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The Impact of Artificial Intelligence on Enterprise Innovation

—Analysis of Mediating Effect based on Financing Constraint

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Abstract

This dissertation examines the impact of AI on firm innovation and the mediating role of financing constraints. This dissertation uses the panel data of China's A-share listed companies from 2016 to 2025 to conduct two-way fixed effect regression analysis on the collected data. AI is measured by AI investment relative to total assets, corporate innovation is measured by R&D expenditure relative to operating income, and financing constraints are measured by SA index. The results show that AI significantly promotes firm innovation by alleviating financing constraints. Financing constraints mediate the relationship between AI and innovation, suggesting that AI supports innovation both directly and by improving access to finance. Robustness tests using AI word frequencies confirm the reliability of the main conclusions. The analysis of ownership heterogeneity shows that the innovation effect of AI is stronger in non-SOEs, while its role in alleviating financing constraints is stronger in SOEs. These findings highlight the importance of institutions and financial conditions in shaping AI-driven innovation.

Key words: Artificial Intelligence; Enterprise innovation; Financing constraint

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1. Introduction

1.1 Background

AI has been transformed from a specialized computing technology to a general organizational resource, affecting firms to search, coordinate, and compete. Digital technologies enable continuous innovation by enhancing connectivity, generation, and knowledge recombination within organizational boundaries (Nambisan, et al., 2019). For multinational firms, this shift is linked to globalization because digital capabilities can reduce coordination barriers and expose firms to different national institutions, data systems, and geopolitical constraints (Autio, et al., 2021)). Therefore, AI adoption should not just be seen as an IT investment to improve efficiency. It may reshape strategic decisions and innovation opportunities, although these benefits rely on management of algorithms as well as complementary human expertise (Berente, et al., 2021).

In China, the innovation impact of AI is important. Listed firms combine rapid technology adoption with wide variation in ownership and access to finance (Meyer, et al., 2023). Artificial intelligence is closely related to product innovation and growth, and AI can create meaningful innovation capabilities in addition to automating existing tasks (Babina, et al., 2024). However, innovation is costly, the results are difficult to predict, and it is difficult for outside investors to evaluate accurately. Therefore, the effect of AI may be influenced partly by whether it changes the access of firms to finance, making financing constraints a mechanism of theoretical importance.

1.2 Theoretical and practical significance

This dissertation has both theoretical and practical implications. Research on digital innovation emphasizes that innovation can be reshaped by digital technologies through

reconfigurability, distributed knowledge and new organizational arrangements (Nambisan, et al., 2017). However, AI also creates automation enhancement problems. Greater algorithmic capabilities can complement managerial judgment while displacing tasks and raising coordination problems (Raisch & Krakowski, 2021). Studying financing constraints can add new financing mechanisms to this organizational perspective. When the cost of external capital is high, access to finance can greatly affect innovation because R&D investment is sensitive to financing conditions (Brown, et al., 2009).

Practically, identifying such mechanisms can help managers separate AI investments from the organizational and financial conditions needed to turn them into innovations (Hsu, et al., 2014). It can provide useful information to policymakers without if digital investments will make benefits. In China, because SOEs and non-SOEs may face different financing environments, the same AI investment facing different ownership may produce different innovation paths.

1.3 Research objective

The main objective is to explore the impact of firm-level AI investment on firm innovation and whether financing constraints constitute a mediating mechanism. The analysis revolves around two research questions. Can AI investment significantly promote corporate innovation? Does AI promote innovation by easing financing constraints? Therefore, instead of estimating a reduced-form association, this study links technological resources, innovation outcomes and financial access. Financing constraints are measured by size-age index to avoid reliance on potentially endogenous financial variables (Hadlock & Pierce, 2010). The analysis also examines whether these relationships differ between SOEs and non-SOEs. Because financing dependence will change innovation incentives under different organizational forms, it will provide a more institutionally based explanation for the main effect (Acharya & Xu, 2017).

1.4 Research method

This dissertation adopts a quantitative longitudinal research design using firm-level panel data from the CSMAR database. The sample covers Chinese A-share listed companies (excluding ST and financial companies) from 2016 to 2025. The collected data are processed to eliminate missing observations and outliers, and the variables are winsorized at the level of 1%. The explained variable is corporate innovation, the explanatory variable is artificial intelligence, the mediating variable is financing constraint, and the control variables are ROA, total asset turnover, leverage, total asset growth rate, proportion of independent directors and supervisory board shareholding ratio. The empirical analysis carries out descriptive statistics, correlation analysis, regression analysis, robustness test and heterogeneity test. Using Two-Way Fixed Effects Model, the regressions control for year and industry. Mediating effects are assessed by following an established ordinal regression model of mediating inference. The AI word frequency index is used to replace the explanatory variable to test the robustness. Heterogeneity is tested by different ownership of firms. All analyses are conducted in Stata 18.0 to maintain a consistent empirical implementation.

