes	Yes
Year	No	No	Yes	Yes
N	26964	26964	26964	26964
r2_a	0.604	0.607	0.611	0.613

Note: t-statistics in parentheses, * p < 0.1, ** p < 0.05, *** p < 0.01.

Table 4. Model 2 benchmark regression results

Variable Name	(1)	(2)	(3)	(4)
	EVM	EVM	EVM	EVM
AIAL	1.072***	0.366***	0.366***	0.444***
	(9.49)	(3.61)	(3.61)	(4.43)
Control variable	No	67%	67%	100%
Firm	No	No	Yes	Yes
Year	No	No	Yes	Yes
N	15959	15959	15959	15959
r2_a	0.552	0.649	0.649	0.658

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Table 5. Robustness test (Model 1)

Variable Name	Standard error is robust	Excluding 2021	Sample before 2021	Add industry fixed
	Tobin's Q	Tobin's Q	Tobin's Q	Tobin's Q
AIAL	0.0325***	0.0394***	0.0231***	0.0315***
	(6.28)	(7.70)	(3.23)	(6.58)
Control variable	Yes	Yes	Yes	Yes
Firm	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
Industry	No	No	No	Yes
N	26964	23273	14903	26962
r2_a	0.613	0.601	0.623	0.616

Table 6. Robustness test (Model 2)

Variable Name	Standard error is robust	Excluding 2021	Sample before 2021	Add industry fixed
	EVM	EVM	EVM	EVM
AIAL	0.444***	0.439***	0.562***	0.424***
	(4.09)	(3.90)	(3.54)	(4.24)
Control variable	Yes	Yes	Yes	Yes
Firm	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
Industry	No	No	No	Yes
N	15959	12857	6506	15957
r2_a	0.658	0.641	0.693	0.661

before 2021 (2014-2020), the coefficient of AIAL is significantly positive, indicating that the relationship between AI applications and company value is not limited to a specific period. The fourth column shows that after adding industry fixed effects, the estimated AIAL coefficient remains robust, with a Tobin Q value of 0.0315 and an EVM value of 0.424. The unobserved differences at the industry level can lead to abnormal research results. The above robustness analysis confirms that AI applications can enhance the enterprise market value.

3.3. Endogeneity test

This research addresses the endogeneity problem from two aspects: the lagged variable method and the two-stage least squares (2SLS).

The first and second columns of Table 7 show the regression results of lagged AIAL as a regression variable for one and two periods. The lagged AIAL is still significantly positively correlated with Tobin's Q value, indicating that the impact of AI

Table 7. Model 1 endogeneity test

Endogenous analysis results	1	2	3	4
	Lag first stage	Lag second stage	2 SLS first stage	2 SLS second stage
	AIAL	Tobin's Q	AIAL	Tobin's Q
AIAL				0.188***
				4.46
L.AIAL	0.0252***			
	5.17			
L2.AIAL		0.0185***		
		3.48		
IV			0.0618***	
			17.56	
Anderson canon. corr. LM				362.768
Cragg–Donald Wald F statistic				308.222
Control variable	Yes	Yes	Yes	Yes
Firm	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
N	21625	17279	26964	26964
r2_a	0.661	0.682	0.719	−0.217

Table 8. Model 2 endogeneity test

Variable Name	1	2	3	4
	Lag first stage	Lag second stage	2 SLS first stage	2 SLS second stage
	AIAL	EVM	AIAL	EVM
AIAL				23.03***
				7.66
L.AIAL	0.588***			
	5.09			
L2.AIAL		0.365***		
		2.63		
IV1			0.0593***	
			8.4	
Anderson canon. corr. LM				91.501
Cragg-Donald Wald F statistic				70.507
Control variable	Yes	Yes	Yes	Yes
Firm	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
N	11248	7525	15959	15959
r2_a	0.698	0.716	0.735	–4.087

applications is persistent rather than purely synchronous. In the 2SLS estimates of the third and fourth columns, RDSSR is highly correlated with AIAL in the first stage (F = 96), and the Anderson LM statistic and Cragg-Donald statistic indicate that this instrumental variable is effective and not weak. The second stage coefficient of AIAL remains positive at a significance level of 1%. The conclusion has been confirmed that the application level of AI can enhance the enterprise market value.

