ISSN: 2710-0723

The Impact Mechanism of Artificial Intelligence Technology Application on Corporate Market Value: An Empirical Analysis of Listed Companies in China

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Abstract

Under the wave of digital transformation, artificial intelligence (AI) technology is profoundly transforming corporate production and operational models, with its role in shaping corporate value becoming a focal point of current research. Based on data from Chinese listed companies between 2015 and 2023, this paper investigates the impact of AI technology adoption on corporate market value. The study finds that the application of AI technology significantly enhances corporate market value, and this conclusion remains valid after robustness tests. Heterogeneity analysis reveals that the value-enhancing effect of AI is more pronounced in non-state-owned enterprises, companies audited by the Big Four accounting firms, and non-regulated industries. Mechanism tests indicate that AI elevates corporate market value through three pathways: reducing production costs, mitigating inefficient investment, and promoting R&D innovation. These findings hold significant implications for enterprises to rationally adopt AI technology, enhance corporate value, and advance digital transformation.

Keywords

Artificial Intelligence (AI); Corporate Value; Production Costs; Inefficient Investment; R&D Innovation.

1. Introduction

In the current global economic landscape, artificial intelligence (AI) has evolved from a technological concept into a core force driving industrial transformation. The 2024 Government Work Report proposed deepening the research and application of big data and AI, launching the "AI+" initiative, and creating internationally competitive digital industry clusters. With breakthroughs in deep learning, natural language processing, and computer vision, AI applications have penetrated diverse industries such as finance, healthcare, manufacturing, and insurance, becoming a key engine for enterprises to improve efficiency, optimize decision-making, and reconstruct business models. According to data from the China Academy of Information and Communications Technology (CAICT), the market size of China's software industry exceeded 8 trillion yuan in 2023, with emerging applications represented by AI occupying an increasingly important position. Despite the revolutionary breakthroughs in AI technology that have built significant competitive advantages for some enterprises, the valuation system of the capital market still generally lags behind. A 2022 report from the McKinsey Global Institute showed that approximately 63% of listed companies have not fully reflected their technological application potential in their market value. This structural contradiction between technological value and market valuation highlights the theoretical urgency of exploring the commercialization path of AI technology and its value transmission mechanism for enterprises. A thorough analysis of the value creation mechanisms of AI through technological iteration, application scenario expansion, and production factor reconstruction

ISSN: 2710-0723

can not only improve the theoretical framework for technological innovation value assessment but also provide a key analytical perspective for judging the evolution of industrial patterns in the digital economy era.

In recent years, the academic community has conducted multidimensional empirical research on the impact mechanism of AI technology on corporate value. Numerous studies have shown that the application of AI technology significantly enhances corporate market value through optimizing production processes, reducing inefficient investment, and stimulating innovation vitality. For example, Huang et al. (2021)[10] found that digital transformation (especially the application of AI and cloud computing) can narrow information asymmetry, improve financing constraints, and enhance innovation momentum, thereby promoting corporate value enhancement, which is more pronounced in non-state-owned and high-tech enterprises. Regarding the impact of AI on enterprises, specifically, AI technology application can promote corporate innovation by increasing knowledge diversity, breaking organizational routines, and improving resource allocation efficiency (Li et al., 2024)[15]; identify and control financial risks (Li, 2021)[13]; and enhance production efficiency and optimize labor structure (Yao et al., 2024)[26]. Wu and Xu (2022) further pointed out that AI enhances corporate value by reducing production costs, reconstructing labor structure (e.g., increasing demand for high-skill positions), and improving innovation efficiency (e.g., increasing the conversion rate of R&D investment)[23]. Additionally, the value realization of AI technology requires the collaborative support of digital infrastructure and regulatory systems. For example, the World Bank's (2023) Technology Diffusion Index report indicated that a one-standard-deviation increase in the maturity of digital infrastructure can improve AI application efficiency by 23% to 37%. This positive feedback effect of the technology-economic paradigm means that countries with well-developed digital infrastructure, data governance systems, and innovation ecosystems are more likely to achieve large-scale conversion of AI benefits (Brynjolfsson et al., 2020)[40]. Based on the literature review, this paper explores the impact of AI technology application on corporate market value.

From a theoretical perspective, the endogenous driving mechanism of AI on corporate market value is realized through three transmission paths: production structure, efficient investment, and innovation research and development. On the one hand, AI is conducive to reducing production costs. AI can help enterprises effectively assess and predict market environments through rich information channels (Agrawal et al., 2019)[34], thereby optimizing production plans, reducing labor costs, and improving production efficiency. On the other hand, AI is conducive to reducing inefficient investment. AI can reduce inefficient investment through data-driven decision support and optimization of investment portfolios. Failure to fully utilize investment opportunities leads to idle resources or failure to achieve potential growth, while over-investment consumes corporate funds, reduces corporate profitability, and ultimately leads to a decline in corporate market value. For example, Xin et al. (2018) found that local state-owned entities have a tendency for irrational expansion driven by distorted compensation incentive mechanisms[24]. Moreover, AI can promote R&D innovation (Li et al., 2024)[15]. Through AI analysis, enterprises can predict risks in the R&D process in advance, optimize R&D resource allocation, and reduce R&D costs. Thus, AI reshapes the corporate value creation model through the endogenous driving mechanisms of optimizing production structure, reducing inefficient investment, and promoting innovation research and development, with core paths of cost-efficiency optimization, rationalization of resource allocation, and breakthroughs in technological frontiers.