2. Literature Review

2.1 Artificial Intelligence

2.1.1 The concept and development of artificial intelligence

AI broadly refers to a computing system that is responsible for performing cognitive tasks such as prediction, classification, learning, and decision support. In organizations, AI is not an isolated technology but is understood as part of a broader digital architecture. Digital components allow flexible reorganization and modular layering, changing the way products and services are generated (Yoo, et al., 2010). Digital business strategy also blurs the boundary between IT and business strategy, making technology resources an indispensable part of competitive positioning (Bharadwaj, et al., 2013). AI introduces unique management challenges because learning algorithms can reallocate expertise, power, and accountability (Berente, et al., 2021).

This development implies a shift from automation to enhanced functions and organizational restructuring. Rather than merely improving existing processes, AI research looks at technology to create new value (Nambisan, et al., 2019). In this dissertation, artificial intelligence is regarded as a technological investment at the enterprise level. It affects resource allocation, knowledge reorganization and information processing, simply investing in it is not sufficient to ensure that the organization can successfully utilize it (Bailey, et al., 2022).

2.1.2 Influencing factors of artificial intelligence

The value generated by AI depends on complementary organizational and knowledge conditions. Raisch and Krakowski (2021) argue that enhancement and automation are interdependent, and companies need to re-engineer the division of labor between employees and algorithms. Opaque algorithms may be resisted by professionals when

outcome judgments cannot be easily explained (Lebovitz, et al., 2022). Excessive delegation may undermine human learning capacity and reduce the benefits of human-AI collaboration (Fügener, et al., 2022). The implementation of algorithms may also disrupt established professional knowledge and trigger political reactions within organizations (Pachidi, et al., 2021).

Knowledge connectivity provides another condition. Digital collaboration tools can expand access to expertise, but the impact is still biased toward existing network structures (Wu & Kane, 2021). Similarly, the adoption of digital technologies can increase knowledge flows across R&D sites, but this depends on technology linkages and joint adoption (Forman & van Zeebroeck, 2019). Therefore, AI capabilities aren't just generated by spending; human expertise, organizational routines, data access, and absorptive capacity collectively determine whether an investment is productive.

2.2 Enterprise Innovation

2.2.1 The concept and development of enterprise innovation

Corporate innovation involves the search, development and commercial application of new knowledge. Organizational learning distinguishes between exploring unfamiliar possibilities and leveraging existing capabilities (March, 2008). Enterprises must absorb external knowledge and combine it with previous capabilities, and R&D not only contributes to invention, but also contributes to absorptive capacity (Cohen & Levinthal, 1990). Technical search involves restructuring uncertainty, and unfamiliar combinations can increase the probability of failure and breakthrough (Fleming, 2001).

Innovation involves strategic trade-offs. Process management can improve efficiency, but when companies overemphasize standardization, exploratory activities will be reduced (Benner & Tushman, 2003). Teece (2007) believed that continuous performance requires enterprises to perceive opportunities, seize opportunities and

reallocate resources when the environment changes. In this dissertation, R&D intensity is innovation commitment, which captures inputs rather than the commercial quality or novelty of the final output.

2.2.2 Influencing factors of enterprise innovation

Innovation is formed by internal search and external knowledge. Katila and Ahuja (2002) showed that the depth and scope of search had obvious nonlinear effects on the creation of new products. Openness can expand available ideas, but excessive breadth and depth will produce diminishing returns (Laursen & Salter, 2006). Cross-border exploration can go beyond the local technical field, thus creating inventions with greater impact (Rosenkopf & Nerkar, 2001).

The inter-organizational network plays a further restrictive role. Alliance structure can provide information and complementary resources to support innovation (Ahuja, 2000). When networks promote knowledge transfer, partner diversity can increase exploratory innovation (Phelps, 2010). Strategic alliances are related to the growth and innovation of technology-intensive industries (Stuart, 2000). When the acquired knowledge has enough relevance and novelty to be absorbed and increase diversity, technology acquisition can expand the knowledge base of enterprises (Ahuja & Katila, 2001). Therefore, resource availability is important, but allocative and absorptive use determine innovation outcomes.

2.3 Financing constraint

Financing constraints arise when firms are unable to finance value-creating investments at the costs that prevail in frictionless capital markets. Kaplan and Zingales (1997) challenge the assumption that high investment cash flow sensitivity necessarily identifies constrained firms, showing that common agents may misclassify financial conditions. Whited and Wu (2006) developed an alternative index by using corporate

characteristics. Hadlock and Pierce (2010) found that enterprise size and age contained a large amount of financing information, and proposed SA index. These methods are still indirect measurements rather than observations of rejected applications for funding.