Table 8 shows the lagged AIAL regression and two-stage least squares (2SLS) estimation for EVM. The results all indicate a significant positive correlation between AIAL and EVM. The above results alleviate concerns about reverse causality and omitted variables in the model, and further support the explanation of the causal relationship between AI and enterprise value.

3.4. Value transmission mechanisms: GCE and PER

Table 9 reports the results of intermediary analysis. In the green low-carbon mechanism, AIAL is positively correlated with GCE: In the first column, the coefficient of AIAL is 0.00842, and it has statistical significance at the 5% significance level, t = 2.43. In the second column, there is also a significant positive correlation between GCE and Tobin's Q value, with a coefficient of 0.294, t ≈ 140. The results indicate that the application of AI can improve the green and low-carbon ef-

Table 9. Value transmission mechanism

Variable Name	Green low-carbon		P/E ratio	
	GCE	Tobin's Q	PER	EVM
	1	2	3	4
AIAL	0.00842**	0.0320***	0.0118***	0.254***
	(2.43)	(6.72)	(3.40)	(3.05)
GCE		0.294***		
		140.19		
PER				16.05***
				(73.65)
Control variable	Yes	Yes	Yes	Yes
Firm	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
N	26837	26837	15932	15932
r2_a	0.663	0.613	0.767	0.763

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ficiency of enterprises, and high green and low-carbon capabilities will enhance the long-term market valuation of enterprises. This set of results supports hypothesis H2a.

In the mechanism of investor profit expectations, AIAL has a significant positive impact on PER, with a coefficient of 0.0118 in column (3), t = 3.40. In column (4), PER is significantly positively correlated with EVM, with a coefficient of 16.05, t ≈ 73.65. The analysis results indicate that the application of AI can help improve investors' expectations of a company's future profitability, which in turn translates into higher market valuations. This set of results supports hypothesis H2b.

3.5. Moderating effect

Table 10 reports on the moderating effect of MSR and BDPR. In Model 1, the interaction between AIAL and MSR, MSR * AIAL, is positive and statistically significant, coefficient of 0.307 (t = 3.91). Companies with a larger market share have a stronger positive impact of AI applications on Tobin's Q. Companies with market advantages can extract more long-term value from AI applications. This result provides empirical support for hypothesis H3a.

In Model 2, the interaction between AIAL and BDPR, BDPR * AIAL, is also positive and significant, with a coefficient of 0.903, t = 2.7. This indicates that companies with a higher proportion of employees holding at least a bachelor's degree are better able to convert AI applications into enterprise value multiples. From the perspective of absorptive capacity theory, high-quality human capital can help convert investments in AI into better valuations, thereby supporting hypothesis H3b.

3.6. Heterogeneity analysis

Table 11 reports a heterogeneity analysis of the impact of AI applications on firm value, including firm size, industry, and ownership.

The estimation of Tobin's Q value shows that the AIAL coefficient of large enterprises is not significant, with a coefficient of 0.00636, t = 1.24. However, the AIAL coefficient for small and medium-sized enterprises is significantly positive, with a coefficient of 0.0209, t = 2.57. The application of AI has a more significant marginal effect on the market value of small businesses.

The industry nature regression results of EVM show that the manufacturing coefficient is significant, with a coefficient of 0.399, t = 3.33. The impact of AI applications in manufacturing is stronger than in non-manufacturing industries, and the coefficient for non-manufacturing industries is not significant. This result is consistent with the view that the manufacturing industry provides quantifiable applications for AI-embedded operations. The path to realizing the value of AI is clearer.