Despite the theoretical promotion logic, the application of AI technology may also inhibit market value through increased compliance costs and resource misallocation risks. For example, Adner (2016) empirically found that due to the high difficulty in recovering the costs of technological upgrades in the computer industry, there is no positive impact on corporate

ISSN: 2710-0723

value[32]. Bae et al. (2008) found that the impact of R&D technology upgrades on corporate value is time-lagged, with a negative correlation in the early stages of technological upgrades[35]. Moreover, the CAICT pointed out that some traditional industries (such as textiles and retail) have weak data infrastructure and low AI technology adaptability, resulting in a lower technology input-output ratio than expected, further inhibiting market value growth.

Through the analysis of previous literature, the direction of the impact of AI technology application on corporate value is still unclear and needs further empirical testing. Based on this, the empirical analysis of this paper proves that the application of AI technology significantly enhances the value of listed companies by crawling financial indicators and annual report text content of Chinese listed companies from 2015 to 2023. This result remains robust after using different variable measurement methods, adding fixed effects, using instrumental variable methods, and propensity score matching methods. This effect also significantly differs among enterprises with different equity natures, whether audited by the Big Four, and whether in regulated industries. In terms of pathways, the mechanism test found that AI promotes corporate market value enhancement by reducing production costs, reducing inefficient investment, and promoting corporate R&D innovation activities.

The contributions of this paper may include: First, it expands the research on the economic consequences of AI technology application. Existing studies on AI technology application mostly focus on macroeconomic growth perspectives, discussing inclusive growth, industrial structure, and labor employment (Chen and Qin, 2022[3]; Guo and Hu, 2022[8]; Long et al., 2020[17]). This paper discusses the impact on the market value of listed companies from a micro perspective. Second, it extends the theoretical mechanism of AI. Current research on the impact mechanism of AI technology on corporate value mainly focuses on optimizing costs and improving efficiency to achieve efficient corporate operations and driving new growth and breakthroughs through innovation (Li et al., 2024)[15]. This paper discusses the impact of inefficient investment, expanding the research on the theoretical mechanism of AI. Third, it has practical significance in promoting the application of AI technology. Clarifying the pathways and mechanisms of AI's impact is important for enterprises to undergo digital transformation and allocate resources reasonably using AI technology.

The structure of this paper is as follows: Section II is the literature review, Section III is the research hypotheses and empirical design, Section IV is the empirical analysis, Section V is the mechanism test, and Section VI is the conclusion and recommendations.

2. Literature Review

2.1. Research on Artificial Intelligence

AI, as a key technological driver in the digital economy era, is not only a core engine for boosting productivity but also a vital support for digital transformation. In the wave of economic digitalization, AI injects new vitality into economic growth through intelligent technology applications and has become a critical support for innovation breakthroughs across various fields. Similar to human societal technological progress, AI development has experienced three stages: weak AI, which substitutes for human computing, prediction, and search capabilities; strong AI, which possesses human thinking and cognitive abilities; and super AI, which surpasses human thinking and cognitive power. Regarding the economic characteristics of AI technology, it can be categorized into the following aspects (Cai and Chen, 2019)[2]: First, its penetrative nature allows AI technology to deeply integrate into the real economy and drive traditional industrial digital transformation. Second, its substitutive nature is reflected in AI's substitution of non-mechanical production factors. Third, its coordinative nature emphasizes AI's ability to enhance the matching efficiency of various production factors and optimize

ISSN: 2710-0723

resource allocation. These three characteristics interact to jointly promote the formation of creative economic value and become a vital driving force for digital economic development.

New-generation AI exhibits significant advantages in addressing complex socioeconomic issues (Davenport and Kirby, 2016)[43]. Its operational mechanism involves decomposing systematic complex problems into multiple relatively simple prediction and classification tasks, configuring different algorithms based on task attributes for identification and processing, thereby improving work targeting and problem-solving efficiency. Wang (2018) highlighted the importance of machine learning, a core AI technology, in data analysis and decision optimization[20]. Machine learning simulates human learning and behavioral patterns, utilizes reinforcement learning mechanisms for optimized decision-making, and achieves complex problem-solving through distributed computing and swarm intelligence, thereby enabling intelligent applications across various fields. During the second wave of weak AI development, the concept of knowledge engineering provided a foundation for knowledge graph generation and is also a key AI technology (Yang et al., 2018)[25]. Yu et al. (2013) consider natural language processing an essential aspect of AI research, aimed at enabling communication between humans and intelligent machines through natural language, including natural language recognition, understanding, and generation modules[28].

