



The Impact of Financing Structures on Total Factor Productivity in AI-Listed Companies

Zhongyi Xue*

Department of Accounting, The University of Queensland, Brisbane, Australia

*Corresponding author: xzyazyx666@163.com

Abstract. The rationality of financing structures in the artificial intelligence (AI) industry plays a crucial role in shaping firms' innovation capacity and total factor productivity (TFP). Using panel data of AI-listed companies in China, this study constructs a fixed-effects model to systematically examine the impact of various financing channels on enterprise TFP. The empirical results reveal that internal financing, debt financing, firm age, and operational performance exert significant positive effects on TFP, whereas firm size shows a significant negative relationship. In contrast, government support, equity financing, R&D intensity, and ownership concentration are found to be statistically insignificant. Further analysis identifies several structural issues in the financing of AI enterprises, including the dominance of internal funds, limited access to debt financing, low efficiency of equity capital utilization, and insufficient conversion of policy support into productivity gains. Accordingly, this paper proposes several policy recommendations—optimizing corporate capital structures, expanding debt financing channels, improving the effectiveness of equity financing, and refining the system of government support—to enhance the financing efficiency and productivity of AI-listed firms in China.

Keywords: Artificial Intelligence; Listed Companies; Financing Structure; Total Factor Productivity (TFP)

1 Introduction

As one of the core forces propelling the new wave of global economic and technological transformation, the artificial intelligence (AI) industry plays a vital role in fostering innovation and productivity growth. However, the inherent contradiction between its high research intensity and prolonged return periods continues to constrain industrial expansion. Understanding the influence of financing structures on total factor productivity (TFP) is thus essential for clarifying how financial resource allocation shapes innovation efficiency and competitive performance within AI enterprises[1]. A growing body of literature confirms a strong connection between financing structures and total factor productivity (TFP). Using listed manufacturing firms as a sample, Liu (2020) found that both debt and internal financing significantly promote TFP

growth[2]. Debt financing operates mainly through the channel of technological progress, while internal financing enhances productivity via improvements in scale efficiency; in contrast, the short-term impact of equity financing is not significant. At the micro-industry level, studies on the media sector indicate that a higher share of internal funding markedly improves corporate performance, whereas greater reliance on equity or debt financing tends to hinder it (Internal Capital Market and Total Factor Productivity, 2025)[3,4]. Moreover, the application of digital technologies and artificial intelligence has been shown to amplify the marginal contribution of financial capital to TFP by easing financing constraints and enhancing governance and resource allocation efficiency[5]. Drawing on panel data from China's A-share market, Zhang (2024) demonstrated that digital transformation substantially increases TFP, with strengthened internal control and reduced financing constraints serving as the key transmission mechanisms[6]. Similarly, Ding (2024) revealed that AI adoption raises firms' TFP through the combined pathways of labor structure optimization, improved investment efficiency, and innovation upgrading[7].

Tu et al. (2025) conducted an empirical analysis showing that the advancement of digital technologies significantly enhances the total factor productivity (TFP) of manufacturing enterprises by improving capital allocation efficiency and stimulating innovation activities[8]. Likewise, Jin (2024) found that the development of digital finance contributes to higher TFP levels by alleviating financing constraints and enhancing human capital as well as corporate governance efficiency[9]. From the perspective of digital transformation, Lei (2023) demonstrated that digital technologies can markedly raise firms' TFP by optimizing resource allocation, strengthening innovation capacity, and improving the efficiency of capital utilization[10].

In summary, although existing studies have explored the mechanisms linking financing structures, digital transformation, and total factor productivity (TFP), research specifically focusing on the financing of the artificial intelligence (AI) industry remains limited. In particular, the heterogeneous effects of different financing sources on productivity improvement in AI enterprises have not been fully examined. To address this gap, this paper takes China's AI-listed firms as the research sample and systematically investigates the impacts of internal financing, debt financing, equity financing, and government support on corporate TFP. The findings aim to provide empirical evidence and policy insights for enhancing the efficiency of capital utilization and promoting the sustainable development of the AI industry.