The link between R&D and innovation is strong because R&D has a long-term horizon, uncertain returns, and limited collateral value. Brown et al. (2009) found that internal cash flow and external equity made significant contributions to the R&D boom, indicating that innovation investment responded to financing supply. Open market access can change the scale and direction of innovation, but more financing does not mechanically improve the quality of innovation (Bernstein, 2015). Thus, financial constraints constrain innovation, but access to finance interacts with governance, incentives, and project selection.

2.4 The relationship between artificial intelligence, enterprise innovation and financing constraint

The above literature suggests an interconnected mechanism. AI can influence how knowledge is generated and evaluated, but innovation requires a continuous commitment of resources, and financing conditions determine whether firms can finance uncertain R&D (Nambisan, et al., 2019). These relationships are theoretically complementary rather than independent.

2.4.1 The impact of artificial intelligence on enterprise innovation

AI can promote enterprise innovation through information, knowledge and resource allocation channels. AI-intensive organizations can identify patterns in large data sets, reducing some technical search costs. Babina et al. (2024) showed that AI-related human capital investment is related to product innovation and enterprise growth. This is consistent with the digital innovation theory, which emphasizes the generation and reorganization of distributed knowledge (Nambisan, et al., 2017). Digital connectivity

can also increase knowledge flows between separate R&D sectors, expanding opportunities for internationally active firms (Forman & Van Zeebroeck, 2019).

However, positive relationships are not formed automatically. AI may effectively leverage existing data and routines while enforcing path dependencies, and opaqueness may limit organizational learning. Efficiency-oriented technologies may favour incremental search unless managers retain the ability to explore (March, 2008). Dynamic capabilities also require complementary management processes to transform technical resources into strategic renewal (Teece, 2007). Thus, AI investments should increase innovation on average, but the impact still depends on organizational capabilities rather than technological determinism.

2.4.2 The impact of artificial intelligence on financing constraint

AI may affect innovation indirectly by altering financing frictions. External financiers face asymmetric information problems when evaluating firms with uncertain future cash flows. Digital data and algorithmic analysis can improve screening by extracting predictive information that is missing from traditional credit records. Berg et al. (2020) showed that digital footprint can predict creditworthiness and supplement traditional credit rating agency information. Machine learning lending may not necessarily eliminate inequality outcomes, but it can change the information used in credit allocation (Bartlett, et al., 2022).

At the firm level, better information processing and transparency can reduce the information component of perceived risk and financing costs. However, this mechanism is not necessarily beneficial. Algorithms can improve risk assessment while remaining opaque, and financiers may still discount AI intensive investments with uncertain returns. The evidence that bank credit supply affects corporate innovation shows that financing does not prove that artificial intelligence will lead to easier financing, but it can transmit technical effects (Amore, et al., 2013).

2.4.3 The impact of financing constraint on enterprise innovation

Financing constraints inhibit innovation because firms may not be able to sustain R&D during periods of uncertain returns. Financial development greatly benefits innovation intensive industries, which is consistent with the dependence on external financing (Hsu, et al., 2014). The credit supply shock indicates that financing conditions affect innovation input and output (Amore, et al., 2013). Although the mechanism depends on borrower risk and lender incentives, greater bank competition is also related to stronger innovation (Cornaggia, et al., 2015).

Market position and ownership complicate the relationship. There are differences in financing dependence and innovation behaviour between public and private companies (Acharya & Xu, 2017). Public offering rights can increase available resources for innovation but will change inventor incentives and project selection (Bernstein, 2015). Capital still must be allocated to productive R&D, so governance and technological opportunities remain boundary conditions.

2.5 Critical evaluation

Existing research provides a solid foundation but leaves three gaps. First, much of the digital innovation research doesn't study firm-level AI investments, but rather broad technology, platform, or organizational transformations. AI has the unique characteristics of learning, opacity, and human complementarity. Second, credit conditions affect R&D, but AI is rarely used as a prerequisite for financing constraints. Third, digitalization interacts with national institutions and cross-border organizations, but institutional heterogeneity within emerging economies remains important (Meyer, et al., 2023). SOEs and non-SOEs in China differ in resource access and governance, so average effects may mask differences.

This dissertation addresses these gaps by linking AI investment to R&D intensity,

testing financing constraints as a mediator and examining ownership heterogeneity. However, the design cannot fully establish causality, more powerful innovators may choose to participate in AI investments, and the SA index remains a proxy.