At the corporate level, AI application is significantly enhancing innovation and production efficiency. Li et al. (2024) demonstrated that AI technology promotes corporate innovation by increasing knowledge diversity, breaking organizational routines, and improving resource allocation efficiency, helping enterprises achieve breakthrough innovation[15]. Wang (2020) found that AI technology application enables firms to expand their scale, increase job positions, and improve employee profit per capita[22]. Additionally, Yao et al. (2024) indicated that AI optimizes labor skill structure and enhances corporate production efficiency[26]. In the context of big data, Li (2021) showed that AI technology holds significant value in corporate financial risk prevention. Through intelligent data analysis and risk warning mechanisms, AI helps enterprises identify potential financial risks more efficiently, optimize risk response strategies, and enhance financial management and risk resistance capabilities[13]. These studies indicate that AI is not only a key driver of corporate innovation and production efficiency improvement but also an important promoter of corporate digital transformation and upgrading.

At the Societal Level, Artificial intelligence (AI) has profoundly transformed labor markets, industrial economies, and overall economic development. Regarding labor markets, Long et al. (2020) found that AI's impact is dualistic: its labor substitution effect may automate repetitive jobs, leading to short-term structural unemployment risks. Conversely, its technological spillover effect can foster new industrial ecosystems and indirectly create high-value jobs through productivity gains[17]. This "disruptive innovation" dynamic suggests that AI's impact on employment is not linear but depends on the alignment between technology diffusion and labor skill transformation. However, long-term labor demand remains unaffected by technological advancement. For industrial economies, Guo and Hu (2022) highlighted that the synergy between AI and human capital significantly promotes industrial structure upgrading, particularly when AI integrates with high-skilled labor. This effect is moderated by a double threshold of human capital levels, indicating that varying skill levels differentially influence AI's role in driving industrial upgrades[8]. Chen and Qin (2022) further noted that AI drives inclusive growth by narrowing labor income gaps and promoting inclusive industrial development[3].In terms of economic growth, AI has emerged as a key driver of high-quality economic growth (Chen et al., 2019)[4]. Its mechanisms include: 1. Enhancing production intelligence and automation to reduce labor dependence and mitigate labor cost pressures; 2. Optimizing capital returns through precise resource allocation and risk management, accelerating capital accumulation; 3. Boosting total factor productivity via big data analysis and algorithm optimization, driving overall social productivity. AI can complement or replace capital, enhance

ISSN: 2710-0723

production efficiency, foster innovation, alter factor input and allocation, adjust employment structures, and influence income distribution. It is characterized by high automation, data and algorithm dependence, adaptability, cross-sector applicability, rapid innovation, and labor substitution and augmentation. Collectively, these studies underscore AI's critical role in socio-economic development. It reshapes employment structures and labor markets while driving high-quality economic growth and advancing new productive forces.

2.2. Research on Corporate Value

Corporate value is a critical indicator of a firm's comprehensive competitiveness and future earnings potential in the market, typically reflected in stock market valuations (e.g., Tobin's Q). Corporate value not only reflects current financial conditions and profitability but also embodies market expectations of future growth potential and strategic transformation.

At the macro level, ESG performance significantly enhances corporate value by reducing financing costs, alleviating financial burdens, and boosting market trust, particularly in non-state-owned, smaller firms, and non-polluting industries (Wang and Yang, 2022[19]; Wang et al., 2022[21]). Accelerated corporate digital transformation enhances technological innovation, optimizes factor allocation, and strengthens risk controllability, all of which improve corporate value (Huang et al., 2021)[10]. In international contexts, Deng et al. (2014) noted that politically connected private firms can enhance corporate performance and value through international strategies[7]. Zhan and Wang (2013) found that excessive investment harms corporate value, while moderate investment, influenced by managerial incentives, aids future performance[29].

At the micro level, corporate governance structures significantly impact corporate value, with reasonable governance enhancing profitability, operational flexibility, and governance efficiency (Balachandran and Faff, 2015)[36]. Big data application also significantly boosts corporate market value by improving production efficiency and R&D input (Zhang et al., 2021[30]; Brynjolfsson et al., 2011[39]). Factors such as CEO career experience (He et al., 2019)[9] and managerial incentives (Jiang and Huang, 2011) also directly impact internal operations by strengthening core competitiveness and elevating corporate value[12]. Furthermore, corporate social responsibility towards stakeholders differentially affects corporate value, with shareholder responsibilities contributing the most (Jia et al., 2016)[11].

In summary, corporate value is influenced by various factors, including macro-level ESG performance and big data application, as well as micro-level corporate governance, managerial incentives, and stakeholder responsibilities. These studies provide multi-faceted analyses of corporate value formation mechanisms.

2.3. Literature Synthesis

Despite extensive research on macroeconomic environments, policies, corporate governance, and operational efficiency, studies directly examining AI's impact on corporate value remain scarce. While some reports and studies explore AI's economic potential in specific industries or functions, they often focus on broader economic impacts rather than the specific mechanisms through which AI shapes corporate value. Thus, investigating AI's direct impact on corporate value holds significant theoretical and practical importance. It not only fills a literature gap and enriches corporate value research but also offers strategic guidance for digital transformation and AI application, helping enterprises better understand and leverage AI to enhance their value.

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3. Research Hypotheses and Empirical Design

3.1. Research Hypotheses

Firms can significantly enhance their market value through the deep integration of AI technologies, such as machine learning algorithms, natural language processing, and intelligent decision support systems. This positive effect stems from AI's optimization of production costs, enhancement of efficient investment, and stimulation of innovation, ultimately driving market value growth.