2 Analysis of the Financing Structure of AI-Listed Companies

2.1 Internal Financing Remains the Dominant Source

Between 2021 and 2024, internal financing within China's artificial intelligence (AI) sector showed a steady upward trajectory, rising from roughly RMB 60 billion to RMB 72 billion (see Figure 1). Cross-sectional data for 2024 indicate that the 354 sampled

AI-listed firms collectively achieved RMB 2,546.182 billion in internal financing, averaging RMB 7.193 billion per company. Among the four major financing channels, internal funds represented the largest share and the most stable source of capital. (Figure 1)

This suggests that, given the industry’s characteristics of intensive R&D spending and high uncertainty, AI firms continue to depend primarily on retained earnings and capital reserves. Such reliance reflects a preference for stable, self-generated capital as the foundation of their financial structure.

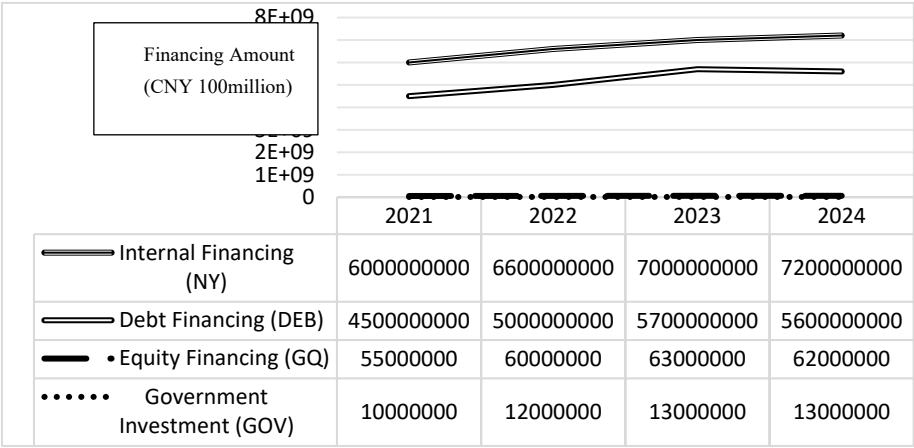


Fig. 1. Trends in the Financing Structure of AI-Listed Companies

Source: Compiled by the author based on data from the CSMAR and Wind databases, as well as annual reports of listed companies

2.2 Debt Financing Expands Steadily with Increasing Concentration Among Leading Firms

Sample data reveal an overall expansion in debt financing. In 2024, the total debt financing of AI-listed companies reached RMB 2,006.046 billion, averaging RMB 5.667 billion per firm, with the largest single case amounting to RMB 172.897 billion. Financing resources have become increasingly concentrated among top-tier enterprises with stronger credit ratings, sound asset quality, and stable cash flows.

In terms of financing channels, bank loans remain the primary source, supplemented by corporate bonds and convertible bonds. Regarding maturity structure, medium- and short-term instruments dominate, adequately supporting operational and stage-based R&D expenditures, though still insufficiently aligned with the long-term innovation cycles of certain AI firms.

2.3 Equity Financing: Active but Limited in Scale and Stability

Data from 354 sample firms show that equity financing generally increased from 2021 to 2023 but slightly declined in 2024, with the total market capitalization dropping to

around RMB 620 million. In 2024, total equity financing among the sample reached RMB 577 million, averaging approximately RMB 16 million (about RMB 1631 million) per company. Overall, the scale remained modest and sensitive to large individual projects and short-term market fluctuations.

In terms of financing instruments, additional share issuance, rights offerings, and mergers and acquisitions served as the main channels. The distribution was notably skewed—median values were far below the mean—indicating a “low-median, long-tail” pattern. This suggests that leading firms possess stronger capabilities to attract equity capital, whereas most enterprises tend to use equity financing as a temporary or supplementary funding source.