3. Research Methodology

3.1 Research hypothesis

AI can enhance enterprise innovation by improving information processing, accelerating knowledge reorganization, and supporting more efficient allocation of R&D resources (Babina, et al., 2024). Firm-level AI investments are associated with higher product innovation capabilities and growth performance (Babina, et al., 2024). Moreover, because innovation depends so much on access to finance, lowering barriers to finance can sustain R&D spending and innovation growth (Brown, et al., 2009). Based on these arguments, the following two hypotheses are developed.

Hypothesis 1: Artificial Intelligence positively promotes enterprise innovation. The higher the degree of artificial intelligence, the higher the level of enterprise innovation.

Hypothesis 2: Artificial Intelligence promotes corporate innovation by alleviating financing constraints, and financing constraints play a mediating role between artificial intelligence and enterprise innovation.

3.2 Data collection and sample selection

This dissertation takes Chinese A-share listed companies (excluding ST companies and financial industry companies) as the research object and conducts empirical analysis. I set the object for the 10-year period from 2016 to 2025. All data are obtained from the CSMAR database. To ensure the quality of the research, I process the samples as follows: Delete missing values. Remove outliers. The variables are Winsorized at the level of 1%. In the end, 29621 observations are obtained. Stata18.0 is used to process the data during data collection.

3.3 Selection of variables

3.3.1 Explained variable

Enterprise Innovation (RDI). R&D expenditure divided by operating revenue. This ratio measures innovation intensity and reflects resource commitment to knowledge creation and technology development (Cohen & Levinthal, 1990).

3.3.2 Explanatory variable

Artificial intelligence (AI_Inv). Total investment in artificial intelligence divided by total assets. Scaling AI investment by total assets provides a size-adjusted indicator of technology commitment, allowing AI adoption to be compared in empirical analyses (Babina, et al., 2024)

3.3.3 Mediating variable

Financing Constraint (SA). $SA = (-0.737 * \text{enterprise size coefficient}) + (0.043 * \text{square term of enterprise size coefficient}) - (0.040 * \text{enterprise operation years})$. Basic indicators such as the stability of corporate cash flow reflect the ability of enterprises to obtain funds. Composite indicators include KZ index, WW index and SA index, which provide a more comprehensive perspective through multi-dimensional consideration (Hadlock & Pierce, 2010). In this dissertation, I choose the SA index. Hadlock and Pierce (2010) suggested that it can better deal with the endogeneity problem, it avoids the use of endogenous financial variables such as cash flow and leverage, and it also has better discrimination. The larger the absolute value of the SA index, the higher the degree of financing constraints.

3.3.4 Control variables

Return on Assets (ROA). Net profit divided by total assets.

Total Asset Turnover (TAT). Operating revenue divided by average total assets.

Leverage (LEV). Total liabilities divided by total assets.

Total Asset Growth Rate (Growth). Change in total assets during the period divided by total assets at the beginning of the period.

Proportion of Independent Directors (INDEP). Number of independent directors divided by board size.

Supervisory Board Shareholding Ratio (RS). Number of shares held by supervisors divided by the total number of shares.

See Appendix for a table of research variables.

3.4 Econometric model

Establish the benchmark regression model.

$$RDI_{it} = a_0 + a_1 AI_Inv_{it} + a_2 controls_{it} + \delta_i + \gamma_t + \varepsilon_{it} \quad (1)$$

RDI_{it} is the explained variable, representing the corporate innovation of Company i during period t . AI_Inv_{it} is the explanatory variable, representing the degree of artificial intelligence of Company i during period t . $controls_{it}$ represents a series of control variables that may influence the corporate innovation level. δ_i represents the fixed effect of the year. γ_t represents the fixed effect of the industry. ε_{it} represents the random error term. (Zhao, et al., 2010)

Establish the following mediating effect test model.

$$RDI_{it} = \beta_0 + \beta_1 AI_Inv_{it} + \beta_2 controls_{it} + \delta_i + \gamma_t + \varepsilon_{it} \quad (2)$$

$$SA_{it} = \theta_0 + \theta_1 AI_Inv_{it} + \theta_2 controls_{it} + \delta_i + \gamma_t + \varepsilon_{it} \quad (3)$$

$$RDI_{it} = \gamma_0 + \gamma_1 AI_Inv_{it} + \gamma_2 SA_{it} + \gamma_3 controls_{it} + \delta_i + \gamma_t + \varepsilon_{it} \quad (4)$$

SA_{it} is the mediating variable. The coefficient β_1 in Model 2 indicates the extent to which AI affects enterprise innovation. The coefficient θ_1 in Model 3 represents the degree of impact of AI on financing constraints. Model 4 conducts regression analysis combining explanatory variable and mediating variable and uses stepwise regression to test the mediating effect. (Zhao, et al., 2010)

