深圳技术大学
SHENZHEN TECHNOLOGY UNIVERSITY

UNDERGRADUATE GRADUATION THESIS

Artificial Intelligence Adoption and Corporate Investment Efficiency: Evidence from Chinese Listed Firms

Name	谢娜 XIE Na
College	Business School
Major	Financial Management
Student ID	202200702038
Thesis Supervisor	崔頔 CUI Di
Supervisor Title	Associate Professor
Submission Date	2026/04/11

深圳技术大学本科毕业论文（设计）诚信声明

Shenzhen Technology University Undergraduate Graduation Thesis (Design) Integrity Statement

本人郑重声明：所呈交的毕业论文（设计）,题目《Artificial Intelligence Adoption and Corporate Investment Efficiency: Evidence from Chinese Listed Firms 》 是本人在指导教师的指导下,独立进行研究工作所取得的成果。对本文的研究做出重要贡献的个人和集体,均已在文中以明确方式注明。除此之外,本论文不包含任何其他个人或集体已经发表或撰写过的作品成果。本人完全意识到本声明的法律结果。

I solemnly declare that: the graduation thesis (design) submitted with the title < Artificial Intelligence Adoption and Corporate Investment Efficiency: Evidence from Chinese Listed Firms > is the result of my independent research work under the guidance of supervisor. Individuals and collectives who have made important contributions to the research in this paper have been clearly identified in the paper. In addition, this paper does not contain the results of any other work that has been published or written by any other individual or group. I am fully aware of the legal consequences of this statement.

毕业论文（设计）作者签名 Signature of Author of the Graduation Thesis (Design):

谢娜

日期 Date: 2026 年/Y 4 月/M 11 日

Contents

Abstract.. 1

1. Introduction... 2

    1.1 Research background.. 2

    1.2 Research significance 3

2. Literature review and hypothesis development............................ 4

    2.1 Determinants of corporate investment efficiency 5

    2.2 Economic consequences of artificial intelligence (AI) adoption... 6

    2.3 AI and corporate investment efficiency............................... 6

    2.4 Hypothesis development.. 7

3. Research design 8

    3.1 Data sources and sample selection 8

    3.2 Variable measurement.. 9

        3.2.1 Dependent variable 9

        3.2.2 Independent variable.. 9

        3.2.3 Control variable 10

        3.2.4 Moderating variable.. 10

        3.2.5 Model specification.. 10

4. Empirical results and analysis 10

    4.1 Descriptive statistics 10

    4.2 Correlation analysis 11

4.3 Baseline regression 14
4.4 Robustness check 15
4.4.1 Difference-in-Differences (DID) 15
4.4.2 Instrumental variable method 17
4.5 Mechanism test 19
4.5.1 Company opacity 20
4.5.2 Analyst attention 20
4.5.3 Report attention 21
4.6 Moderating effect 22
4.6.1 Full sample 22
4.6.2 High-financing-constraints subsample 23
4.6.3 Low-financing-constraints subsample 24
4.7 Heterogeneity analysis 26
4.7.1 Heterogeneity analysis by ownership structure 26
4.7.2 Heterogeneity analysis of industry technology intensity 28
5. Conclusion and implications 30
5.1 Summary 30
5.2 Suggestions 31
5.3 Limitations and future research 32
5.3.1 Limitations 33
5.3.2 Future research directions 33

Abstract and keywords in Chinese 34

References 35

Acknowledgement 38

Abstract

Leveraging a large number of Chinese A-share listed companies from 2007 to 2024, this research examines the impact of the application of artificial intelligence (AI) technology on corporate investment efficiency. An indicator of AI adoption at the firm level is established by analyzing the annual reports, and investment inefficiency is measured according to the Richardson (2006) residual model. The empirical results show that: (1) AI technology adoption is related to lower investment inefficiency, and the effect becomes more significant after controlling for endogeneity; (2) AI attracts more attention from analysts and receives more research report comments; (3) firms with less financing constraints show a greater influence of AI on their investment efficiency; (4) Heterogeneity tests indicate that the positive effect on efficiency from artificial intelligence differs greatly with respect to the ownership structure: the effect is evident in non-state enterprises, but not statistically significant in public listed companies; additionally, compared with high-tech industries, the efficiency improvement obtained by non-high-tech industries from AI application is more obvious. These findings enrich the literature on digital transformation and corporate governance, and give policy suggestions for deepening the reform of state-owned enterprises, improving the financing environment and promoting the widespread use of AI to maximize the benefits of technology.

Keywords: Artificial Intelligence; Investment Efficiency; Financing Constraints; Ownership Structure

1. Introduction

1.1 Research background

Artificial intelligence has developed from a new technology to an essential factor in the economic growth and social progress in this period of continuous innovation. The rapid progress of generative AI, such as large language models, has greatly changed not only the way businesses function and people live, but also the basic framework and thinking methods of the decision-making of executives (Furman & Seamans, 2019).

Since 2019, the Seventh Meeting of the Central Committee for Comprehensive Reform has promulgated the Guidelines on promoting the comprehensive integration of Artificial Intelligence and the Physical Economy. It suggests embedding Artificial Intelligence deeply into the real economy and developing an intelligent economic system based on data-driven management, human-machine collaboration, cross-border integration and cooperative value creation. In the 2024 Government Work Report, big data and Artificial Intelligence were given priority in the research, officially establishing the "AI+" project. The "AI+" project was again emphasized in the 2025 Government Work Report. With the continuous development of technological revolution, Artificial Intelligence has already entered some main industries, but the implementation varies among different enterprises. The integration with the real economy is proceeding rapidly and the promoting effect of technology is becoming more obvious.

As an important production element, artificial intelligence is spreading into various parts of the main procedures of the enterprise, from research and development to the operations of supply chain, production and manufacture, and marketing. Its usage fields are becoming deeper in the actual economic industries like industry, agriculture and energy. The close combination of artificial intelligence and the physical economy has now become an essential way to obtain high-economic growth. However, the introduction of artificial intelligence into the physical economy encounters some steady obstacles. The enterprises have difficulties in motivating the intelligent transformation and applying the intelligent technology because of the shortage of talents and capital limitations. These restrictions hinder the adoption of AI, resulting in the unattainable improvement of operating efficiency. The economic development of actual economy is affected. Therefore, the combination of AI and the physical economy is now an urgent governmental issue.

Investment efficiency is an important aspect influencing the rapid progress of the real economy. It not only indicates the effective use of capital and the increase of enterprise value, but also affects the sustainable and refined growth of the macroeconomic situation. However, with the increase of production costs, low labor productivity and small profit margins of products, there is still a large difference in investment efficiency among Chinese enterprises, which needs to be improved in the rational distribution of resources. For the promotion of high-quality economic development, the operation mode of enterprises should change from "driven by investment scale" to "driven by investment efficiency". In the field of intelligent development, the influence of artificial intelligence on enterprises has already reached various levels: artificial intelligence can assist enterprises in constructing intelligent information exchange systems, enlarging the range of information required for decision-making by managers; according to the machine learning algorithms, establishing dynamic cooperative mechanisms can realize cross-departmental data sharing and optimize the resource allocation; artificial intelligence also modifies the traditional investment methods with its strong functions of data collection, analysis and forecasting. Under such circumstances, it is significant to investigate whether the application of artificial intelligence can enhance the corporate investment efficiency.