2.4 Policy Support Funds: Persistent but Limited in Scale

From 2021 to 2024, government funding for China’s artificial intelligence (AI) industry showed a gradual upward trend. In 2024, total government investment among the sampled firms reached RMB 373.833 billion, with an average of about RMB 106 million per enterprise. Fiscal subsidies, R&D grants, and tax incentives have played a positive role in easing short-term financial pressures. However, compared with the magnitude of internal and debt financing, the overall scale of policy support remains limited. Significant disparities also exist across regions and firms, reflecting a pattern of “broad coverage but small funding amounts.”

Table 1. Average Growth Rates and Volatility of Different Financing Channels

Types of Financing	Average Annual Growth Rate (%)	Standard Deviation (SD)
Internal Financing NY	4.3	2.1
Debt Financing DEB	9.8	4.5
Equity Financing GQ	7.2	7.9
Government Investment GOV	2.5	1.3

The average annual growth rates of the four main financing channels in the AI industry are shown in Table 1. Debt financing recorded the highest average growth rate (9.8%), indicating a sharp rise in firms’ demand for external credit. Internal financing grew at a steadier pace (4.3%), reflecting its role as a stable core funding source. Although equity financing expanded relatively quickly (7.2%), it exhibited the highest volatility (standard deviation = 7.9), suggesting strong sensitivity to capital market conditions. Government funding showed the slowest growth (2.5%) and the lowest volatility (1.3%), implying that fiscal support remains steady but limited in overall scale.

3 Empirical Analysis of the Impact of Financing Structures on TFP in AI-Listed Companies

Building on the preceding theoretical framework and descriptive analysis, this chapter examines how different types of financing—internal funds, external financing, and government support—affect productivity growth. The analysis begins with the description of data sources and the construction of an indicator framework to examine the varying impacts of these financing channels on total factor productivity (TFP) improvement.

3.1 Data Sources and Variable Construction

Sample Selection. This study examines financial data from 354 AI-related firms listed on China’s Shanghai and Shenzhen A-share markets between 2021 and 2024. The sample was initially identified using the CSRC secondary industry classification and AI-related thematic tags, followed by manual verification through annual reports, corporate announcements, and third-party databases to ensure that each firm’s primary business is closely linked to the AI sector.

Financial and governance variables were sourced mainly from the CSMAR and Wind databases, along with companies’ annual reports. The identification of AI-related firms was based on CSRC industry codes, the Wind thematic database, and manual text screening of annual report disclosures. Macroeconomic data were obtained from the National Bureau of Statistics and the People’s Bank of China. To improve data reliability, firms marked as ST, PT, or classified as financial institutions were excluded, and all key variables were winsorized at the 1% level to mitigate the impact of extreme values.

Dependent Variable. The core dependent variable is total factor productivity (TFP). TFP is estimated using the Solow (1957) residual production function approach, expressed as:

$$TFP=Y/(K^{\alpha}\cdot L^{(1-\alpha)}) \quad (1)$$

Where Y denotes firm output (proxied by operating revenue), K represents capital input (measured by net fixed assets or capital stock), and L refers to labor input (number of employees). The capital output elasticity α is set at 0.4, reflecting the industry-average value.

Core Explanatory Variables. The main explanatory variables include internal financing, debt financing, equity financing, and government support.

Internal financing reflects a firm’s capacity for self-accumulation and reinvestment, characterized by low cost and high stability, serving as an internal driver of TFP growth. Debt financing represents a firm’s ability to access external capital and ease financial constraints. Equity financing captures the capacity to raise long-term funds through capital markets, influencing productivity through mechanisms such as risk sharing,

governance improvement, and innovation incentives. Finally, government support, as a policy-oriented funding source, plays an essential role in mitigating financing constraints and directing resources toward high-quality, innovation-driven projects.