4. Empirical test and result analysis

4.1 Descriptive statistics

In this dissertation, the mean, standard deviation, minimum and maximum values of the main variables are analyzed by descriptive statistics. The analysis results are shown in Table 1. The mean value of RDI is 0.063, the standard deviation is 0.067, the minimum value is 0, and the maximum value is 0.403. It shows that different enterprises have significant differences in resource input for innovation activities. The mean value of AI_Inv is 0.014, the standard deviation is 0.023, the minimum value is 0, and the maximum value is 0.146. The standard deviation is significantly higher than its mean, indicating that there are significant differences in the degree of AI application among different enterprises. The mean value of SA is -3.901 and the standard deviation is 0.257. The value ranges from -4.572 to -3.259. The low dispersion of SA indicates that although there are differences in the degree of financing constraints among different firms, the overall distribution is relatively concentrated. Among the control variables. The mean value of ROA is 0.038, and the minimum value is negative, indicating that some enterprises have losses. The mean value of LEV is 0.380, indicating that enterprises have a certain level of debt financing. The value range of TAT, Growth and RS is relatively large, indicating that there are significant differences in asset operation efficiency, growth rate and shareholding ratio of regulators in different enterprises. In contrast, the value of INDEP is relatively concentrated, indicating that the overall proportion of independent directors is relatively stable.

Table 1 Descriptive Statistics

Variables	Number of Sample	Mean	Standard Deviation	Min	Max
RDI	29621	0.063	0.067	0.000	0.403
AI_Inv	29621	0.014	0.023	0.000	0.146
SA	29621	-3.901	0.257	-4.572	-3.259
ROA	29621	0.038	0.059	-0.197	0.196
TAT	29621	0.582	0.354	0.098	2.240

LEV	29621	0.380	0.187	0.054	0.826
Growth	29621	0.164	0.311	-0.233	1.820
INDEP	29621	0.380	0.053	0.333	0.571
RS	29621	0.127	0.179	0.000	0.665

4.2 Correlation analysis

To predict the relationship between variables and whether there is a collinearity problem, this dissertation uses the correlation analysis to determine the correlation between enterprise innovation (RDI), artificial intelligence (AI_Inv), financing constraints (SA) and the other six control variables. The results are shown in Table 2. The correlation coefficient between AI_Inv and RDI is 0.269 (significant at the level of 1%), indicating that the higher the application degree of AI is, the higher the innovation investment level is. The correlation coefficient between AI_Inv and SA is -0.042 (significant at 1% level), which preliminarily indicates that there is a negative relationship between AI and financing constraints. The correlation coefficient between SA and RDI is 0.112 (significant at the level of 1%), showing a positive correlation. However, the correlation analysis only reflects the simple linear relationship between variables and does not control other enterprise characteristics, so the specific impact needs to be further judged through subsequent regression analysis. In terms of control variables, RDI is significantly negatively correlated with ROA, TAT and LEV, respectively, while it is significantly positively correlated with Growth, INDEP and RS. ROA is significantly negatively correlated with LEV (-0.323), ROA is positively correlated with Growth (0.301), LEV is negatively correlated with RS (-0.265), and Growth is positively correlated with RS (0.233). The absolute value of the correlation coefficient among the variables is relatively low, with the highest value being 0.333, which is significantly lower than the commonly used judgment standard of 0.7. Moreover, the mean value of VIF is 1.16, which is significantly lower than 5. Indicating that there is no serious multicollinearity among variables, which fully proves the rationality of variable selection.

Table 2 Correlation Analysis

	RDI	AI_Inv	SA	ROA	TAT	LEV	Growth	INDEP	RS
RDI	1.000								
AI_Inv	0.269***	1.000							
SA	0.112***	-0.042***	1.000						
ROA	-0.184***	-0.177***	0.068***	1.000					
TAT	-0.333***	0.002	-0.047***	0.168***	1.000				
LEV	-0.288***	-0.008	-0.078***	-0.323***	0.228***	1.000			
Growth	0.027***	-0.107***	0.214***	0.301***	-0.035***	-0.127***	1.000		
INDEP	0.029***	0.030***	0.049***	-0.024***	-0.015***	-0.012**	-0.014**	1.000	
RS	0.075***	-0.069***	0.195***	0.129***	-0.056***	-0.265***	0.233***	0.062***	1.000

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

4.3 Regression analysis

In this dissertation, Hausman test and F-test are used to determine the choice of model. The results show that the Tow-Way Fixed Effects Model is selected to complete the subsequent regression analysis.