1.2 Research significance

Theoretical level:

This investigation investigates the adoption of AI as a new factor affecting the corporate investment efficiency. Compared with the previous studies which mainly consider the information system and financing obstacles, this research offers empirical evidence that AI can increase the investment efficiency by enhancing the information processing ability and attracting the attention of analysts. The results also indicate that the above relationship is different under various ownership forms and financing conditions, with some preliminary findings showing industry differences: AI significantly increases the efficiency mainly in companies with less financing restrictions, in non-SOEs instead of SOEs, and particularly in non-high-tech industries rather than high-tech industries. These results imply that the relationships between technology and performance are influenced by institutional, financial and technological backgrounds. Moreover, the observation that AI has greater impacts in non-high-tech industries might suggest the decreasing marginal returns in technologically intensive environments compared with the remarkable progress made in firms with lower initial technological bases.

Practical level:

This research makes a contribution to the corporate investment efficiency literature by investigating the impact of AI adoption as a new influencing element and determining the contextual limitations affecting its efficacy. The results provide strategic suggestions for corporate managers to improve AI application in various organizational settings, for investors to recognize and assess the opportunities of technological investments, and for policymakers to formulate specific measures to create an advantageous atmosphere for the integration of AI into the real economy.

2. Literature review and hypothesis development

The current part presents a systematic review of the existing studies arranged according to three main themes: the macro- and micro-level impacts of AI, and the existing research on the efficiency of corporate investments in AI. This helps to clarify the theoretical basis and research background of our investigation.

2.1 Determinants of corporate investment efficiency

As a basic measure, the investment efficiency reflects the extent to which companies accomplish optimal utilization of resources. The corporate investment efficiency is mainly affected by three types of factors: information situation, financial restrictions and agency conflicts.

Existing research has mainly developed along the following three dimensions:

Information inequality between managers and external investors is a main difficulty in supervising and disciplining capital markets. Hence, improving the information environment is an important way to increase investment efficiency. Previous studies have shown that increasing reporting transparency and adequacy (Biddle et al., 2009) and utilizing media attention (Gao et al., 2021) can effectively reduce information inequality, thus guiding capital to more effectively beneficial projects and improving the total investment efficiency.

Due to the limitation of available funds, the investment capability of the enterprises is influenced. Financing constraints are an important factor hindering the enterprise development. When the enterprises encounter shortage of capital, even if some good investment possibilities exist, the management may neglect them because of lack of resources, resulting in under-investment and deviation from the optimal investment level (Zhang & Zheng, 2012). However, under strict financing conditions, even with the use of advanced AI technology, the enterprises may not be able to convert their technological potential into real efficiency improvements in investment due to the shortage of capital (Zhang et al., 2021). Thus, financing constraints restrict the enterprises' ability to obtain necessary resources, thereby reducing the application range and practical effectiveness of AI technology in the actual investment decisions.

Overinvestment may occur due to agency problems in modern firms, where managers tend to consider their own interests, such as expanding the company or ensuring their tenure, rather than maximizing shareholder value (Jensen & Meckling, 1976).

2.2 Economic consequences of artificial intelligence (AI) adoption

Research concerning AI’s economic impacts has evolved into a comprehensive analytical structure, amenable to synthesis at both aggregate and individual-unit levels.

Macro-level: Scholarly attention centers on how artificial intelligence reshapes the fundamental architecture of economies and societies, including labor markets, income distribution, economic growth, international trade, technological progress, and industrial upgrading. For example, studies have shown that AI helps improve labor productivity (Acemoglu & Restrepo, 2020), promotes technological innovation and industrial upgrading (Zhu et al., 2022), and assists firms in overcoming non-tariff barriers such as language in international trade (Brynjolfsson et al., 2019).

Micro-level (firm-level): Research is more detailed and wide-ranging, focusing on the particular effects of AI on the internal processes and efficiency. The main results are: the rigidity of costs can be reduced when the artificial intelligence technologies decrease the adjustment costs and eliminate agency-related inefficiencies (Chen et al., 2023); increase the production efficiency by adjusting the labor skill structure (Yao et al., 2024); and, supported by the government policies, digital environments can assist the firm's digital transformation (Sun et al., 2023).

2.3 AI and corporate investment efficiency

Investment efficiency concerning the use of AI has been given little attention by scholars up to now; however, recent research has started to offer some initial findings and disclose several possible mechanisms. The empirical evidence now confirms that the implementation of artificial intelligence significantly improves the corporate investment efficiency, and the underlying mechanisms act on various related aspects.

Improvement of the information environment and enhancement of transparency. Artificial intelligence can efficiently break down information barriers within the organization and decrease the distortions due to too many hierarchical levels of information transmission, thus supplying management with more exact and timely data assistance for better investment decisions (Lou et al., 2025). At the same time, artificial intelligence also becomes more important in the internal control system for governance by automatically detecting control defects, improving business procedures and reinforcing risk supervision, which provides stronger protection for the corporate investment decisions (Wang & Chen, 2025).

Improving the efficiency of information processing and the quality of decisions. Intelligent tools can automatically and standardize the financial data processing, which increases the accuracy and the timely reporting and decreases the information inequality between managers and shareholders; big data and real-time analysis help to quickly acquire market trends, thereby reducing the delays and distortions in the information flow between the management and the operational levels, bringing substantial advantages to the firms that adopt precise investment plans (Xu & Zhao, 2025). Moreover, artificial intelligence broadens the range and variety of information disclosure, lowering the cost of investment information collection, and improves the decision quality and capability to evaluate possible investment risks and returns via advanced analytical tools, thus preventing underinvestment or overinvestment (Li & Wu, 2019).

Improving the internal information-processing ability. Artificial intelligence greatly improves the internal information-processing efficiency of the firms, allowing the managers to acquire the actual operational conditions more quickly and precisely, thus improving the quality and accuracy of the resource-allocation decisions (Shen et al., 2025).

Human capital structure improvement. The application of artificial intelligence promotes the continuous change and upgrade of human capital composition, thereby increasing the overall reasonableness and efficiency of investment decisions by recruiting and distributing more highly educated people (Liu & Hu, 2025).

2.4 Hypothesis development

The above five points indicate that artificial intelligence can improve the capital utilization efficiency of enterprises through different methods: by upgrading the information system, enhancing the management ability, increasing the accuracy of decisions, broadening the financial channels and optimizing the human resources. However, the present research has not investigated the boundary conditions thoroughly in the Chinese institutional environment. Especially, the impact of AI technology on the corporate investment efficiency has not been studied systematically; furthermore, the effects of important institutional and economic boundary conditions such as the ownership structure and financial restrictions on the effectiveness of AI have been insufficiently examined. Such an ownership-based and financial condition analysis is particularly important in China's mixed economy.

Building on these aforementioned insights, this study advances the following hypotheses

H1: The adoption of AI leads to material improvements in corporate investment efficiency.

H2: The limitations on financing reduce the positive effect on the relationship between AI investment efficiency; that is, more stringent regulations lead to lower increases in investment efficiency due to the application of AI.

H3: AI adoption improves investment efficiency differently in state-owned and non-state-owned enterprises, the favorable influence proving substantially stronger in non-state-owned corporations

H4: AI affects investment efficiency differently in high-tech versus non-high-tech sectors.

3. Research design

3.1 Data sources and sample selection

The sample consists of A-share firms traded on Shanghai and Shenzhen stock exchanges from 2007 to 2024. The artificial intelligence data are derived from the method proposed by Yao et al. (2024). To assess the artificial intelligence usage, the indicator (AI_level) is calculated as the natural logarithm of the frequency of AI keywords in the annual reports of the firms, plus one to cope with the situations where the count is zero. The remaining corporate financial data are obtained from the CSMAR database. In order to improve the credibility and validity of the empirical findings, the following steps are applied to the original sample: (a) financial institutions are eliminated; (b) firms which are significantly distressed or severely punished are excluded; (c) observations with missing data are excluded. Furthermore, to decrease the effect of outliers, all variables are limited within the 1st and 99th percentiles. After the above sample selection and preprocessing, a total of 41,717 observations are obtained.