(1) AI Reduces Production Costs

AI significantly reduces production costs. First, AI enhances production efficiency through information integration. It provides vast, real-time, and multidimensional data support, enabling firms to acquire diverse knowledge across fields and industries and identify combinations of cross-field knowledge (Gruber et al., 2013)[44]. This information advantage allows firms to accurately assess and predict market environments based on macroeconomic factors, industrial dynamics, and consumer preference changes (Agrawal et al., 2019)[34], thereby optimizing production plans, reducing resource waste and inventory backlog (Abaku et al., 2024)[31], and improving resource utilization efficiency. Second, AI application helps reduce labor costs and enhance production efficiency (Wang, 2020)[22]. By promoting automated production processes, AI reduces labor dependence and optimizes labor structure, lowering labor costs while expanding business scale, creating more job opportunities, and increasing employee profit per capita. Lastly, AI plays a vital role in financial management. Li (2021) demonstrated that AI technology significantly improves the efficiency of financial data processing and provides real-time monitoring and analysis, timely identifying potential financial risks and offering financial risk warnings[13]. This intelligent financial management approach effectively reduces financial risks and further optimizes operational costs.

(2) AI Reduces Inefficient Investment

AI plays a significant role in reducing inefficient investment by supporting data-driven decision-making and optimizing investment portfolios, effectively addressing resource misallocation in investment. Inefficient investment typically manifests as either underinvestment or overinvestment, both of which negatively impact corporate market value. Underinvestment can lead to underutilization of potential opportunities, causing resource idleness or missed growth potential. For example, Cheng et al. (2008) noted that local state-owned enterprises may underperform due to external interventions. Overinvestment, on the other hand, can deplete funds, weaken profitability, and ultimately reduce market value[6]. Xin et al. (2008) found that some local government-controlled listed companies exhibit overinvestment due to managerial compensation issues[24]. AI technology, through precise data analysis and real-time decision support, helps managers identify opportunities and risks, optimize resource allocation, and avoid inefficient behaviors stemming from underinvestment or overinvestment. Additionally, AI dynamically monitors market changes and financial conditions, further enhancing the scientific and efficient nature of investment decisions.

(3) AI Promotes R&D Innovation

AI application can drive corporate innovation and facilitate breakthroughs (Li et al., 2024)[15]. AI enables firms to grasp consumer demands more accurately through big data channels, automate customer service and market research, and learn from large text datasets, thereby avoiding overinvestment (Antoncic, 2020)[33]. Chandra and Rahman (2024) proposed that AI can enhance user experience and emotional connection through human-like interaction and algorithmic optimization[42]. AI intervention allows firms to clearly identify production shortfalls and provides clear guidance for technological innovation, stimulating R&D investment, optimizing resource allocation, reducing R&D failure probabilities, and enhancing

ISSN: 2710-0723

efficiency. Moreover, AI significantly reduces uncertainty in the R&D process, lowers R&D costs, and strengthens firms' willingness to invest in R&D. AI analysis can predict R&D risks in advance, optimize resource allocation, and reduce R&D costs. Additionally, AI accumulates rich resources and information for the R&D process, enhancing efficiency. In R&D, AI technology rapidly integrates cross-field knowledge, optimizes resource allocation, accelerates innovation, and improves product development efficiency (Briscoe and Rogan，2016)[38]. AI technology can also integrate and connect internal departments, promoting cross-departmental collaboration and information sharing, thereby reducing redundant work and resource waste. Through precise resource allocation, firms can channel more resources into innovative activities, accelerating new product development and enhancing market competitiveness. AI applications, through improving resource allocation efficiency, promote corporate innovation.

Based on the above analysis, the following hypotheses are proposed:

Hypothesis H1: AI technology application has a positive effect on corporate market value.

3.2. Model Specification

To examine the impact of corporate AI technology application on market value, this study adopts the model specified in equation (1)[23]:

$$TobinQ_{i,t} = \varphi_0 + \varphi_1 AI_{i,t} + \sum \beta CVs_{i,t} + \sum \gamma Ind + \sum \mu year + \varepsilon_{i,t}$$

Where *TobinQ* is the dependent variable, *AI* is the core independent variable, *CVs* represent control variables, and εis the error term. A positive and significant coefficient φ_1 would indicate that AI technology application enhances corporate market value, thereby supporting Hypothesis H1.

3.3. Variable Definitions

(1) Dependent Variable: Corporate Value

Following Zhang et al. (2021), this study uses Tobin's Q to measure corporate value[30]. Tobin's Q is calculated as the sum of a firm's market value of equity and the book value of debt divided by the book value of total assets. This metric is commonly used to evaluate corporate performance and growth potential. Compared to traditional financial metrics like *ROA* or *RO*E, Tobin's Q better captures long-term value creation (Brynjolfsson et al., 2021)[41], as it reflects market expectations of future growth and is adjusted for overall market risk, inflation, and systematic risk exposure.Since big data investment may affect the information content of a company's stock price and its cost of capital (Begenau et al., 2018), Tobin's Q value provides more comprehensive and critical information in reflecting corporate value[37].