4.3.1 Baseline model regression analysis

Regression analysis is conducted on Models 1 and 2 to explore the relationship between artificial intelligence and enterprise innovation. The regression results are shown in Table 3. Without financing constraints, the regression coefficient of AI_Inv is 0.257 (significant at the level of 1%), indicating that the application of artificial intelligence can significantly promote corporate innovation, which verifies Hypothesis 1. This may be because artificial intelligence can improve the information processing efficiency, resource allocation efficiency and decision-making ability of enterprises, quickly identify market demand and technical opportunities, reduce the cost of information

search and decision-making in R&D, thus enhancing the motivation of enterprises to carry out innovation activities, and ultimately improving the level of enterprise innovation. For the control variables, the coefficients of ROA, TAT, LEV and Growth are -0.144 , -0.033 , -0.031 and -0.012 respectively, and all are significant at the level of 1%. It indicates that these variables are significantly negatively related to firm innovation. Higher debt levels may increase debt service pressure and reduce R&D investment. Higher return on assets and asset turnover may make firms more inclined to expand operations rather than increase R&D investment. The negative effect of Growth may indicate that rapid expansion crowds out R&D resources. In addition, INDEP is significantly positive at the 10% level and RS is significantly negative at the 5% level. In general, after controlling year and industry, AI still has a significantly positive impact on corporate innovation, so Hypothesis 1 holds true.

Table 3 Regression Results (Model 1 and Model 2)

Variables	Model 1 and Model 2 RDI
AI_Inv	0.257*** (16.59)
ROA	-0.144*** (-36.44)
TAT	-0.033*** (-28.74)
LEV	-0.031*** (-16.12)
Growth	-0.012*** (-22.50)
INDEP	0.009* (1.95)
RS	-0.003** (-2.00)
Year	Control
Industry	Control
Constant	0.091*** (5.56)
R-squared	0.18
N	29621

t-statistics in parentheses

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

4.3.2 Regression analysis of mediating effect

It has been proved above that artificial intelligence can significantly and positively promote enterprise innovation. Then, regression analysis is conducted on Models 3 and 4 to test the mediating effect of financing constraints, as shown in Table 4. The causal step-by-step analysis method was used. First, in Model 3, the regression coefficient of AI_Inv is -1.494 (significant at the level of 1%), indicating that artificial intelligence is significantly negatively correlated with financial constraints, artificial intelligence can alleviate corporate financial constraints. This may be because the application of AI can improve the information transparency and operating efficiency of enterprises, alleviate the information asymmetry between enterprises and investors, and improve the external financing environment, thus helping enterprises to obtain more financial support. Further, after financing constraints are added to Model 4, the regression coefficient of AI_Inv is 0.234 (significant at the level of 1%). Combined with the benchmark regression coefficient of AI_Inv of 0.257 in Table 3, the coefficient of AI_Inv has decreased after the addition of SA, but it remains significant at the level of 1%, indicating that artificial intelligence can still directly promote corporate innovation. At the same time, the regression coefficient of SA is -0.015 (significant at the level of 1%), indicating that financing constraints will significantly inhibit corporate innovation. Combined with the significant negative impact of AI_Inv on SA in Model 3, it can be shown that artificial intelligence can promote corporate innovation by alleviating financing constraints. Therefore, financing constraints play a partial mediating role between AI and enterprise innovation. Hypothesis 2 holds true.

Table 4 Regression Results (Model 3 and Model 4)

Variables	Model 3 SA	Model 4 RDI
AI_Inv	-1.494^{***} (-26.05)	0.234^{***} (14.93)
SA		-0.015^{***} (-9.08)
ROA	0.120^{***}	-0.142^{***}

	(8.21)	(-35.98)
TAT	0.020***	-0.033***
	(4.59)	(-28.51)
LEV	-0.281***	-0.035***
	(-39.70)	(-17.86)
Growth	0.061***	-0.011***
	(30.90)	(-20.39)
INDEP	-0.120***	0.007
	(-6.80)	(1.56)
RS	0.403***	0.003*
	(66.74)	(1.67)
Year	Control	Control
Industry	Control	Control
Constant	-3.717***	0.034*
	(-60.92)	(1.95)
R-squared	0.38	0.19
N	29621	29621

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

4.4 Robustness test

Change the explanatory variable. The index $AI_Freq = \ln(1 + \text{total AI word frequency in annual reports})$ constructed by the total AI word frequency in annual reports is used to replace the original AI investment level index AI_Inv , and the results are shown in Table 5. Without considering SA, Model 2 shows that the regression coefficient of AI_Freq is 0.002 (significant at the level of 1%), indicating that artificial intelligence can still significantly promote enterprise innovation after adopting the new AI measurement index. Further, the coefficient of AI_Freq in Model 3 is -0.043 (significant at 1% level), indicating that the improvement of artificial intelligence level can alleviate corporate financing constraints. After SA is added, the coefficient of AI_Freq in Model 4 is 0.001 (significant at the level of 1%), indicating that the promotion effect of artificial intelligence on enterprise innovation is still valid. At the same time, the coefficient of SA is significantly -0.018 at the level of 1%, indicating that financing constraints will inhibit corporate innovation. Combined with the results of Model 3 and 4, artificial

intelligence can promote corporate innovation by alleviating financial constraints, and financial constraints still play a partial mediating role. Therefore, after replacing the AI measurement indicators, the main conclusions above remain unchanged, indicating that the research results have good robustness.