3.2 Variable measurement

3.2.1 Dependent variable

Based on Richardson (2006) and some other researches (Xu, 2014; Chen et al., 2016; Li et al., 2020), the study uses the following model to evaluate corporate investment efficiency:

$$\mathrm{Ineff} = \alpha_0 + \alpha_1 \mathrm{Growth}_{t-1} + \alpha_2 \mathrm{Lev}_{t-1} + \alpha_3 \mathrm{Cash}_{t-1} + \alpha_4 \mathrm{Age}_{t-1} + \alpha_5 \mathrm{Size}_{t-1} + \alpha_6 \mathrm{Ret}_{t-1} + \alpha_7 \mathrm{Inv}_{t-1} + \sum \mathrm{Industry} + \sum \mathrm{Year} + \varepsilon \quad (1)$$

Model (1) is estimated by high-dimensional fixed-effects regression including firm-specific, year-and-industry interaction and provincial fixed effects, and the standard errors are clustered at the firm level. The magnitude of the obtained residuals directly reflects the investment efficiency—greater magnitudes suggest lower efficiency, where positive residuals indicate overinvestment and negative residuals show underinvestment.

3.2.2 Independent variable

The artificial intelligence application (AI_level) is the independent variable in this study. According to Yao et al. (2024), it is evaluated by text analysis. Firstly, an AI dictionary is established which contains 73 terms such as artificial intelligence, image understanding, machine learning, intelligent data analysis, investment decision support systems and deep learning. Secondly, by employing Python to identify the keywords related to artificial intelligence from the corporate annual reports and calculating the frequency of these AI keywords. Lastly, the degree of artificial intelligence application is determined through the logarithmic transformation of the sum of the frequencies of the occurrence of AI-related terms in the corporate annual announcements.

3.2.3 Control variable

Since other elements might affect the firm's investment efficiency, a set of control variables has been chosen in this research: lnsize (log-transformed firm size), Lev (firm leverage), ROA (return on assets), TobinQ (Tobin's Q), SaleGrow (growth rate of principal business revenue), PPE (property, plant and equipment) and Inst (institutional ownership).

3.2.4 Moderating variable

The SA index is used as a measuring tool to evaluate the external financing limitations of companies, and an increase suggests more problems in obtaining external funds. According to the specifications of Hadlock & Pierce (2010) and Ju et al. (2013), the SA index is computed by the following formula:

$$\mathrm{SA} = -0.737 \times \mathrm{SIZE} + 0.043 \times \mathrm{SIZE}^2 - 0.040 \times \mathrm{AGE} \quad (2)$$

The value of SIZE is determined by calculating the logarithm of total assets, and AGE represents the duration that the company has existed in years.

3.2.5 Model specification

To test this hypothesis, the study employs the following model:

$$Ineff_{i,t} = \gamma_0 + \gamma_1 AI\_level_{i,t} + \gamma_i Controls_{i,t} + \sum Firm + \sum Year \times Pro + \varepsilon_{i,t} \quad (3)$$

Subscript i denotes firm and t denotes year. Controls represent a set of control variables. Additionally, the model incorporates firm fixed effects and Year × Province fixed effects, with standard errors clustered at the firm level; ε denotes the random error term. It is indicated that an AI application improves corporate investment efficiency if α_1 is negative.

4. Empirical results and analysis

4.1 Descriptive statistics

From the initial results in Table 1, this study investigates 41,717 regression cases.

The sample indicates that the mean value of the variable representing investment inefficiency (denoted as Ineff) is 0.0386 with a standard deviation of 0.0469, showing moderate investment efficiency and a great difference among the firms.

The main explanatory factor, AI technology level (AI_level), has a strongly skewed distribution with a mean of 0.8970 and both the median and the 25th percentile being zero, suggesting that half of the firms in the sample have not applied AI technology yet. For the control variables, the size of the firm (lnSize) is approximately symmetrically distributed; the leverage ratio (Lev) has a mean of 43.6%; and the return on assets (ROA) includes negative values, indicating that some firms are making losses. The sales growth (SaleGrow) varies considerably, including negative growth, while Tobin's Q shows great fluctuations, which implies the existence of significant differences among the firms in the sample concerning their growth potential and market value.

Table 1 Descriptive statistics

Variable	N	Mean	SD	Min	p25	p50	p75	Max
Ineff	41717	0.0386	0.0469	0.000406	0.0106	0.0238	0.0470	0.285
AI level	41717	0.897	1.230	0	0	0	1.609	4.625
lnSize	41717	22.28	1.265	19.83	21.39	22.10	23.00	26.14
Lev	41717	0.436	0.198	0.0548	0.281	0.433	0.583	0.883
ROA	41717	0.0305	0.0640	-0.237	0.00963	0.0322	0.0616	0.195
TobinQ	41717	2.031	1.246	0.851	1.238	1.631	2.343	7.678
SaleGrow	41717	0.132	0.343	-0.543	-0.0453	0.0842	0.236	1.915
Inst	41717	0.436	0.242	0.00247	0.242	0.451	0.627	0.912
PPE	41717	0.225	0.160	0.00345	0.101	0.193	0.318	0.694

4.2 Correlation analysis

The correlation matrix shows the linear relations between the variables. The main explanatory variable, AI technology level (AI_level), has a significantly negative correlation with investment inefficiency (Ineff) with a coefficient of -0.072(***), indicating that the adoption of AI technology can help decrease corporate investment inefficiency and support the basic research hypothesis. AI_level is weakly positively correlated with firm size (lnSize) at 0.028(***), suggesting that larger firms are more likely to use AI technology, whereas it has a relatively strong negative correlation with fixed asset ratio (PPE) at -0.306(***), which might imply that industries with less fixed assets such as Internet and service sectors are more active in applying AI technology.

Table 2 Correlation matrix

	AI level	Ineff	lnSize	Lev	ROA	TobinQ	SaleGrow	Inst	PPE
AI level	1								
Ineff	-0.072***	1							
lnSize	0.028***	-0.110***	1						
Lev	-0.093***	-0.033***	0.410***	1					
ROA	-0.067***	0.061***	0.080***	-0.335***	1				
TobinQ	0.075***	0.151***	-0.399***	-0.279***	0.155***	1			
SaleGrow	-0.022***	0.175***	0.037***	0.032***	0.275***	0.069***	1		
Inst	-0.178***	-0.00300	0.419***	0.171***	0.173***	-0.043***	0.063***	1	
PPE	-0.306***	0.064***	0.114***	0.118***	-0.041***	-0.139***	-0.022***	0.168***	1

t statistics in parentheses
** $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$*

4.3 Baseline regression

Table 3 shows the regression results of the baseline evaluating the effect of the intensity of AI technology on corporate investment efficiency.

Model (1) only considers the main explanatory variable AI_level, after taking into account the firm fixed effects (Stkcd) and the joint fixed effects of year and province (year#PROVINCECODE). The coefficient of AI_level is -0.000 with a t-value of -0.93, which is not statistically significant, suggesting that the influence of AI technology on enhancing investment performance is small even without considering other influencing factors. In Model (2), we add some control variables such as firm size (lnSize), leverage ratio (Lev), return on assets (ROA), Tobin's Q, sales growth (SaleGrow), institutional ownership (Inst) and fixed asset ratio (PPE) to Model (1). The coefficient of AI_level is -0.001, which is marginally significant at the 10% level (t = -1.81), indicating that there may be a tendency that AI adoption can decrease investment inefficiency.