(2) Independent Variable: AI Technology Application

This study measures AI technology application using a text-based approach. Specifically, we collected annual report text data from listed firms on the Shanghai and Shenzhen Stock Exchanges using Python web scraping techniques. We then employed Jieba for word segmentation to identify keywords related to AI, aggregated the word frequency of these keywords, and took the logarithm to construct a proxy for AI technology application levels.

(3) Control Variables

Drawing on prior literature, this study controls for variables that may influence the relationship between AI and corporate value, including firm size (*Size*), asset-liability ratio (*Lev*), cash flow ratio (*Cashflow*), inventory ratio (*INV*), fixed asset ratio (*Fixed*), firm growth (*Growth*), loss status (*Loss*), board size (*Board*), independent director ratio (*Indep*), largest shareholder stake (*Top1*), firm age (*Age*), and management shareholding (*Mshare*).

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Table 1. Variable Definitions and Descriptions

	Variable Name	Variable Symbol	**Variable Definition**
Dependent Variable	Tobin's Q	*TobinQ*	Calculated as the sum of the market value of equity and the book value of debt divided by the book value of total assets.
Independent Variable	AI Technology	*AI*	Measured by the logarithm of the total frequency of AI-related keywords in the annual report.
Control Variables	Firm Size	*Size*	Natural logarithm of total assets.
	Asset-Liability Ratio	*Lev*	Total liabilities divided by total assets.
	Cash Flow Ratio	*Cashflow*	Net cash flow from operating activities divided by total assets.
	Inventory Ratio	*INV*	Net inventory divided by total assets.
	Fixed Asset Ratio	*Fixed*	Net fixed assets divided by total assets.
	Firm Growth	*Growth*	Revenue growth rate (current year's revenue divided by previous year's revenue minus 1).
	Loss Status	*Loss*	Equals 1 if net profit is negative, 0 otherwise.
	Board Size	*Board*	Natural logarithm of the number of board members.
	Independent Director Ratio	*Indep*	Percentage of independent directors on the board.
	Largest Shareholder Stake	*Top1*	Shares held by the largest shareholder divided by total shares.
	Firm Age	*Age*	Calculated as the current year minus the founding year plus 1.
	Management Shareholding	*Mshare*	Shares held by management divided by total shares.

3.4. Data Sources

Table 2. Descriptive Statistics of Variables

VARIABLES	(1)	(2)	(3)	(4)	(5)
	Sample Size	**Mean**	**Variance**	**Minimum**	**Maximum**
TobinQ	24050	1.893	0.980	0.829	6.746
AI	24050	0.423	0.795	0.000	3.401
Size	24050	22.320	1.239	20.140	26.240
Lev	24050	0.419	0.199	0.0612	0.894
Cashflow	24050	0.047	0.063	-0.139	0.226
INV	24050	0.131	0.117	0.000	0.646
Fixed	24050	0.203	0.152	0.002	0.668
Growth	24050	0.131	0.351	-0.561	1.936
Loss	24050	0.149	0.356	0.000	1.000
Board	24050	2.102	0.195	1.609	2.639
Indep	24050	37.840	5.321	33.330	57.140
Top1	24050	0.327	0.144	0.082	0.720
Age	24050	3.016	0.286	2.197	3.584
Mshare	24050	14.310	19.200	0.000	67.660

This study uses financial data from the China Stock Market and Accounting Research (CSMAR) database and annual report text data from the CNInfo website for listed firms from 2015 to

ISSN: 2710-0723

2023. Data cleaning procedures included excluding firms with abnormal operations (e.g., ST, *ST, PT), financial institutions, newly listed firms (IPOs), and firms with incomplete data. Continuous variables were winsorized at the 1st and 99th percentiles.

Sample SizeMeanVarianceMinimumMaximum.

4. Empirical Results

4.1. Benchmark Regression

The benchmark regression results in Table 3 show that the coefficient for AI is significantly positive across all specifications, supporting Hypothesis H1. Specifically, AI's impact remains positive and significant after controlling for industry and year fixed effects. Additionally, smaller firms, those with lower asset-liability ratios, higher cash flow ratios, and higher growth potential tend to have higher market values.

Table 3. Benchmark Regression

VARIABLES	(1)	(2)	(3)	(4)
	TobinQ	*TobinQ*	*TobinQ*	*TobinQ*
AI	0.286***	0.163***	0.212***	0.163***
	(18.031)	(9.195)	(14.790)	(10.117)
Size			-0.264***	-0.264***
			(-24.039)	(-22.801)
Lev			-0.515***	-0.364***
			(-8.230)	(-5.845)
Cashflow			1.887***	1.889***
			(11.650)	(12.645)
INV			0.012	-0.014
			(0.160)	(-0.158)
Fixed			-0.467***	-0.470***
			(-7.873)	(-6.661)
Growth			0.286***	0.237***
			(14.467)	(12.384)
Loss			0.088***	0.072***
			(4.512)	(3.809)
Board			0.132**	0.095*
			(2.255)	(1.652)
Indep			0.009***	0.007***
			(4.427)	(3.707)
Top1			-0.276***	-0.075
			(-4.249)	(-1.156)
Age			-0.279***	-0.089**
			(-8.486)	(-2.572)
Mshare			-0.007***	-0.006***
			(-11.798)	(-10.848)
Constant	1.772***	2.815***	8.288***	8.638***
	(159.226)	(14.641)	(28.619)	(25.266)
Observations	24050	24050	24050	24050
R^2	0.054	0.211	0.225	0.323
Industry FE	NO	YES	NO	YES
Year FE	NO	YES	NO	YES

Note:***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. t-values are in parentheses, with standard errors clustered at the firm level. The same applies to subsequent tables.