Table 5 Robustness Results

Variables	Model 2 RDI	Model 3 SA	Model 4 RDI
AI_Freq	0.002*** (7.01)	-0.043*** (-47.71)	0.001*** (3.85)
SA			-0.018*** (-10.00)
ROA	-0.153*** (-38.79)	0.162*** (11.51)	-0.150*** (-38.04)
TAT	-0.032*** (-27.55)	0.010** (2.41)	-0.031*** (-27.45)
LEV	-0.031*** (-16.36)	-0.256*** (-37.15)	-0.036*** (-18.24)
Growth	-0.012*** (-23.17)	0.056*** (29.45)	-0.011*** (-21.00)
INDEP	0.011** (2.23)	-0.136*** (-7.93)	0.008* (1.74)
RS	-0.004** (-2.56)	0.376*** (63.75)	0.002 (1.35)
Year	Control	Control	Control
Industry	Control	Control	Control
Constant	0.094*** (5.69)	-3.710*** (-62.66)	0.029 (1.63)
R-squared	0.18	0.42	0.18
N	29612	29612	29612

t-statistics in parentheses

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

4.5 Heterogeneity test

Ownership heterogeneity test. In this dissertation, the samples are divided into state-owned enterprises and non-state-owned enterprises according to the nature of enterprise ownership to test the heterogeneity of the impact of artificial intelligence on enterprise innovation. The regression results are shown in Table 6. In Model 2, the regression

coefficients of AI_Inv of SOEs and non-SOEs are 0.216 and 0.235 respectively (significant at the level of 1%), indicating that regardless of the nature of enterprise ownership, AI can significantly promote enterprise innovation. From the coefficient size, the promotion effect of AI on the innovation of non-SOEs is relatively stronger, which may be because non-SOEs face more fierce market competition and are therefore more motivated to use AI to improve operating efficiency and innovation ability. In Model 3, the AI_Inv coefficients of state-owned enterprises and non-state-owned enterprises are -2.109 and -1.369 respectively (significant at the level of 1%), indicating that AI investment is significantly negatively correlated with financial constraints, AI can alleviate the financial constraints of the two types of enterprises. In terms of the absolute value of the coefficient, artificial intelligence has a stronger easing effect on the financing constraints of state-owned enterprises, indicating that artificial intelligence may be more helpful to improve the financing conditions and capital acquisition ability of state-owned enterprises. In Model 4, the SA coefficients of SOEs and non-SOEs are -0.031 and -0.011 respectively (significant at the level of 1%), indicating that financing constraints will significantly inhibit corporate innovation. After SA is added, the coefficients of AI_Inv in SOEs and non-SOEs are significantly 0.150 and 0.220 respectively. Combined with Model 3, AI promotes corporate innovation by alleviating financial constraints in both state-owned and non-state-owned enterprises, and financial constraints play a partial mediating role in both types of enterprises. In general, artificial intelligence has a significant promoting effect on the enterprise innovation with different ownership, but the direct promoting effect of artificial intelligence on the innovation of non-state-owned enterprises is relatively stronger, while the alleviating effect of financing constraints is more obvious in state-owned enterprises.

Table 6 Heterogeneity Results

	State-owned enterprises			Non-state-owned enterprises		
Variables	Model 2	Model 3	Model 4	Model 2	Model 3	Model 4
	RDI	SA	RDI	RDI	SA	RDI