The regression results of the ownership nature of EVM show that the coefficient of private enterprises is significant, with a coefficient of 0.596, t = 4.79. The impact of AIAL on EVM is minimal for state-owned enterprises. Private enterprises place greater emphasis on market incentives and

Table 10. Moderation mechanism

Variable Name	Model 1	Model 2
	Tobin's Q	EVM
AIAL	0.0315***	0.461***
	6.6	4.59
MSR*AIAL	0.307***	
	3.91	
BDPR*AIAL		0.903***
		2.7
Control variable	Yes	Yes
Firm	Yes	Yes
Year	Yes	Yes
N	26925	15959
r2_a	0.614	0.659

Table 11. Heterogeneity analysis

Variable Name	Model 1		Model 2			
	large-lot producer	minor enterprises	manufacturing industry	non-manufacturing industry	state-owned enterprise	private enterprise
	Tobin's Q	Tobin's Q	EVM	EVM	EVM	EVM
AIAL	0.00636	0.0209**	0.399***	0.297	0.0317	0.596***
	1.24	2.57	3.33	1.49	0.19	4.79
Control variable	Yes	Yes	Yes	Yes	Yes	Yes
Firm	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes
N	13324	13235	11784	4097	4273	11603
r2_a	0.688	0.604	0.644	0.699	0.734	0.634

governance structures, thus placing greater emphasis on transforming AI applications into performance and market value growth.

Heterogeneity analysis shows that the value effect of AI is not evenly distributed: its impact is more significant on small and medium-sized enterprises, manufacturing enterprises, and private enterprises. These findings elucidate the boundary conditions for AI applications to promote enterprise value creation.

4. DISCUSSION

The empirical results of this article indicate that for every 1% increase in the AIAL, it can drive a 0.03% increase in Tobin's Q value and a 0.44% increase in EVM. This finding is consistent with the research findings of Tingbani et al. (2024) on the promotion of enterprise value through AI application and provides support for core hypothesis H1. AIAL is reflected not only in the enterprise replacement value indicator but also in the investor's expected enterprise value multiple. Enterprise-level AIAL has a significant economic impact on its market value.

This research reveals the transmission mechanism of AIAL driving the growth of enterprise market value. It includes a dual process of creating enterprise value: improving the operational optimization process and enhancing the market expectations process. These two value transfer mechanisms validate hypotheses H2a and H2b and supplement the existing theoretical framework from two dimensions: green low-carbon capacity and investor expectations. AI enhances green efficiency mechanisms, reduces carbon emissions and energy costs for enterprises (Benzidia et al., 2021), and translates efficiency improvements into business profit growth (Cheng et al., 2022). This process can also promote a significant improvement in the level of green innovation (Ye et al., 2023). The application of AI will drive enterprises to transform towards green and efficient production models. The recognition of low-carbon capability as a signal of future profitability and sustainability in the capital market will give companies a higher premium (Hussain et al., 2024). Therefore, Model 1 reveals the transmission path from AIAL to low-carbon capability, and then to enterprise market value evaluation. AI has increased the external market's expected valuation of enterprises by shaping profit expectation mechanisms. AIAL, as a manifestation of innovation capability, triggers positive market sentiment (Fredström et al., 2022). This theory is consistent with the results of Model 2: AIAL directly enhances the expected value (EVM). This logic is in line with investors' expectations that the company can achieve new product breakthroughs and business growth through AI (Corrado et al., 2021), thereby increasing profit expectations and leading to an increase in the price-to-earnings ratio. Model 2 reveals the propagation path of AIAL, enhancing the expected value.

