

The Impact of Artificial Intelligence Development on the Market Value of Enterprises: An Empirical Study based on Chinese Listed Companies

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Abstract

Against the backdrop of the accelerating development of the digital economy, artificial intelligence (AI) has increasingly emerged as a key driver of enterprise transformation, efficiency improvement, and value creation. Based on a sample of Chinese A-share listed companies from 2015 to 2023, this study constructs a firm-level indicator of AI development by extracting and quantifying AI-related information disclosed in annual reports. Employing a two-way fixed effects model, the paper systematically investigates the relationship between corporate AI development and firm market value. The empirical results show that firms with a higher degree of AI adoption and development exhibit significantly higher market valuations, indicating that AI serves as an important source of value enhancement in capital markets. Further mechanism analysis reveals that this positive valuation effect is primarily driven by improvements in total factor productivity and enhanced information transparency, which help reduce information asymmetry and optimize resource allocation. In addition, heterogeneity analysis suggests that the market value premium associated with AI development is more pronounced among firms operating in high-technology industries and among larger enterprises, reflecting differences in technological absorption capacity and scale advantages. Overall, this study provides robust empirical evidence for enterprises to optimize their digital transformation strategies and offers valuable insights for investors seeking to evaluate firm value in the context of rapid digital and intelligent economic development.

Keywords

Artificial Intelligence; Corporate Market Value; Digital Transformation; Panel Data; Signaling Theory.

1. Introduction

In recent years, the global economy has entered a crucial stage of transformation from a traditional industrial economy toward a digital economy [1]. Digital technologies are increasingly becoming the core drivers of economic growth and structural upgrading. Among them, artificial intelligence (AI), as a representative general-purpose technology of the fourth industrial revolution, is not only reshaping firms' production processes and organizational structures, but also fundamentally altering the logic through which capital markets evaluate corporate value. By embedding intelligent algorithms, data analytics, and automation into business activities, AI has the potential to change firms' cost structures, innovation patterns, and competitive advantages. In China, artificial intelligence is regarded as a strategic industry, and its development has been incorporated into national policy priorities. A series of national-level policy initiatives, including the New Generation Artificial Intelligence Development

Plan[2], have been introduced to accelerate technological innovation and promote the deep integration of AI with the real economy. These policies aim to guide enterprises to adopt intelligent technologies, enhance industrial upgrading, and cultivate new sources of economic growth.

Despite strong policy support and substantial corporate investment, whether enterprises' invest in AI can be effectively translated into capital market recognition remains an open and debated question. On the one hand, AI adoption may improve operational efficiency, reduce production costs, and enhance decision-making accuracy, thereby strengthening profitability expectations and increasing firm valuation. On the other hand, AI-related investment is often characterized by high upfront costs, long payback periods, and considerable technological uncertainty. These features may raise business risks and financial pressure, potentially leading investors to apply valuation discounts rather than premiums.

Existing studies mainly concentrate on the macroeconomic effects of AI or its impact on firms' productivity and innovation performance at the micro level. In contrast, empirical research that directly examines the relationship between firms' internal AI development and their stock market value is still relatively limited. Moreover, due to data constraints, measuring enterprise-level AI capability remains challenging, which further restricts empirical analysis in this area.

Against this background, this paper uses Chinese A-share listed companies from 2015 to 2023 as the research sample. By applying text mining techniques to corporate annual reports, we construct a firm-level AI development index and empirically investigate the effect of AI development on enterprise market value, as well as the underlying mechanisms.

First, by utilizing text-based information, this study provides a new approach to assessing firms' AI-related focus and activities, compensating for the inability of traditional indicators to fully reflect firms' digital and technological soft strength.

Second, by identifying the channels through which AI development influences market value, this paper helps uncover the internal mechanisms of technology-driven value creation, thereby shedding light on the "black box" linking intelligent technologies and capital market valuation.

2. Literature Review

2.1. Digital Transformation and Enterprise Value

From the perspective of the Resource-Based View (RBV), sustainable competitive advantage originates from scarce, valuable, and hard-to-imitate internal resources. With the rapid advancement of digital technologies, data has gradually become a critical strategic asset and an essential production factor for modern enterprises. Existing studies generally agree that digital transformation reshapes firms' production and operation models by integrating digital technologies into traditional business processes, thereby enhancing overall value creation capacity.