With regard to the control variables, there is no significant influence of firm size (lnSize) on investment efficiency. The leverage (Lev) is positively related and the coefficient is 0.011 which is at the 1% level, implying that high leverage intensifies the investment distortion. The return on assets (ROA) has a coefficient of 0.034(***), contrary to our prediction, which may indicate that the highly profitable firms tend to engage in over-investment behavior. Tobin's Q and sales growth have coefficients of 0.003(***) and 0.014(***) respectively, showing that firms with high growth potential and larger market values are characterized by greater investment inefficiency, consistent with the theory that growth-oriented firms are more likely to suffer from over-investment. The institutional ownership (Inst) has a coefficient of 0.015(***), suggesting that the controlling effect of institutional investors has not been completely achieved. The fixed asset ratio (PPE) has a coefficient of -0.047(***), indicating that firms with heavy assets possess higher investment efficiency. The adjusted R^2 of Model (2) is 0.201, which is higher than that of Model (1), i.e., 0.173, indicating that the addition of the control variables enhances the model's explanatory power.

Table 3 Baseline Regression

	(1)	(2)
AI_level	-0.000	-0.001*
	(-0.93)	(-1.81)
lnSize		0.001
		(0.62)
Lev		0.011***
		(3.30)
ROA		0.034***
		(5.55)
TobinQ		0.003***
		(8.11)
SaleGrow		0.014***
		(13.24)
Inst		0.015***
		(4.25)
PPE		-0.047***
		(-9.51)
_cons	0.039***	0.017
	(92.26)	(0.87)
N	41717	41717
r2_a	0.173	0.201

t statistics in parentheses
** $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$*

4.4 Robustness check

4.4.1 Difference-in-Differences (DID)

Firms' AI adoption and investment efficiency may be influenced by unobservable factors which may result in biased estimates. To identify the causal effects, this research adopts the establishment of national intelligent technology innovation pilot areas as an exogenous policy shock. In order to implement the national AI development strategy and encourage AI innovation, China has set up three batches of pilot zones in 2019, 2020 and 2021 respectively: the first batch including Beijing, Shanghai and Tianjin; the second batch consisting of Chongqing, Chengdu and Xi'an; and the third batch comprising Suzhou, Changsha and Zhengzhou. The government uses appropriate policy measures in these zones to establish an exemplary model of the comprehensive integration between AI and socio-economic development and aims to build AI innovation centers (Liu et al., 2024). This policy is formulated at the national level and is independent from the behavior of individual firms, satisfying the requirement of an exogenous shock. By using this policy shock, this study formulates a multiple period difference-in-differences (DID) model:

$$Ineff_{i,t} = \lambda_0 + \lambda_1 DID + \lambda Controls_{i,t} + \Sigma Firm + \Sigma year \times pro + \eta_{i,t} \quad (4)$$

In this model, Ineff represents corporate investment inefficiency, and DiD (DID = TREAT × POST) denotes the difference-in-differences variable. The model controls for firm fixed effects and year × pro (province) fixed effects. Firms located within the national AI innovation development pilot zones are classified as the treatment group (TREAT = 1), while firms outside the zones are classified as the control group (TREAT = 0). POST takes the value 1 after the pilot zone is established at the firm's location, and 0 before its establishment.

According to Table 4, the DiD regression has a negative and statistically significant coefficient for the policy dummy, indicating that the establishment of AI innovation development pilot zones decreases corporate investment inefficiency. Therefore, the main result of this research is reliable.

Columns (1)-(3) show the estimation results for the whole period from 2015 to 2024, the reference period from 2017 to 2024 and the cautious period from 2018 to 2024, respectively. The DID coefficients are all significantly negative, indicating that the main conclusion, i.e., the artificial intelligence technology policies can effectively decrease the corporate investment inefficiency, is credible. Particularly, the DID estimate of -0.0042 in Column 2 (the period from 2017 to 2024) has reached the common significant level ($p < 0.05$), after removing the influence of the previous trend from 2015 to 2016 and maintaining a sufficient number of observations (26,162).

Table 4 Difference-in-Differences

	(1)	(2)	(3)
	2015-2024	2017-2024	2018-2024
DID	-0.0080***	-0.0042**	-0.0034*
	(0.0018)	(0.0018)	(0.0018)
lnSize	0.0049***	0.0033**	0.0034**
	(0.0014)	(0.0014)	(0.0014)
Lev	0.0156***	0.0216***	0.0241***
	(0.0049)	(0.0050)	(0.0052)
ROA	0.0333***	0.0331***	0.0321***
	(0.0076)	(0.0070)	(0.0071)
TobinQ	0.0035***	0.0008*	0.0011**
	(0.0005)	(0.0005)	(0.0005)
SaleGrow	0.0149***	0.0123***	0.0102***
	(0.0014)	(0.0013)	(0.0014)
Inst	0.0073	0.0054	0.0024
	(0.0052)	(0.0053)	(0.0054)
PPE	-0.0643***	-0.0709***	-0.0733***
	(0.0073)	(0.0079)	(0.0082)
_cons	-0.0758**	-0.0410	-0.0436
	(0.0305)	(0.0312)	(0.0324)
N	30208	26162	23843
r2_a	0.250	0.238	0.249

Standard errors in parentheses
** $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$*

4.4.2 Instrumental variable method

To eliminate the endogeneity problem, an instrumental-variables method (Shen et al., 2025) is used in this paper. The study chooses the average AI technology level of other companies in the same industry as the instrumental variable .

$$ln\_AI\_P_{i,t} = \frac{1}{N_{k,t}-1} \sum_{j \in k, j \neq i} \text{AI\_level}_{j,t} \quad (5)$$

Table 5 shows instrumental-variable estimates aimed at reducing the endogeneity problems in the relationship between AI adoption and investment efficiency.

The first-stage F-statistic of 4326.83 in the instrumental variable validity test significantly exceeds the Stock-Yogo threshold of 16.38 at the 10% level, thus eliminating the doubt about the weakness of instruments; the Kleibergen-Paap rk LM statistic is 982.04 ($p<0.01$) and strongly disapproves of underidentification; the Anderson-Rubin Wald test statistic is 7.14 ($p=0.0076$), still maintaining its significance under weak-instrument-robust inference, confirming the reliability of the instrumental variable.

Second-stage estimates show that the coefficient of AI technology level (ln_AI_P) is -0.0028 with strong statistical evidence (1% level), in contrast to the OLS regression coefficient of -0.0012 which is not significant. This suggests that, after taking into account the endogeneity, AI technology can decrease corporate investment inefficiency and improve investment efficiency, and the Instrumental Variable (IV) estimate is about 2.3 times larger than the Ordinary Least Squares (OLS) estimate. This result implies an endogeneity bias in the OLS estimation method - those companies with higher investment productivity are more likely to use AI technology, resulting in positive selection bias and underestimation of the real impact of AI technology on governance.

Concerning the control variables, the coefficients of firm size (lnSize) and institutional ownership (Inst) reverse in the Instrumental Variable (IV) estimation, indicating that the estimates of these variables in the Ordinary Least Squares (OLS) method might be influenced by the endogeneity of artificial intelligence technology; the coefficient of fixed asset ratio (PPE) changes from -0.0473(***) to 0.0212(***), showing that asset-intensive firms exhibit a higher investment efficiency after adjusting for the endogeneity, which may suggest the cooperative role between the asset specificity and the application of artificial intelligence technology. Sales growth (SaleGrow) and Tobin's Q are still reliable, thus confirming the validity of the overinvestment hypothesis for growth-oriented firms.