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4.2. Robustness Checks

(1) Replacing the Dependent Variable Measurement

Following Wang et al. (2022)[19], this study uses Tobin's Q to measure firm market value in the benchmark regression. To address potential measurement bias, financial accounting metrics like Return on Assets (ROA) and Return on Equity (ROE) are used as alternative dependent variables. Columns (1) and (2) of Table 4 present the regression results for ROA and ROE, respectively, with AI coefficients remaining significantly positive, supporting the benchmark results.

(2) Replacing the Independent Variable

Beyond the aggregate AI keyword frequency, this study examines AI mentions in the Management Discussion and Analysis section of annual reports, termed MDA_AI. Column (3) of Table 4 shows that MDA_AI remains significantly positive, confirming the original findings.

(3) Using Firm-Year Fixed Effects

To ensure robustness, the study replaces industry-year fixed effects with firm-year fixed effects (see Table 6). Introducing firm fixed effects controls for time-invariant unobserved heterogeneity, such as governance structure, strengthening causal inference. Column (4) of Table 4 shows consistent coefficient signs and significance levels with the benchmark model, confirming the robustness of the results across different fixed effect specifications and effectively mitigating omitted variable bias.

(4) Propensity Score Matching (PSM)

To address potential bias from sample self-selection, PSM is employed. Using AI adoption as the treatment variable and firm characteristics as covariates, a Logit model calculates propensity scores. A 1:1 nearest-neighbor matching with a caliper width of 0.05 is applied. Post-matching covariates show standardized biases below 5%, satisfying the common support condition. Regression results on matched samples (Column (5) of Table 4) maintain a significantly positive AI coefficient after controlling for year, industry, and firm characteristics, confirming the robustness of the findings.

(5) Instrumental Variable (IV) Method

To tackle potential endogeneity from omitted variables or reverse causality, an IV approach using the average *AI* adoption rate of other firms in the same province and year is employed. A two-stage least squares (2SLS) model is constructed. This method isolates endogenous variable effects, enhancing estimation reliability. Firms in the same province share similar policy and market conditions, creating spatial correlation in AI diffusion, while the provincial *AI* usage level affects individual firm decisions without directly impacting firm value (*TobinQ*), satisfying exclusion restrictions. After controlling for firm characteristics, year, and industry fixed effects, the AI coefficient remains significantly positive, further supporting the robustness of the conclusions.

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Table 4. Robustness Tests

VARIABLES	(1)	(2)	(3)	(4)	(5)
	ROA	*ROE*	*TobinQ*	*TobinQ*	*TobinQ*
	Replace Dependent Variable	Replace Dependent Variable	Replace Independent Variable	Individual Fixed Effects	PSM
AI	0.002***	0.006***		0.044***	0.122***
	(4.395)	(5.153)		(2.820)	(5.903)
MDA_AI			0.138***		
			(7.173)		
Size	0.006***	0.017***	-0.261***	-0.456***	-0.235***
	(15.467)	(19.058)	(-22.311)	(-17.995)	(-10.075)
Lev	-0.079***	-0.141***	-0.373***	0.162**	-0.602***
	(-32.445)	(-20.739)	(-5.947)	(2.051)	(-4.989)
Cashflow	0.237***	0.323***	1.896***	0.743***	2.636***
	(33.700)	(23.836)	(12.577)	(8.068)	(8.195)
INV	0.017***	0.073***	-0.029	0.085	0.153
	(4.378)	(7.592)	(-0.316)	(0.795)	(0.797)
Fixed	-0.031***	-0.029***	-0.514***	0.150	-0.633***
	(-10.390)	(-4.346)	(-7.177)	(1.505)	(-4.272)
Growth	0.024***	0.048***	0.240***	0.120***	0.419***
	(24.112)	(22.709)	(12.448)	(8.493)	(9.673)
Loss	-0.098***	-0.225***	0.074***	-0.067***	0.142***
	(-69.226)	(-61.761)	(3.897)	(-4.764)	(3.592)
Board	0.004*	0.007	0.098*	-0.002	0.202*
	(1.874)	(1.306)	(1.709)	(-0.026)	(1.664)
Indep	-0.000	0.000	0.007***	0.001	0.011***
	(-0.226)	(0.194)	(3.700)	(0.761)	(2.603)
Top1	0.026***	0.045***	-0.085	-0.338***	-0.177
	(10.821)	(9.052)	(-1.303)	(-2.617)	(-1.384)
Age	0.000	-0.001	-0.100***	0.423**	-0.224***
	(0.109)	(-0.281)	(-2.874)	(2.238)	(-3.439)
Mshare	0.000***	0.000***	-0.006***	-0.003***	-0.008***
	(11.071)	(8.211)	(-10.746)	(-3.131)	(-8.285)
Constant	-0.088***	-0.317***	8.610***	11.404***	8.183***
	(-7.433)	(-12.694)	(24.896)	(14.892)	(11.868)
Observations	24049	24037	24050	24050	7526
R^2	0.648	0.598	0.318	0.249	0.253
Industry FE	YES	YES	YES	NO	YES
Year FE	YES	YES	YES	YES	YES
Individual FE	NO	NO	NO	YES	NO