Control Variables. To account for firm characteristics, operational conditions, and governance factors that may influence TFP, several control variables are introduced: firm size (size, measured as the natural logarithm of total assets), firm age (YE), R&D intensity (RD, calculated as R&D expenditure divided by operating revenue), operating performance (ROA), and ownership concentration (JZ, measured by the shareholding ratio of the top ten shareholders).

A summary of these variables is presented in the following Table 2:

Table 2. Description of indicators

Indicator Type	Code	Indicator	Indicator Calculation
Dependent Variable	TFP	Total Factor Productivity	$TFP=Y/K^\alpha L^{1-\alpha}$, Where Y represents operating income or value added, K denotes capital input, and L denotes labor input.
Independent Variable	NY	Internal Financing	Capital Reserve + Surplus Reserve + Retained Earnings
	GOV	Government Investment	The total amount of all government grants recognized in profit or loss for the current period
	DEB	Debt Financing	Short-term Borrowings + Long-term Borrowings
	GQ	Equity Financing	Total Market Value at the End of the Period
Control Variable	size	Firm Size	Total Assets
	YE	Firm Age	The number of operating years from the year of establishment to the sample period
	RD	Research and Development Innovation	Artificial Intelligence Intangible Assets + Artificial Intelligence Fixed Assets
	ROA	Operating Performance	Net Profit ÷ Total Assets
	JZ	Shareholding Ratio of the Top Ten Shareholders	Shareholding Ratio of the Top Ten
Panel Index	corp	Firm ID	Unique Firm Identifier
	year	Year	Fiscal Year

3.2 Model Construction

Baseline Model. To examine the impact of financing structure on firms’ total factor productivity (TFP), a two-way fixed-effects panel regression model is constructed as follows:

$$TFP_{i,t}=\beta_0+\beta_1NY_{i,t}+\beta_2DEB_{i,t}+\beta_3GQ_{i,t}+\beta_4GOV_{i,t}+\sum_k\gamma_kControl_{k,i,t}+\mu_i+\lambda_t+\varepsilon_{i,t} \quad (2)$$

Where *I* denotes the firm, *t* the year, μ_i represents the firm fixed effect, λ_t the time fixed effect, and $\varepsilon_{i,t}$ the random disturbance term.

Variable Treatment. To address potential heteroskedasticity and serial correlation, all regressions employ firm-clustered robust standard errors. Continuous variables are logarithmically transformed or standardized to minimize the impact of scale differences on the interpretation of regression coefficients. The descriptive statistics are presented in Table 3.

Table 3. Descriptive Statistics

Variable	Mean	Std. Dev.	Min	Max	Observations
corp overall	177.5	102.2267	1	354	N=1416
year overall	2022.5	1.118429	2021	2024	N=1416
TFP overall	4951.717	5155.24	0	66268.92	N=1416
NY overall	6.72e+09	1.04e+10	-1.81e+09	9.20e+10	N=1416
GOV overall	1.08e+08	3.13e+08	-1.33e+07	4.78e+09	N=1416
DEB overall	5.20e+09	1.42e+10	8900000	1.74e+11	N=1416
GQ overall	1.75e+07	3.01e+07	1136638	3.17e+08	N=1416
size overall	2.33e+10	4.58e+10	8.77e+08	4.52e+11	N=1416
YE overall	22.9661	6.07389	7	45	N=1416
RD overall	15.30627	12.52079	0.05	91.5	N=1416
ROA overall	0.0213364	0.0590128	-0.4203	0.439095	N=1416
JZ overall	54.41058	15.28727	12.74	92.73	N=1416

Overall, the distribution of the sample data is reasonable, reflecting the characteristics of the industry and providing a stable foundation for the subsequent regression analysis.