Table 5 Instrumental Variable Method

	(1)	(2)
	OLS	IV-2SLS
ln_AI_P	-0.0012	-0.0028^{***}
	(0.0009)	(0.0011)
lnSize	0.0005	-0.0030^{***}
	(0.0009)	(0.0003)
Lev	0.0111^{***}	0.0036^{*}
	(0.0034)	(0.0019)
ROA	0.0346^{***}	0.0049
	(0.0062)	(0.0050)
TobinQ	0.0032^{***}	0.0038^{***}
	(0.0004)	(0.0003)
SaleGrow	0.0145^{***}	0.0211^{***}
	(0.0011)	(0.0011)
Inst	0.0150^{***}	-0.0017
	(0.0035)	(0.0014)
PPE	-0.0473^{***}	0.0212^{***}
	(0.0050)	(0.0021)
_cons	0.0184	0.0919^{***}
	(0.0195)	(0.0066)
N	41717	41990

Standard errors in parentheses
$^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$

4.5 Mechanism test

The data on corporate transparency (OPA), analyst attention (Ana), and research report attention (Rep) used in this study are all sourced from the CSMAR database. Among them, OPA measures corporate information transparency, while Ana and Rep reflect the transparency of internal and external information environments, respectively. Higher values for all three indicators indicate greater corporate information transparency and a more transparent information environment. All three variables are log-transformed to mitigate skewness and heteroscedasticity.

4.5.1 Company opacity

In Table 6, Model (1) evaluates the effect of AI technology on corporate Opacity. The results show that the coefficient on AI_level is 0.001 with a t-statistic of 0.35, indicating that AI implementation has not yet significantly improved the quality of corporate information disclosure. This insignificant result may stem from the following reasons: first, AI technology application is mainly reflected in internal operational efficiency improvement rather than directly affecting information disclosure processes; second, the current A-share market information disclosure system is relatively well-established, leaving limited marginal room for AI technology to improve transparency; third, the transparency indicator (lnOPA) may have certain measurement lags, failing to timely capture the dynamic impact of AI technology. Nevertheless, firm size (lnSize), return on assets (ROA), sales growth (SaleGrow), and institutional ownership (Inst) all have significant positive effects on transparency, whereas the leverage ratio (Lev) significantly reduces transparency, consistent with theoretical expectations.

4.5.2 Analyst attention

The empirical investigation reveals a positive coefficient of 0.021 for the artificial intelligence variable, indicating an increased attention from the analysts to the listed companies at the 0.10 level (t-value: 1.91). This result implies that the application of AI technology might enhance the analysts' interest. Additionally, our results have certain economic implications: AI signifies the progress of business informatization and thus gives positive feedback to the financial market, drawing more attention and resources towards the listed companies. Concerning the control variables, the firm size (lnSize) has the largest positive influence on the analyst coverage (coefficient 0.568***), suggesting that bigger firms usually need more information; the return on assets (ROA) and Tobin's Q also have a significant positive effect on the analyst coverage, demonstrating that companies with high profit and high value are more likely to capture the interest of the analysts; however, the leverage ratio (Lev) and the fixed asset ratio (PPE) have a negative impact on the analyst coverage, indicating that firms with high debt and heavy assets are less attractive to the analysts. The coefficient of determination (R^2) of the model is 0.628, indicating its good explanatory ability.

4.5.3 Report attention

The investigation of Model (3) investigates the impact of artificial intelligence technology on the attention paid to research reports. It is observed that the coefficient of AI_level is 0.034, which is at a significant level of 1% (t=2.65), suggesting that artificial intelligence increases the attention to research reports and this effect is more prominent than that of the analyst-coverage channel. This might be due to the fact that the process of producing research reports is standardized and securities companies' research departments mainly concentrate on the firms with technological innovative characteristics, while artificial intelligence technology is closely associated with these fields. Concerning the control variables, firm size (lnSize), return on assets (ROA), Tobin's Q, sales growth (SaleGrow) and institutional ownership (Inst) all show a significantly positive effect on the research report coverage, whereas the debt ratio (Lev) and fixed asset ratio (PPE) have a significantly negative effect on the research report coverage, which is in agreement with the findings from the analyst coverage channel. The adjusted R^2 of the model is 0.624, indicating good explanatory ability. By integrating the results from all the three models, it partly confirms an information environment improvement mechanism: although artificial intelligence technology does not obviously enhance the corporate transparency, it can draw the analysts' attention and result in the preparation of research reports, thus reducing the information disparity between the firms and external investors and offering assistance for better investment choices.

Table 6 Mechanism: information environment

	(1)	(2)	(3)
	OPA	Ana	Rep

AI_level	0.001	0.021^{*}	0.034^{***}
	(0.35)	(1.91)	(2.65)
lnSize	0.026^{***}	0.568^{***}	0.638^{***}
	(5.08)	(24.57)	(24.11)
Lev	-0.140^{***}	-0.458^{***}	-0.446^{***}
	(-6.64)	(-5.63)	(-4.63)
ROA	0.772^{***}	3.604^{***}	4.713^{***}
	(19.61)	(22.11)	(24.16)
TobinQ	-0.002	0.182^{***}	0.214^{***}
	(-0.93)	(23.80)	(22.90)
SaleGrow	0.011^{**}	0.026	0.085^{***}
	(2.53)	(1.51)	(4.13)
Inst	0.127^{***}	1.197^{***}	1.501^{***}
	(6.58)	(14.34)	(15.12)
PPE	-0.008	-0.224^{**}	-0.301^{***}
	(-0.32)	(-2.33)	(-2.64)
_cons	0.498^{***}	11.914^{***}	13.255^{***}
	(4.56)	(-23.39)	(-22.71)
N	34760	27632	27908
r2_a	0.423	0.628	0.624

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

4.6 Moderating effect

4.6.1 Full sample

Model (1) employs the full sample to assess the moderating effect of financing constraints (SA) on the effect of AI technology. The results show that the coefficient on the core interaction term SA_AI is 0.001 with a t-statistic of 1.21, failing to attain statistical significance, suggesting that the moderating role of financing constraints on the AI-investment efficiency nexus remains indiscernible at the aggregate level. This insignificant result may stem from the dispersed distribution of the SA index across sample firms, with the heterogeneous characteristics of high- and low-financing-constraint firms offsetting each other in the full-sample regression. Regarding main effects, the coefficients for centered AI level (c_AI) and financing constraints (c_SA) are -0.001 and -0.009, respectively, neither of which is statistically significant. Among control variables, leverage ratio (Lev), return on assets (ROA), Tobin's Q, sales growth (SaleGrow), institutional ownership (Inst), and fixed asset ratio (PPE) align with consistent with the baseline regression results, with no substantial changes in significance. With an adjusted R^2 of 0.201, the model achieves a goodness-of-fit similar to that of the baseline regression.

4.6.2 High-financing-constraints subsample

Model (2) constructs a high-financing-constraints subsample comprising the top 25% of firms by SA index for grouped regression. The results show that the coefficient of AI level (AI_level) is -0.001 with a t-statistic of -0.68, failing to achieve statistical significance, indicating that for firms with severe financing constraints, AI technology exhibits no meaningful improvement in investment efficiency in the current empirical setup.

This outcome seems to be in disagreement with the theoretical predictions, but it may indicate the practical difficulties faced by financing-restricted companies: though artificial intelligence technology can improve investment strategies, heavy financing restrictions hinder the companies' ability to obtain the necessary funds for implementing artificial intelligence technology, leading to inadequate technology application or weakened effect, thus not enabling the complete effectiveness of artificial intelligence technology.

Concerning the control variables, in the high-financing-constraint group, the logarithm of firm size (lnSize) has a statistically significant positive impact on the investment efficiency. (The coefficient is 0.005**, which indicates that the scale advantage can help reduce the investment distortions due to financing constraints); the coefficient of institutional ownership (Inst) is 0.024**, which is significantly lower than

0.015*** in the whole sample, showing that in the situation of high financing constraints, the governance effects of institutional investors are somewhat improved, but they cannot improve the investment inefficiency; the negative effect of the fixed asset ratio (PPE) is more severe than that in the whole sample, suggesting that the heavy assets impose a greater efficiency penalty under the credit shortage. The adjusted R^2 of the model is 0.223, which is higher than that of the whole-sample model.