Prior research indicates that digital transformation can significantly reduce firms' marginal operating costs by improving automation levels and optimizing internal processes, while simultaneously enhancing the efficiency of resource allocation across departments and business units [3]. Through digital platforms and data-driven decision-making, enterprises are able to respond more flexibly to changes in market demand and improve operational coordination. Sun (2021) further finds that firms with stronger digital capabilities demonstrate greater resilience in the face of external shocks and market volatility, which strengthens investors' confidence and leads to valuation premiums in the capital market [4]. Overall, the literature suggests that digital transformation not only improves firm performance from an operational perspective but also positively affects how firms are perceived and priced by investors.

2.2. The Value Creation Effect of Artificial Intelligence

As an advanced and representative digital technology, artificial intelligence plays a particularly important role in enterprise digital transformation. Existing studies mainly explain the value creation effect of AI from two complementary dimensions: substantive business improvement and market signaling effects.

First, AI contributes directly to firm value by enhancing core business performance. By applying machine learning algorithms, intelligent analytics, and automation technologies, AI enables enterprises to optimize supply chain management, improve precision marketing, and promote intelligent manufacturing. These applications help reduce production costs, increase output efficiency, and improve resource utilization, thereby enhancing key financial indicators such as return on equity (ROE) and total factor productivity (TFP). Moreover, the adoption of machine learning techniques can improve the efficiency of capital market pricing by facilitating more accurate information processing and performance forecasting [5].

Second, AI development also generates value through a signaling mechanism. According to signaling theory (Spence, 1973), firms can convey private information about their quality and future prospects to the market through observable actions or disclosures. When enterprises actively disclose AI-related strategies, investments, or technological layouts, they send a positive signal of innovation orientation and long-term growth potential. This signal helps reduce information asymmetry between corporate managers and external investors, improves market expectations, and lowers financing constraints and capital costs [6]. As a result, AI-related disclosures may be positively reflected in stock prices and market valuation even before the full economic benefits of AI investment are realized.

2.3. Research Hypothesis

Based on the above theoretical analysis and existing empirical evidence, artificial intelligence development is expected to enhance enterprise value through both internal performance improvement and external information transmission mechanisms. Accordingly, this paper proposes the following core hypothesis:

H1: Under the condition that all other factors remain constant, the higher the level of enterprise artificial intelligence development, the firm is associated with a higher level of market valuation.

3. Research Design

3.1. Sample and Data Source

This study selects Chinese A-share listed companies from 2015 to 2024 as the initial sample. The data comes from the CSMAR database and the Wind financial terminal. To ensure data quality, the following criteria are used for screening: (1) Exclude ST, *ST, and PT type companies; (2) Exclude financial and insurance listed companies; (3) Exclude observations with missing main variables. Eventually, 21,340 company-year observation samples are obtained.

3.2. Variable Definition

3.2.1. Dependent Variable: Enterprise Market Value (lnMV)

Following prior studies, enterprise market value is defined as the logarithmic transformation of total market capitalization at the end of the fiscal year, computed using the formula below:

$$\ln MV_{it} = \ln(\text{Price}_{it} \times \text{Share}_{it}) \quad (1)$$

Among them, $Price_{it}$ represents the closing price of the i -th enterprise at the end of year t , and $Share_{it}$ represents the total share capital.

3.2.2. Core Explanatory Variables: Artificial Intelligence Development Index (AI)

Following the text-based digital technology measurement approach proposed by Wu Fei et al. (2021), this study further refines the framework to construct an AI-specific development index. [7] The procedure consists of collecting the annual reports of listed firms and applying Python-based jieba word segmentation to identify the frequencies of AI-related terms, including "artificial intelligence," "deep learning," "machine learning," "image recognition," "neural networks," and "big data." The indicator is then constructed as the natural logarithm of the sum of these keyword frequencies plus one:

$$AI_{it} = \ln(\sum \text{Keywords}_{it} + 1) \quad (2)$$

3.2.3. Control Variables

Enterprise size, debt-to-asset ratio, ROA, cash flow, proportion of the largest shareholder's shareholding, etc.

3.3. Model Specification

To test Hypothesis H1, the following two-way fixed effects model is constructed:

$$\ln MV_{it} = \alpha_0 + \beta_1 AI_{it} + \gamma \sum \text{Controls}_{it} + \mu_i + \lambda_t + \varepsilon_i \quad (3)$$

Here, μ_i represents the individual fixed effect, controlling for the characteristics of the enterprise that do not change over time; λ_t represents the year fixed effect, controlling for macroeconomic shocks; ε_i is the random disturbance term. If β_1 is significantly positive, then Hypothesis H1 is established.

4. Empirical Result Analysis

4.1. Descriptive Statistics

Table 1 reports the descriptive statistics of the main variables.