4.3. Heterogeneous Analysis

(1) Ownership Structure

To explore the heterogeneous impact of firm ownership, this study introduces an interaction term between AI technology and state-owned enterprise (SOE) status (AI×SOE) into the benchmark model. Column (1) of Table 6 shows a significantly positive coefficient for AI and a significantly positive coefficient for the interaction term AI×SOE, indicating that AI's value-enhancing effect differs significantly between SOEs and non-SOEs. This may stem from SOEs' lower innovation efficiency due to policy burdens, resource misallocation, or insufficient market incentives (Wang et al., 2022)[21], which alter the impact of AI on firm market value.

(2) Big 4 Audit

ISSN: 2710-0723

To examine the moderating role of information transparency and oversight mechanisms, this study analyzes whether firms are audited by the Big 4 accounting firms (Big4). Column (2) of Table 5 shows a significantly positive coefficient for the interaction term AI×Big4, suggesting that AI's market value enhancement is more pronounced in Big 4-audited firms. This is likely due to the high-quality audit services provided by Big 4 firms: strict internal controls that prevent AI implementation abuse and signaling effects that enhance investor confidence in AI-driven returns, thereby amplifying market valuation premiums (Bao, 2020)[1].

(3) Regulated Industries

Table 5. Instrumental Variable Based on Provincial Average

VARIABLES	(1)	(2)
	AI	*TobinQ*
AI		0.474***
		(2.676)
IV	0.315***	
	(6.727)	
Size	0.025***	-0.273***
	(2.911)	(-21.208)
Lev	-0.097**	-0.328***
	(-2.214)	(-4.954)
Cashflow	0.158*	1.835***
	(1.817)	(11.982)
INV	-0.123*	0.027
	(-1.835)	(0.281)
Fixed	-0.489***	-0.305***
	(-8.530)	(-2.648)
Growth	0.002	0.237***
	(0.157)	(12.248)
Loss	0.005	0.069***
	(0.281)	(3.588)
Board	0.024	0.088
	(0.519)	(1.510)
Indep	0.001	0.007***
	(0.428)	(3.514)
Top1	-0.138***	-0.033
	(-2.712)	(-0.469)
Age	-0.084***	-0.061
	(-2.900)	(-1.616)
Mshare	-0.000	-0.006***
	(-0.870)	(-10.525)
Constant	-0.338	8.774***
	(-1.492)	(24.344)
Observations	24050	24050
R^2	0.415	0.314
Industry FE	YES	YES
Year FE	YES	YES

ISSN: 2710-0723

Column (3) of Table 5 shows a significantly negative coefficient for the interaction term between AI and regulated industries (AI×Regulated), indicating that AI's value-enhancing effect is significantly weaker in regulated industries. The net effect of AI in regulated industries (AI main effect + interaction term) is only 0.140. This may result from external governance factors such as government intervention, legal system strength, and financial market maturity, which constrain irrational investment behaviors in regulated industries (Li et al., 2013)[14]. These factors reduce overinvestment and inefficient investment costs, thereby affecting firm market value. Additionally, strict entry restrictions and price controls in regulated industries limit firms' autonomy in technological innovation, weaken the role of managerial cognition in driving innovation, and constrain AI's resource allocation optimization, reducing firms' intrinsic motivation to leverage AI for cost reduction and efficiency improvement (Yu and Fan, 2022)[27].

5. Mechanism Tests

While prior analysis confirms AI's positive impact on firm value (Tobin's Q), the specific mechanisms require further exploration. This study tests three pathways: cost reduction, inefficient investment mitigation, and R&D innovation promotion, with regression results presented in Table 6.

5.1. Cost Reduction Mechanism

This study uses the management cost ratio (Mcost), calculated as operating costs divided by operating revenue, to measure cost reduction efficiency. Column (1) of Table 6 shows a significantly negative coefficient for AI, indicating that AI significantly reduces marginal costs. This suggests that AI-driven automation and intelligent scheduling minimize labor and inventory waste, thereby lowering management cost ratios (Wu and Xu, 2022)[23].

5.2. Inefficient Investment Mitigation Mechanism

To capture inefficient investment reduction, this study uses the inefficient investment ratio (Abinvest), calculated as the net value change of fixed assets, construction in progress, intangible assets, and long-term investments divided by average total assets (Chen and Xie, 2011)[5]. Column (2) of Table 6 shows a significantly negative coefficient for AI, indicating that AI reduces inefficient investment by improving information processing and mitigating agency conflicts that cause investment distortions. AI's algorithm-assisted decision-making identifies low-return projects (e.g., overexpansion or self-serving mergers), optimizes capital allocation, and reduces inefficient investment. This alleviates financing constraints, addresses underinvestment due to funding limitations, and avoids overinvestment from aggravated agency problems, thereby enhancing resource and investment efficiency (Tong, 2021) and promoting firm value[18].