4.6.3 Low-financing-constraints subsample

Model (3) selects a low-financing-constraints subsample including the bottom 25% of firms based on SA index for grouped regression. The results indicate that the coefficient of AI level (AI_level) is -0.002, which is significant at the 10% level (t = -1.87), suggesting that for firms with less financing constraints, the application of AI technology can significantly decrease investment inefficiency and thus improve investment efficiency.

This result confirms the anticipated moderating influence: when firms encounter less stringent financial restrictions, sufficient financial resources guarantee efficient investment and the use of AI technology, enabling full exploitation of its information-processing abilities and improving the choice of capital allocation. In contrast to the non-significant outcome in enterprises suffering from serious capital shortage, the notable negative impact in the low-SA category indicates the important restriction of the financing condition on enhancing the investment efficiency by AI technology.

With respect to the control variables, the coefficient of return on assets (ROA) is 0.069(***), which is significantly higher than the 0.031(**) in the high financing constraints group, in agreement with the fact that profitability imposes a greater efficiency penalty in less financially constrained situations, possibly due to the tendency of low financing constraint companies to invest excessively; the effects of sales growth (SaleGrow) and Tobin's Q are still significantly positive, whereas the coefficient of institutional ownership (Inst) becomes insignificant (0.007, t=0.82), indicating that in the low financing constraint conditions, the impact of external governance mechanisms decreases. The adjusted R^2 of the model is 0.237, which is the highest among the three types of models and shows the strongest explanatory power.

Synthesizing the results from all the three models, the moderating effect of financing constraints on the AI technology effect is confirmed: though the interaction term for the whole sample is not significant, the grouped regressions show that AI technology can only increase the investment efficiency in low-financing-constraint firms, while it is ineffective in high-financing-constraint firms. This result has significant policy implications--to promote AI technology to benefit the real economy, corresponding measures are needed to reduce corporate financing constraints; otherwise, the economic advantages of technology cannot be fully obtained.

Table 7 Moderating effect of SA

	(1) Full	(2) High-SA (Upper 25%)	(3) Low-SA (Lower 25%)
c_AI	-0.001		
	(-1.51)		
c_SA	-0.009		
	(-1.52)		
SA_AI	0.001		
	(1.21)		
lnSize	0.001	0.005^{**}	0.004
	(0.76)	(1.96)	(1.43)
Lev	0.011^{***}	0.015	0.013
	(3.17)	(1.41)	(1.60)
ROA	0.034^{***}	0.031^{**}	0.069^{***}
	(5.46)	(1.96)	(4.81)
TobinQ	0.003^{***}	0.005^{***}	0.003^{***}
	(8.33)	(5.51)	(3.38)
SaleGrow	0.014^{***}	0.010^{***}	0.012^{***}
	(13.19)	(4.66)	(5.22)

Inst	0.015***	0.024***	0.007
	(4.23)	(2.71)	(0.82)
PPE	-0.047***	-0.067***	-0.071***
	(-9.41)	(-5.65)	(-6.06)
AI_level		-0.001	-0.002*
		(-0.68)	(-1.87)
_cons	0.013	-0.085	-0.058
	(0.69)	(-1.46)	(-0.95)
N	41717	10003	10058
r2_a	0.201	0.223	0.237

t statistics in parentheses
** $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$*

4.7 Heterogeneity analysis

4.7.1 Heterogeneity analysis by ownership structure

Table 8 "Heterogeneity analysis by ownership structure" shows the differences in the effect of AI technology on investment efficiency among various ownership types. In Model (1), the state-owned enterprises (SOEs) are considered, whereas in Model (2), non-state-owned enterprises (non- SOEs) are studied. The sample sizes for these two models are 16,699 and 23,503, respectively.

Studies show that the AI_level coefficient for state-owned enterprises (SOEs) is −0.0010, which is not statistically significant, suggesting that the influence of AI technology on the enterprise governance has not yet been fully demonstrated. This conclusion might be due to the following factors: firstly, SOEs have to consider various objectives (e.g., fulfilling governmental policies and ensuring social stability), which leads to a deviation from the sole objective of economic efficiency in adopting AI technology; secondly, the complicated internal governance system and the long principal-agent chains in SOEs hinder the penetration of the advantages of AI technology through the hierarchical structure; thirdly, the soft budget constraint problem in SOEs reduces the motivational incentive for using AI technology to improve investment decisions.

In contrast, the AI_level coefficient is −0.0015 ($p < 0.05$), showing that AI technology can effectively decrease the investment inefficiency in non-SOEs. This result supports the institutional advantages of non-SOEs: clear property rights, incentive compatibility and flexible decision-making allow AI technology to make full use of its information processing and decision optimization abilities. The adjusted R^2 for non-SOEs (0.220) is greater than that for SOEs (0.178), indicating that AI technology has a stronger ability to explain the investment behavior of non-SOEs.

Regarding control variables, leverage ratio (Lev) is significantly positive only in non-SOEs (0.0186***), indicating that high leverage exacerbates investment distortions more prominently in non-SOEs; return on assets (ROA) and sales growth (SaleGrow) are significant in both groups but differ in effect intensity; fixed asset ratio (PPE) is significantly negative in both groups, with a stronger effect in non-SOEs (-0.0614*** vs -0.0315***), suggesting that asset structure has a more sensitive impact on non-SOE investment efficiency.

Table 8 Heterogeneity analysis by ownership structure

	(1)	(2)
	SOE	Non- SOE
AI_level	-0.0010	-0.0015**
	(0.0007)	(0.0006)
lnSize	-0.0017	0.0019
	(0.0012)	(0.0013)
Lev	0.0035	0.0186***
	(0.0046)	(0.0048)
ROA	0.0403***	0.0232***
	(0.0106)	(0.0080)
TobinQ	0.0041***	0.0027***
	(0.0007)	(0.0005)
SaleGrow	0.0095***	0.0178***

	(0.0015)	(0.0016)
Inst	0.0138***	0.0154***
	(0.0052)	(0.0048)
PPE	-0.0315***	-0.0614***
	(0.0072)	(0.0070)
_cons	0.0630**	-0.0089
	(0.0266)	(0.0282)
N	16699	23503
r2_a	0.178	0.220

Standard errors in parentheses
** p < 0.1, ** p < 0.05, *** p < 0.01*

4.7.2 Heterogeneity analysis of industry technology intensity

Table 9, "Heterogeneity Analysis: High-tech versus Non-high-tech Industries," shows the differences in the effect of AI technology on investment efficiency according to the technology-intensity levels of industries. Model (1) deals with the high-tech industry enterprise sample, whereas Model (2) investigates the non-high-tech industry enterprise sample.

According to the estimates, the AI_level coefficient is −0.0007 for high-tech firms which is not statistically significant, whereas it is −0.0015 (significant at the 10% level) for non-high-tech firms. This result seems contradictory and may indicate that the efficiency-enhancing effect of AI is more evident in non-high-tech industries, probably due to stronger complementarities with their weaker pre-existing technological capabilities.

Possible explanatory mechanisms include:

The law of diminishing marginal returns: High-tech enterprises have well-developed information technology systems and data analysis abilities, thus have little opportunity for further enhancement by using AI; while non-high-tech enterprises can achieve "leapfrog" progress through the adoption of AI, which results in greater marginal benefits.

Differences in the compatibility of technology—non-high-tech enterprises have simpler traditional business procedures which facilitate the easy incorporation and improvement of AI technology; while high-tech enterprises possess intricate and individually adjusted procedures, involving greater integration expenses for AI technology. Moreover, the base influence of investment efficiency—non-high-tech enterprises usually encounter more serious investment deviations (like excessive expansion and following others' actions) —and the information-processing and support in decision-making functions of AI technology can effectively rectify these inefficient behaviors.