The value creation process of AI is constrained by the internal conditions of an enterprise. This research identified two contingency factors: structural resources and intellectual resources. Market share can amplify the value created by AIAL at the structural resource level of the enterprise. The results of Model 1 indicate that companies with

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a large market share can obtain a higher market value driving force from AIAL, which will guide companies to invest in AI research and development (Piekkola & Rahko, 2020). The early return on AI investment can consolidate their market dominance (Dong et al., 2025), thereby forming economies of scale and entry barriers. AIAL has strengthened the existing market structure and provided supporting evidence for hypothesis H3a. High-quality human capital provides impetus for AI value transformation at the level of enterprise intellectual resources. The results of Model 2 confirm that the higher the average education level of employees, the stronger the role of AI in improving EVA. High quality human capital (Kangalakova et al., 2024) empowers the realization of the value of AI through three ways: enhancing the knowledge absorption ability of enterprises, thereby improving the application ability of AI technology (Li et al., 2022), and promoting enterprise innovation output; Scientific operation and management can improve the return on investment (Jin et al., 2023); Enhance the agility and resilience of organizations in responding to market changes (Cai et al., 2024). This indicates that the technological effects of AIAL require corresponding human capital to be fully utilized. This conclusion supports hypothesis H3b.

This study further analyzes the triple differentiation pattern of AI applications by industry, scale, and ownership. Industry analysis, the value enhancement effect of AI is particularly prominent in the manufacturing industry. This is in line with the industry attributes of intellectual property (Zhang & Shan, 2023). The manufacturing process, supply chain management, and quality control provide a large number of quantifiable application scenarios for the deep embedding of AI, making it easier to translate into performance and value. In some service industries, the value realization path may be more indirect and ambiguous. Scale analysis, the market share, and the scale improvement effect of AI on small and medium-sized enterprises are actually more significant. This is because the growth of large enterprises is diluted by their complex business systems and existing market size, and the marginal impact of a technological innovation is relatively insignificant (Poege et al., 2019). On the contrary, for small and medium-sized enterprises, a successful AIAL may become a "strategic lever" for achieving market breakthroughs and challenging industry patterns, thereby generating disruptive growth effects. Ownership analysis, compared to state-owned enterprises, private enterprises can more efficiently convert AIAL into market value. Because the incentive mechanisms for the two types of enterprises are different. Private enterprises pursue profit maximization, prompting them to actively guide AIAL towards commercialization. Heterogeneity analysis reveals the boundaries of AI value effects and highlights the importance of different business contexts.

CONCLUSION

This study aims to evaluate the impact of AI applications in enterprises on the growth of enterprise market value and the transmission mechanism of these impacts. It confirms, through empirical analysis, that AIAL has a significant impact on the market value of enterprises, revealing the value transmission mechanism and boundary conditions. Research has shown that AIAL has a significant promoting effect on the market value of enterprises. AIAL promotes the long-term market value growth of enterprises by enhancing their green and low-carbon capabilities. AIAL promotes short-term market value growth by raising investors' expectations for the company's future profits. The market share of enterprises and the proportion of highly educated talents can amplify the enhancement effect of AIAL on the market value of enterprises. The role of AIAL is more significant in the manufacturing industry, private enterprises, and small and medium-sized enterprises.

Based on the results of this study, the following suggestions are proposed: At the macro level, government departments should establish an institutional environment to support the application of AI in enterprises and establish fiscal funds to incentivize the intelligent transformation of enterprises. At the micro level, enterprises should proactively adapt to external environmental changes, promote internal

transformation, actively apply AI to empower green and low-carbon capabilities, and enhance the impact of sustainable development. Enterprises should establish a talent management model that adapts to AIAL and fully unleashes the creativity of talent.

This research provides empirical evidence for understanding the impact of AIAL on the market value of enterprises. It should be pointed out that the data in this research is based on AI patent data of listed companies. Although AI patents can reflect an enterprise's AIAL, there may be a gap between this data and the actual usage of the enterprise. Subsequent research can combine field survey data to construct more accurate AIAL indicators. This article preliminarily reveals the regulatory role of structural resources and intellectual resources. Further research can explore more interaction mechanisms.

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