3.3 Empirical Results and Analysis

Total factor productivity (TFP) represents the output growth a firm achieves, given fixed levels of capital and labor input, through technological advancement, managerial improvement, and institutional innovation. A firm with higher TFP is able to create

more value with fewer resources, reflecting stronger efficiency and competitiveness. (Table 4)

Table 4. Regression Results

TFP	Coef.	Std. Err.	t	P> t	95% Conf. Interval (lower)	95% Conf. Interval (upper)
NY	1.83E-07	3.70E-08	4.95	0	1.11E-07	2.56E-07
GOV	4.62E-07	7.15E-07	0.65	0.518	-9.41E-07	1.87E-06
DEB	6.90E-08	3.04E-08	2.27	0.023	9.33E-09	1.29E-07
GQ	9.48E-06	6.27E-06	1.51	0.131	-2.82E-06	2.18E-05
size	-1.13E-07	1.57E-08	-7.22	0	-1.44E-07	-8.26E-08
YE	173.8803	55.5545	3.13	0.002	64.8702	282.8904
RD	33.1138	21.4563	1.54	0.123	-8.9881	75.2157
ROA	4074.971	1364.384	2.99	0.003	1397.751	6752.191
JZ	-22.3542	18.8777	-1.18	0.237	-59.3963	14.688
_cons	2413.737	1989.976	1.21	0.225	-1491.032	6318.506

The empirical results are as follows: after controlling for firm fixed effects, internal financing (NY) shows a significant positive relationship with TFP at the 1% confidence level. This indicates that an increase in retained earnings effectively enhances firms' total factor productivity. The underlying reason is that internally generated funds, characterized by low cost and high flexibility, help ease financial constraints and ensure stable R&D investment, thereby accelerating the transformation of technological innovation and improving production efficiency.

Debt financing (DEB) is also significantly positive, indicating that debt capital effectively enhances the total factor productivity (TFP) of AI-listed firms. This can be attributed to the relatively low cost and scalability of debt financing, which helps ease the long-term funding pressure associated with R&D activities. Moreover, creditor monitoring mechanisms can reduce agency costs, thereby improving efficiency in technological innovation and resource allocation.

The estimated coefficient for equity financing (GQ) is not statistically significant. This suggests that, during the study period, funds raised through equity financing did not translate effectively into higher total factor productivity (TFP) for AI-listed firms. Possible explanations include diversified use of raised capital leading to insufficient R&D investment, inefficiencies in market valuation that increase financing costs, and weaker governance discipline from equity investors, all of which diminish the direct impact of equity capital on productivity improvement.

The empirical results show a significant negative correlation between firm size (size) and total factor productivity (TFP). This indicates that as AI-listed companies expand, they may experience diminishing marginal efficiency in areas such as management hierarchy, resource allocation, and organizational coordination. With increasing firm size, additional managerial layers and longer decision-making chains raise communication and coordination costs, ultimately leading to reduced marginal efficiency and constraining further improvements in TFP.

Firm age (YE) is significantly positive at the 1% level, indicating that the total factor productivity (TFP) of AI-listed firms increases with longer operating years. A longer business history reflects not only greater managerial experience and technological accumulation but also stronger survival and growth capabilities in competitive markets. Continuous knowledge accumulation and prudent resource allocation enable mature firms to achieve higher innovation output and production efficiency.

R&D intensity (RD) is found to be statistically insignificant, suggesting that during the sample period, the research and development efforts of AI-listed firms did not have a substantial impact on total factor productivity (TFP). This may be due to the long time lag between project initiation and commercialization, as well as issues such as fragmented research focus and low output efficiency in some firms, which limit the short-term contribution of R&D investment to productivity growth.

Operating performance (ROA) is significantly positive at the 1% level. Strong profitability indicates that firms possess superior cost control and market competitiveness while also securing the financial capacity for continuous R&D and reinvestment. This creates a virtuous cycle of “profitability → reinvestment → productivity improvement.”

The ownership concentration (JZ), measured by the shareholding ratio of the top ten shareholders, is not statistically significant. This may be because the governance benefits from large shareholders’ oversight are offset by potential expropriation risks. Additionally, given the R&D-driven nature of the AI industry, the marginal impact of ownership structure on productivity tends to be relatively limited.