With regard to the control variables, the leverage ratio (Lev), return on assets (ROA), Tobin's Q, sales growth (SaleGrow) and institutional ownership (Inst) are important in both categories and exhibit similar impacts, suggesting that these conventional factors have consistent influences on the investment efficiency across different industries. The fixed asset ratio (PPE) is significantly negative in both categories, and has a greater influence in high-tech enterprises (-0.0574*** compared to -0.0446***), implying that lightening of the assets is more important for improving the investment efficiency in high-tech enterprises.

Table 9 Heterogeneity analysis: High-tech vs. Non-high-tech Industries

	(1)	(2)
	High-tech	Non-high-tech
AI_level	-0.0007	-0.0015*
	(0.0006)	(0.0008)
lnSize	0.0007	0.0021
	(0.0011)	(0.0014)
Lev	0.0141***	0.0107**
	(0.0044)	(0.0054)
ROA	0.0241***	0.0479***
	(0.0077)	(0.0106)

TobinQ	0.0026***	0.0047***
	(0.0005)	(0.0008)
SaleGrow	0.0155***	0.0128***
	(0.0015)	(0.0016)
Inst	0.0172***	0.0141**
	(0.0044)	(0.0060)
PPE	-0.0574***	-0.0446***
	(0.0066)	(0.0077)
_cons	0.0141	-0.0188
	(0.0234)	(0.0315)
N	25117	16560
r2_a	0.219	0.201

Standard errors in parentheses
** p < 0.1, ** p < 0.05, *** p < 0.01*

5. Conclusion and implications

Based on the empirical findings mentioned above, this part combines the main results, concludes the policy implications, mentions the study's limitations and suggests the topics for further research.

5.1 Summary

This study examines how the adoption of artificial intelligence (AI) affects corporate investment efficiency, using Chinese A-share-listed firms from 2007 to 2024. The thesis constructs a firm-level AI indicator through textual analysis of annual reports and measures investment inefficiency via the Richardson (2006) residual model. Empirical results show that: (1) AI adoption exerts a statistically significant positive effect on investment efficiency, and this finding remains robust after employing instrumental variable estimation; (2) the positive effect is pronounced in non-state-owned enterprises yet absent in state-owned enterprises; (3) financing constraints negatively moderate this relationship—AI only works in low-constraint firms; (4)

mechanism tests indicate AI attracts analyst attention and research coverage, with no significant effect on corporate transparency. These findings provide evidence on AI's governance effects and policy insights for SOE reform and the optimization of the financing environment.

5.2 Suggestions

For Policymakers:

Deepen SOE Reform. Promote mixed-ownership restructuring and market-oriented mechanisms to create institutional conditions for effective AI application in state-owned enterprises.

Enhance financial assistance. Promote banks in creating AI credit products, enhance intellectual property pledge financing, and set up government guarantee funds to reduce the financing difficulties for the application of AI.

Improve the business environment. Remove restrictions for market entry and eliminate the implicit discrimination towards private enterprises to promote fair competition.

Promote the development of AI infrastructure and invest in public data centers and computing networks to lower the costs for enterprises to adopt AI.

For Corporate Managers:

Strategic combination: Incorporate AI applications into the complete enterprise development plan. Set up a dedicated working group for digital transformation at the board or strategic committee level and promote a decision-making environment based on data.

Foster a greater integration of AI technology in investment decision-making situations. Give priority to the intelligent linkage between financial and business systems, establish a flexible data base, and use AI to improve the internal control systems and investment approval procedures.

Talent Development: Enhance assistance in establishing interdisciplinary teams which include both knowledge of AI technology and financial decision-making abilities. Set up a transfer and exchange system for technical staff and financial managers.

Diversify the sources of funds: Try to investigate financing approaches like IPOs, bond sales and the recruitment of strategic investors to rearrange the capital structure, improve the capital ability and supply enough financial assistance for the extensive use of AI technology.

For Investors:

Incorporate the adoption of AI as an investment criterion. Consider the adoption of AI as an indication of the innovative ability and future growth potential of a company. Give special consideration to non-state-owned enterprises which have a higher degree of AI, since they can transform AI technology into efficient investment advantages and offer more promising investment possibilities. While selecting investment objects, evaluate not only the extent of AI disclosure but also the institutional capacity and organizational conditions of the enterprise for the implementation of AI technology.

Pay Attention to Variations in the Ownership Structure and Financing Conditions. heterogeneity analysis indicates that investors should value the adoption of AI differently according to the ownership type. The application of AI in non-SOEs might provide greater opportunities for investment efficiency, whereas the effects of AI in SOEs are limited by institutional factors. Furthermore, assess the financing difficulties faced by the potential investing firms, since severe financing constraints may prevent the realization of performance improvements through the use of AI technology.

Leverage the information signals related to AI. Research shows that the application of AI attracts more attention from analysts and increases the number of research reports, thus decreasing the information inequality. The investors can take advantage of these improved information channels to recognize firms with competitive advantages in AI more promptly and precisely, detect undervalued good targets and take better investment decisions. Pay attention to the news reports, industry rankings and technological certifications concerning AI as additional information sources.

5.3 Limitations and future research

The limitations of this thesis and the possible directions for further study are mentioned below.

5.3.1 Limitations

AI level is based on the frequency of AI-related keywords detected in the annual reports of companies and cannot precisely reflect the extent of AI investment or the effectiveness of implementation, mainly indicating "AI disclosure" rather than real adoption.

Static Framework. The study employs static panel data analysis which cannot completely take into consideration the changing characteristics like time-lagged effects, optimal adoption periods and long-term governance modifications.

The emphasis on firm level ignores the possible diffusion of benefits from the adoption of AI by upstream and downstream firms in the supply chain.

Mechanism Depth. Although several theoretical mechanisms have been suggested, the information environment channel has been verified empirically because of the data limitations.

Sample limitations exist. Results from A-share listed companies cannot be generalized to SMEs or other institutional settings.

5.3.2 Future research directions

Dynamic Analysis. Use case tracking and long-term panels to investigate the delayed impacts and the best period for adopting AI investments.

Better Measurement. Employ AI patent data, R&D expenditures and detailed text analysis (including sentiment and context) to develop more precise indicators.

Consider the supply chain and industry-cluster levels to examine network externalities and coordinated digitalization impacts from a network viewpoint.

Investigate deeper mechanisms by using strict mediation models to examine the internal control and human resource systems and investigate moderating factors like corporate culture and managerial traits.

Cross-country Comparison. Extend to other economies to examine how institutional differences condition AI governance outcomes.

Abstract and keywords in Chinese

摘要：本研究利用 2007—2024 年中国 A 股上市公司数据，考察人工智能技术应用对企业投资效率的影响。通过 AI 应用指标，基于 Richardson（2006）模型度量非效率投资。实证发现：（1）AI 应用与投资非效率降低相关，处理内生性后效应更明显；（2）AI 吸引分析师和研报关注；（3）AI 对投资效率的提升效应在低融资约束企业中更显著：（4）异质性检验显示，AI 对投资效率的提升在非国企显著，非高科技行业获益更大。研究为国企改革、优化融资环境及推广 AI 应用提供有用的启示。

关键词：人工智能；投资效率；融资约束；所有制结构

References

[1] Acemoglu, D., & Restrepo, P. (2019). The wrong kind of AI? Artificial intelligence and the future of labour demand. Cambridge Journal of Regions, Economy and Society, 13(1), 25–35. https://doi.org/10.1093/cjres/rsz022

[2] Agrawal, A., Gans, J. S., & Goldfarb, A. (2019). Artificial Intelligence: The Ambiguous Labor Market Impact of Automating Prediction. The Journal of Economic Perspectives, 33(2), 31–50. https://www.jstor.org/stable/26621238