AI_Inv	0.216*** (8.41)	-2.109*** (-14.36)	0.150*** (5.83)	0.235*** (12.37)	-1.369*** (-20.42)	0.220*** (11.45)
SA			-0.031*** (-13.75)			-0.011*** (-5.38)
ROA	-0.102*** (-14.33)	0.196*** (4.83)	-0.096*** (-13.66)	-0.144*** (-31.83)	0.118*** (7.38)	-0.143*** (-31.51)
TAT	-0.019*** (-12.09)	0.029*** (3.24)	-0.018*** (-11.69)	-0.037*** (-26.42)	0.022*** (4.44)	-0.037*** (-26.25)
LEV	-0.033*** (-10.49)	-0.131*** (-7.22)	-0.038*** (-11.93)	-0.028*** (-12.53)	-0.321*** (-41.32)	-0.031*** (-13.56)
Growth	-0.007*** (-5.59)	0.074*** (9.97)	-0.005*** (-3.83)	-0.013*** (-21.91)	0.059*** (29.28)	-0.012*** (-20.31)
INDEP	0.004 (0.68)	-0.212*** (-6.31)	-0.003 (-0.45)	0.015** (2.51)	-0.100*** (-4.68)	0.014** (2.33)
RS	-0.013 (-1.32)	0.727*** (12.72)	0.010 (0.96)	-0.002 (-0.93)	0.383*** (63.40)	0.003 (1.42)
Year	Control	Control	Control	Control	Control	Control
Industry	Control	Control	Control	Control	Control	Control
Constant	0.059*** (5.35)	-3.822*** (-60.33)	-0.061*** (-4.33)	0.094*** (5.60)	-3.740*** (-63.00)	0.052*** (2.82)
R-Squared	0.13	0.17	0.16	0.20	0.44	0.20
N	6750	6750	6750	22006	22006	22006

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

5. Conclusion

5.1 Findings

This dissertation examines whether AI promotes enterprise innovation and whether financing constraint plays a mediating role. The baseline regression shows a positive significantly coefficient of 0.257 for AI_Inv, supporting Hypothesis 1. Mediation analysis further shows that AI_Inv is negatively associated with financing constraint, while the SA coefficient is negative when included with AI. The AI coefficient falls from 0.257 to 0.234, indicating partial rather than full mediation and supporting Hypothesis 2. Replacing AI investment with annual reported AI frequency measure produces consistent results, validating the reliability of the main conclusions. Ownership heterogeneity justifies this conclusion. AI promotes innovation in both state-owned and non-state-owned enterprises, but the direct innovation effect is stronger among non-SOEs. Conversely, the estimated alleviation of financing constraints is stronger among SOEs firms. As a result, AI does not operate through a uniform path, institutional ownership conditions determine the relative importance of capacity and access to finance.

5.2 Research innovation

This dissertation contributes by integrating technology, innovation and corporate finance perspectives within an empirical framework. Instead of regarding AI as a generic digital transformation agent, it measures the intensity of investment in AI and relates this investment to R&D intensity. More importantly, the analysis identifies financing constraints as a partial transmission mechanism, extending the evidence that finance affects innovation by positioning AI as a potential prerequisite of the corporate financing environment. The ownership analysis also adds institutional distinctions: the same technology is associated with different direct and mediating effects in SOEs and

non-SOEs. Digital strategies remain rooted in institutional environments rather than eliminating them.

5.3 Research limitation

First, AI investment divided by total assets captures expenditure intensity, but not the quality, complexity or organizational effectiveness of AI adoption. Second, R&D intensity measures innovation inputs rather than outputs such as patents or new products. Third, the identification of mediating mechanisms is not comprehensive enough, and AI may affect innovation through other mediating variables or paths such as knowledge reorganization and information processing efficiency. Fourth, although fixed effects and robustness tests reduce some of the estimation concerns, reverse causality and omitted variables cannot be completely ruled out. Finally, focusing on Chinese listed firms limits external validity and ignores smaller firms and other institutional environments.

5.4 Suggestions

Companies should view AI as part of a broader innovation strategy, not as isolated tech spending. Managers should strengthen data capabilities, employee skills, and organizational processes so that AI resources can be transformed into effective R&D activities. Companies facing stronger financing constraints should also improve information transparency and clearly communicate AI-related investment plans to external financiers. Policymakers should encourage financial institutions to use a wider range of information to evaluate technology-intensive firms and provide support for investment in innovation. Finally, because ownership conditions have different effects on financing and innovation outcomes, SOEs and non-SOEs need to adopt differentiated policies.

Reference

Appendix

Table of research variables

Types of Variables	Names of Variables	Symbols of Variables	Definitions of Variables
Explained Variable	Enterprise Innovation	RDI	R&D Expenditure/Operating Revenue
Explanatory Variable	Artificial Intelligence	AI_Inv	Toal AI Investment/Total Assets
Mediating Variable	Financing Constraint	SA	SA Index
Control Variables	Return on Assets	ROA	Net Profit/Total Assets
	Total Asset Turnover	TAT	Operating Revenue/Average Total Assets
	Leverage	LEV	Total Liabilities/Total Assets
	Total Asset Growth Rate	Growth	(Total Assets at the End of the Current Period – Total Assets at the Beginning of the Current Period)/Total Assets at the Beginning of the Current Period
	Proportion of Independent Directors	INDEP	Number of Independent Directors/Board Size
	Supervisory Board Shareholding Ratio	RS	Number of shares held by supervisors/Total number of shares