3.4 Endogeneity Test

To mitigate potential endogeneity between the financing structure and total factor productivity (TFP), the key explanatory variables are standardized, and the fixed-effects regression is re-estimated using these standardized measures to test the robustness of the results across different scales and units.

Endogeneity test results are as follows in Table 5:

Table 5. VIF Test Results

Variable	VIF	1/VIF
size_std	9.11	0.109709
DEB_std	5.60	0.178518
NY_std	4.07	0.245530
GQ_std	2.48	0.403164

GOV std	1.86	0.538907
ROA std	1.17	0.853554
JZ std	1.15	0.866730
RD std	1.10	0.905114
YE std	1.10	0.912806
Mean VIF	3.07	

The results show that the variance inflation factor (VIF) values for all explanatory variables are 3.07, indicating no significant multicollinearity. Therefore, the model's estimates are robust, and multicollinearity remains within a controllable range.

4 Problems in the Financing of AI-Listed Companies

4.1 Imbalanced Financing Structure and Heavy Reliance on Internal Funds

The empirical findings show that internal financing (NY) has a significant positive effect on TFP, indicating that many AI-listed firms rely excessively on retained earnings and operating cash flow, while the share of external capital remains relatively low. On one hand, the long R&D cycles and asset-light nature of AI firms limit their ability to provide sufficient collateral for debt financing. On the other hand, capital markets remain cautious about the profitability uncertainty of AI businesses, leading to higher equity financing costs. This over dependence on internal funds restricts the availability of capital for rapid expansion and technological upgrading and amplifies the impact of operational fluctuations on R&D investment.

4.2 Limited Debt Financing Channels and Elevated Financing Costs

Although debt financing (DEB) exhibits a significant positive effect on TFP in the statistical results, on-site investigations reveal that AI firms often face high entry thresholds and stringent disclosure requirements when seeking bank credit or issuing corporate bonds. Banks tend to have low risk tolerance and lack effective tools to evaluate the cash flows of AI projects, while the bond market shows limited acceptance of early-stage or loss-making companies. Consequently, debt financing for AI enterprises is often characterized by higher interest rates and shorter maturities, making it difficult to fully meet the capital needs for large-scale and long-term R&D investment.

4.3 Inefficient Equity Financing and Imperfect Market Pricing Mechanisms

The insignificance of equity financing (GQ) in the regression results indicates that even when AI-listed firms raise capital through additional share issuance or rights offerings, the short-term impact on productivity remains limited. This outcome partly stems from the underdeveloped risk-pricing mechanisms in China's capital market, where high volatility and substantial issuance discounts prevail. Additionally, some firms exhibit rent-

seeking behavior, diverting raised funds away from core technology R&D, thereby weakening the contribution of equity capital to productivity improvement.

4.4 Mismatch Between Financing and Innovation, with Low Policy Conversion Efficiency

The regression results show that government support (GOV) is not significantly related to TFP, indicating that policy funds have not been effectively translated into productivity gains. This may be due to complex application procedures and delayed disbursement of subsidies; some firms use these funds to cover operational shortfalls rather than for R&D activities. Moreover, fragmented local government policies make it difficult to establish long-term and predictable financial support. As a result, a mismatch exists between policy funding and firms' innovation needs, weakening the leverage effect of fiscal resources.

5 Strategies for Optimizing the Financing Structure of AI-Listed Companies

5.1 Enhancing the Quality of Internal Financing and Building a Sustainable Capital Pool

Firms should strengthen profitability and cash flow management by optimizing cost structures, reinforcing core competitiveness in their main business, and improving profit distribution policies to expand retained earnings. In addition, establishing sound mechanisms for the capitalization of R&D expenditures and the commercialization of research outcomes can help form a virtuous cycle between profits and innovation, ensuring that internal funds remain a stable and sustainable source for technological advancement.