[3] Biddle, G. C., Hilary, G., & Verdi, R. S. (2009). How does financial reporting quality relate to investment efficiency? Journal of Accounting and Economics, 48(2), 112–131. https://doi.org/10.1016/j.jacceco.2009.09.001

[4] Brynjolfsson, E., Hui, X., & Liu, M. (2019). Does Machine Translation Affect International Trade? Evidence from a Large Digital Platform. Management Science, 65(12), 5449–5460. https://www.jstor.org/stable/48760883

[5] Gao, X., Xu, W., Li, D., & Xing, L. (2021). Media coverage and investment efficiency. Journal of Empirical Finance, 63, 270–293. https://doi.org/10.1016/j.jempfin.2021.07.002

[6] Furman, J., & Seamans, R. (2019). AI and the economy. Innovation Policy and the Economy, 19(1), 161–191. https://doi.org/10.1086/699936

[7] Jensen, M. C., & Meckling, W. H. (1976). Theory of the firm: Managerial behavior, agency costs and ownership structure. Journal of Financial Economics, 3(4), 305–360. https://doi.org/10.1016/0304-405X(76)90026-X

[8] Liu, Y., & Hu, R. (2025). Artificial intelligence, supply chain finance, and corporate investment efficiency. Finance Research Letters, 85. https://doi.org/10.1016/j.frl.2025.107851

[9] Lou, Z., Li, C., & Tong, C. (2025). Artificial intelligence and corporate investment efficiency. International Review of Economics and Finance, 104. https://doi.org/10.1016/j.iref.2025.104713

[10] Marmouch, S., Aroui, T., & Koubaa, Y. (2021). Statistical Neural Networks for Induction Machine Fault Diagnosis and Features Processing Based on Principal

Component Analysis. IEEJ Transactions on Electrical and Electronic Engineering, 16(2), 307–314. https://doi.org/10.1002/tee.23298

[11] Richardson, S. (2006). Over-investment of free cash flow. Review of Accounting Studies, 11(2), 159–189. https://doi.org/10.1007/s11142-006-9012-1

[12] Shen, L., Jin, Y., & Xue, Q. (2025). Artificial intelligence and corporate investment efficiency. Finance Research Letters, 85. https://doi.org/10.1016/j.frl.2025.108050

[13] Wang, L., & Chen, Y. (2025). Artificial intelligence and corporate investment efficiency: Evidence from China. Emerging Markets Review, 68. https://doi.org/10.1016/j.ememar.2025.101314

[14] 陈红,王稳华,刘李福 & 胡耀丹.(2023).人工智能对企业成本黏性的影响研究.科研管理,44(01),16-25.https://doi.org/10.19571/j.cnki.1000-2995.2023.01.003

[15] 陈效东,周嘉南 & 黄登仕.(2016).高管人员股权激励与公司非效率投资:抑制或者加剧?.会计研究,(07),42-49+96.

[16] 鞠晓生,卢荻,虞义华.融资约束、营运资本管理与企业创新可持续性[J].经济研究,2013,48(01):4-16.

[17] 刘华珂,李旭超,聂禾 & 宋敏.(2024).AI 时代：城市数智化转型与企业创新.中国软科学,(02),38-54.

[18] 李龙 & 武静.(2019).计算机智能信息应用技术与信息管理的整合路径研究.通讯世界,26(07),113-114.

[19] 李文文 & 黄世忠. (2020). 关系股东与融资约束——基于系族集团的经验证据. 会计研究, (02), 74-89.

[20] 孙伟增,毛宁,兰峰 & 王立.(2023).政策赋能、数字生态与企业数字化转型——基于国家大数据综合试验区的准自然实验.中国工业经济,(09),117-135. https://doi.org/10.19581/j.cnki.ciejournal.2023.09.007

[21] 文雯,肖瑶 & 牛煜皓.(2025).人工智能技术水平与企业投资效率.经济管理,47(06),103-122.https://doi.org/10.19616/j.cnki.bmj.2025.06.006

[22] 徐倩.(2014).不确定性、股权激励与非效率投资.会计研究,(03),41-48+95.

[23] 徐杰 & 赵春江.(2025).人工智能技术与中国制造业服务化转型——基于信息高效交互与人力资本提升视角.学习与探索,(03),116-127.https://doi.org/10.20231/j.cnki.xxyts.2025.03.013

[24] 姚加权, 张锟澎, 郭李鹏 & 冯绪. (2024). 人工智能如何提升企业生产效率？——基于劳动力技能结构调整的视角. 管理世界, 40 (02), 101-116+133+117-122. https://doi.org/10.19744/j.cnki.11-1235/f.2024.0018

[25] 张宗益 & 郑志丹.(2012).融资约束与代理成本对上市公司非效率投资的影响——基于双边随机边界模型的实证度量.管理工程学报,26(02),119-126.https://doi.org/10.13587/j.cnki.jieem.2012.02.005

[26] 诸竹君,袁逸铭 & 焦嘉嘉.(2022).工业自动化与制造业创新行为.中国工业经济,(07),84-102.https://doi.org/10.19581/j.cnki.ciejournal.2022.07.019

[27] 张一林, 郁芸君 & 陈珠明. (2021). 人工智能、中小企业融资与银行数字化转型. *中国工业经济*, (12), 69-87. https://doi.org/10.19581/j.cnki.ciejournal.2021.12.003

Acknowledgement

In 2026, it is time for me to compose the acknowledgments part of my undergraduate thesis.

The achievement of this thesis cannot be accomplished without the support and cooperation of certain individuals. Though it is a significant part of my academic career, I sincerely thank those who have assisted me in both my research and personal growth.

I would like to sincerely thank my supervisor, Associate Professor CUI Di. Her useful suggestions, kind assistance and continuous encouragement have greatly enhanced my research. From the start of the research topic to the submission of the paper, her knowledge in corporate finance and econometrics has effectively improved the quality of our work. Her constructive criticisms have helped me to arrange my analysis in a more logical way and to increase the reliability of my empirical results. I particularly appreciate her support during the difficult period and her trust in my abilities although I was disappointed then. Her comprehensive guidance will certainly be advantageous for my future career, both in academic field and practical work.

I am likewise very thankful to all the faculty members of the Business School in Shenzhen Technology University for their instructive courses and academic encouragement during my study period. From Professor Zhang Yahui's "Principles of Accounting" to Professor Chen Hao's "Management Psychology", the starting point and the ending point seem to summarize the four years of university life in a moment. It seems like I just entered Shenzhen Technology University a day ago.

I am grateful to the administrative staff of Shenzhen Technology University and the library personnel who helped me to obtain the necessary databases and research materials. The CSMAR database and other electronic resources supplied by the university have been useful for the empirical analysis in this thesis.

Furthermore, the cooperative behavior and competitive spirit of the classmates in the Business School have created a favorable environment for both academic advancement and personal development. I will keep in mind the scenes of long-time study meetings, group presentations and shared achievements during these four years.

Thanks are also due to the editors and reviewers of the mentioned journals in my thesis. They have done research on artificial intelligence, corporate investment efficiency and digital transformation which provided the required theoretical foundation and empirical data for my study. On the basis of their research, I have added my limited contributions to this intensive research field.

In summary, I would like to express my gratitude to my family for their continuous emotional and practical assistance, and also to the good friends during this period of study. My parents have always been my main supporters, providing both emotional and financial help. They attach great importance to education and stimulate my academic activities which inspire me to persist. Thank you to my classmates and friends for your jokes, experiences and help when encountering difficult situations. Your presence makes the thesis writing less difficult and more meaningful.

As I finish this period of my academic life, I take with me the experiences, associations and recollections formed during this time, and enter a new chapter with assurance and appreciation.