5.3. R&D Innovation Promotion Mechanism

To measure innovation promotion, this study uses total factor productivity (TFP_LP), calculated via the LP method (Levinsohn and Petrin, 2003)[45], and patent innovation output (lnpati), based on annual patent applications.The invention - patent innovation output, based on the number of patent applications in a year, shows the firm's innovation level (Long and Lin, 2018)[16]. Column (3) of Table 6 shows a significantly positive coefficient for AI, indicating that AI significantly enhances total factor productivity, confirming its role in boosting technical efficiency and fostering innovation through technological synergy. Column (4) shows a significantly positive elasticity coefficient of 0.220 for lnpati, indicating that AI strengthens innovation momentum by accelerating R&D iteration through data mining and improving innovation quality.

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Table 6. Mechanism Tests

VARIABLES	(1)	(2)	(3)	(4)
	Mcost	*Abinvest*	*TFP_LP*	*lnpati*
AI	-0.020***	-0.005***	0.020**	0.220***
	(-8.440)	(-11.732)	(2.450)	(7.667)
Size	-0.002	-0.003***	0.619***	0.247***
	(-0.873)	(-7.715)	(79.612)	(9.447)
Lev	0.238***	0.010***	0.678***	-0.172
	(19.957)	(4.242)	(13.808)	(-1.436)
Cashflow	-0.380***	-0.019***	1.833***	1.061***
	(-15.754)	(-3.467)	(20.895)	(4.942)
INV	0.115***	-0.051***	0.948***	0.346*
	(5.069)	(-12.563)	(9.062)	(1.786)
Fixed	0.106***	0.003	-1.508***	0.215
	(6.605)	(1.110)	(-23.727)	(1.327)
Growth	-0.022***	0.019***	0.180***	-0.074***
	(-6.262)	(14.184)	(13.432)	(-2.660)
Loss	0.052***	-0.001	-0.206***	-0.211***
	(13.319)	(-0.817)	(-13.139)	(-6.098)
Board	-0.015	-0.005**	-0.018	0.424***
	(-1.348)	(-2.478)	(-0.377)	(3.148)
Indep	-0.001**	0.000	-0.002	0.005
	(-2.106)	(0.756)	(-1.163)	(1.065)
Top1	0.017	-0.002	0.261***	0.283*
	(1.349)	(-0.772)	(5.328)	(1.897)
Age	0.037***	-0.006***	0.021	-0.484***
	(5.390)	(-4.324)	(0.798)	(-6.096)
Mshare	-0.001***	0.000***	-0.000	0.009***
	(-7.260)	(2.721)	(-0.735)	(8.733)
Constant	0.625***	0.151***	-5.823***	-4.584***
	(10.834)	(13.439)	(-24.037)	(-6.560)
Observations	24049	21514	24046	24044
R^2	0.460	0.132	0.770	0.355
Industry FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES

6. Conclusion and Recommendations

6.1. Research Conclusion

This study explores how artificial intelligence (AI) technology impacts corporate market value and its mechanisms. Empirical results indicate that AI significantly enhances corporate market value. This conclusion holds after robustness tests, endogeneity corrections, and heterogeneity analyses. Specifically, AI boosts market value through three channels: 1) Cost Reduction: AI optimizes production processes and improves resource efficiency, reducing marginal costs. 2) Inefficient Investment Mitigation: AI minimizes investment distortions through data-driven decision-making and portfolio optimization. 3) R&D Innovation Promotion: AI enhances total factor productivity and stimulates innovation, accelerating technological upgrades and commercialization.

ISSN: 2710-0723

Heterogeneity analyses reveal that AI's value-enhancing effect varies significantly across firms with different ownership structures, audit qualities, and regulatory environments. Notably, AI's impact is more pronounced in non-state-owned enterprises, firms audited by the Big Four accounting firms, and non-regulated industries. This highlights the critical role of corporate governance and external oversight in realizing AI's benefits.

6.2. Policy Recommendations

(1) For Enterprises

Firms should actively invest in AI technology, particularly in optimizing production processes, cost control, and R&D innovation, to enhance competitiveness and market value. Improving governance structures, boosting transparency, and selecting high-quality auditors can strengthen investor confidence. Additionally, firms should prioritize data infrastructure development to ensure effective AI implementation.

(2) For Policymakers

Governments should introduce supportive policies, such as tax incentives and subsidies, to lower AI adoption costs and encourage its application across industries. Strengthening industry regulation, establishing technical standards, and providing application guidelines can ensure safe and efficient AI use while preventing misuse and unfair competition.

(3) For Society:

Society should focus on cultivating and attracting AI talent through educational reforms and vocational training, producing professionals with both technical and managerial skills. Public awareness campaigns and educational initiatives can dispel misconceptions about AI, fostering a supportive environment for technological innovation.

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