5.2 Expanding Debt Financing Channels and Reducing Financing Costs

To address the challenges of limited access and high costs in debt financing for AI enterprises, coordinated efforts should be made through financial innovation and policy support. Financial institutions should accelerate product development by introducing intellectual property-backed loans and cash flow-based lending tailored to AI firms, while building risk assessment systems aligned with the characteristics of technology-oriented enterprises to enhance credit accessibility.

At the same time, the bond market should be further improved to support qualified AI-listed companies in issuing medium- and long-term corporate bonds or convertible bonds, allowing the maturity structure of funds to better align with the long R&D cycles typical of the industry. On this basis, policy-oriented financial institutions should play an active role by leveraging national science and technology innovation funds, policy guarantees, and risk compensation mechanisms to share financial risks. Such measures

would help lower lending rates, improve the overall financing environment, and foster a healthy interaction between technological innovation and capital markets.

5.3 Enhancing the Efficiency of Equity Financing and Improving Capital Market Pricing Mechanisms

At present, the role of equity financing in improving the total factor productivity (TFP) of AI-listed companies has not been fully realized. Nevertheless, as a vital source of long-term capital, equity remains a key channel for supporting continuous innovation and industrial upgrading. With the ongoing development of multi-tiered capital markets such as the STAR Market and ChiNext, efforts should focus on optimizing issuance and refinancing mechanisms to enhance market recognition and valuation accuracy for AI enterprises.

Meanwhile, information disclosure and corporate governance systems should be strengthened. Firms should be required to publicly report on the use of raised funds, R&D progress, and project outcomes, thereby increasing investor confidence in innovation activities. Regulators should also establish post-financing evaluation and tracking systems to ensure compliance in fund allocation and prevent speculative or short-term capital use. Furthermore, capital markets should encourage greater participation from long-term institutional investors, guiding funds toward core technological research and high-value-added sectors through market mechanisms. Such measures can foster a virtuous cycle between capital supply and technological innovation, ultimately improving the efficiency and productivity contribution of equity financing.

5.4 Optimizing Policy Support Structure and Strengthening the Alignment Between Funding and Innovation

The current insignificance of government subsidies in improving total factor productivity (TFP) suggests a mismatch between policy design and firms' actual innovation needs. To enhance the efficiency of fiscal resource allocation, policy support should shift from broad-based, fragmented assistance toward more targeted and structural measures, focusing on high-value areas such as core technology breakthroughs, key equipment acquisition, and original R&D.

A dynamic evaluation mechanism should also be established, linking funding disbursement and renewal to performance indicators such as R&D input-output ratios, patent conversion rates, and technology commercialization outcomes. This performance-oriented approach ensures that policy funds genuinely serve innovation activities. In addition, the funding chain should be extended by leveraging the guiding role of government-backed and industrial investment funds, promoting collaboration between public finance and private capital. Such a multi-tiered investment and financing system would help create a virtuous cycle between innovation investment and productivity outcomes.

6 Conclusion

This study systematically examines the impact of different financing channels on the total factor productivity (TFP) of AI-listed companies in China using panel data from 2021 to 2024. The empirical findings indicate that internal financing and debt financing significantly enhance TFP, while equity financing and government support do not show statistically significant effects. Firm age and operating performance positively contribute to productivity improvement, whereas firm size is negatively associated with TFP.

The results suggest that AI enterprises currently rely heavily on internal funds, while external financing mechanisms—particularly equity capital and policy support—have not yet been fully translated into productivity gains. Structural mismatches between financing supply and innovation demand remain evident.

To promote sustainable development of the AI industry, it is essential to optimize capital structure, expand diversified debt financing instruments, improve capital market pricing efficiency, and enhance the performance-oriented allocation of government subsidies. Strengthening the coordination between financial resources and technological innovation will be crucial for improving long-term productivity growth in AI enterprises.

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