Table 1. Descriptive Statistics of Main Variables

Variable	Sample Size	Mean	Standard Deviation	Minimum Value	Maximum Value
lnMV	21340	22.45	1.12	20.15	26.38
AI	21340	1.84	1.35	0	5.42
Size	21340	22.31	1.28	19.85	26.1
Lev	21340	0.425	0.198	0.055	0.885
ROA	21340	0.038	0.065	-0.18	0.22
RD	21340	0.042	0.035	0	0.185
ln TFP	21340	0.12	0.08	-0.35	0.48
ln Size	21340	22.31	1.28	19.85	26.1

Note: The data is derived from the CSMAR database and is calculated.

From the table, it can be seen that the average value of the AI index is 1.840 and the standard deviation is 1.350, indicating significant differences in the AI layout among different enterprises;

the overall average value of the AI index is relatively low, but there is significant differentiation, suggesting that the AI layout is insufficient but leading enterprises are actively exploring.

4.2. Baseline Regression

Table 2 reports the regression results of the impact of AI development on enterprise market value.

Table 2. Artificial Intelligence and Enterprise Market Value: Baseline Regression

Variable	OLS	FE
AI	0.085*** (12.45)	0.042*** (5.82)
Size	0.52***	0.415***
Lev	-0.63***	-0.38***
ROA	1.85***	1.25***
Top1	0.005***	0.003**
Constant	8.54***	10.21***
Observations	21340	21340
R-squared	0.542	0.615
Individual FE	NO	YES
Year FE	NO	YES

Note: The values in parentheses are t-values. ***, **, * indicate significance at 1%, 5%, and 10% levels respectively.

Column (2) shows that after controlling for relevant financial indicators and bidirectional fixed effects, the regression coefficient of AI is 0.042, and it is significant at the 1% level. This indicates that for every 1% increase in the frequency of AI-related keywords, the average market value of the enterprise increases by approximately 0.042%, verifying Hypothesis H1.

4.3. Mechanism Test

To verify the "cost reduction and efficiency improvement" mechanism, this paper introduces total factor productivity (TFP) as an intermediary variable. The model is as follows:

$$TEP_{it} = \alpha + \theta AI_{it} + \sum Controls + FE + \varepsilon \quad (4)$$

The empirical results show that the regression coefficient of AI on TFP is significantly positive ($\beta = 0.018$, $p < 0.01$). These results suggest that AI adoption enhances firm fundamental value by improving input-output efficiency. Of the enterprise by optimizing the efficiency of input and output through the application of AI technology.

4.4. Heterogeneity Analysis

This paper divides the sample into high-tech industries and non-high-tech industries for grouped regression.

The coefficient of AI in the high-tech group: 0.058 ***

The coefficient of AI in the non-high-tech group: 0.021 **

The results show that in the high-tech industry, the application scenarios of AI technology are broader, and the market gives a higher valuation premium.

5. Robustness Test

To ensure the reliability of the conclusion, the following robustness tests are conducted:

- (1) Replacement of explanatory variables: Replacing the AI index with a dummy variable indicating whether AI research and development has been carried out (Dummy_AI), the coefficient remains significantly positive.
- (2) Replacement of the dependent variable: Using the Tobin Q value (TobinQ) as the dependent variable, the results are robust.
- (3) Endogeneity handling: Considering the reverse causality (companies with higher market capitalization have more funds to invest in AI), an instrumental variable (IV) is adopted. To address potential endogeneity, we employ the contemporaneous industry-level average AI index of peer firms as an instrument, and the 2SLS regression continues to yield a significant coefficient on AI.

6. Conclusion and Recommendations

6.1. Main Conclusion

The empirical results of this study indicate that the development level of AI in listed companies significantly enhances the stock market value of enterprises. This positive effect can be primarily attributed to the improvement of enterprise operational efficiency by AI and the positive innovation signals it conveys to the market. Moreover, the value creation of AI is more strongly manifested in the high-tech industry and large enterprises.

6.2. Policy Recommendations

- (1) Government Level: Continuous improvement of digital infrastructure construction and the formulation of differentiated industrial support policies should be emphasized, with a focus on guiding traditional manufacturing industries to undergo intelligent transformation.
- (2) Enterprise Level: Digital transformation should be regarded as a long-term strategy. Firms should focus not only on symbolic AI disclosure but also on substantive AI implementation. AI should be effectively utilized to reduce costs and increase efficiency.
- (3) Investor Level: When conducting valuation modeling, the digital assets of enterprises and AI research capabilities should be taken into consideration, focusing on high-quality targets with "hard technology" strength.

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