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Digital Transformation and Financial Stability: Does Corporate Competitiveness Make a Difference？

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Abstract

The global economic downturn, intensifying geopolitical tensions, and labor restructuring, coupled with the rapid advancement of digital technologies, have accelerated the digital transformation of enterprises, potentially impacting financial stability. Moreover, the enterprise digital transformation is evolving from a technical concept to an overall strategy, and enterprise competitiveness may play a key role in the success of the transformation. This study uses Chinese listed enterprises as its research sample, categorizing them based on their competitiveness performance. Empirical evidence has demonstrated that the digital transformation of highly competitive groups positively impacts financial stability. This effect is primarily seen in the improvement of financial asset quality and the stabilization of the financial system, achieved by increasing the number of all employees, raising the average salary of ordinary employees, and decreasing commercial credit extended to downstream customers. On the contrary, the digital transformation of the group with lower competitiveness cannot directly foster financial stability. However, it can still indirectly contribute to financial stability by increasing the number of highly educated employees and enhancing the average salary of all employees. Furthermore, the heterogeneity test of regional digital economy development and enterprise ownership attributes yields varying outcomes. This study offers a novel perspective for research into the cross-sector impact of enterprise digital transformation and provides empirical evidence to support more effective strategies for driving the development of the digital economy.

Keywords: *digital transformation, financial stability, corporate competitiveness*

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1. INTRODUCTION

The World Bank projects that approximately 60% of global economies, which account for over 80% of the world's population, will experience growth rates below the 2010 average from 2024 to 2025. Geopolitical tensions, trade fragmentation, high interest rates, and climate disasters present significant risks to the global economy, while the rapid growth of the digital economy has spurred economic growth across countries. The aggregate digital economy of the United States, China, Germany, Japan, and South Korea is projected to reach US$33 trillion in 2023, with a year-on-year growth rate exceeding 8%. (Global digital economy development research report (2024)). Enterprise digital transformation, as the engine of the digital economy, has become a major contributor to economic growth (Claudiu,Anca, 2023; Zheng et al., 2023). Consequently, the economic benefits and potential risks associated with digital transformation (DT) have become a topic of intense debate in academic research.

Numerous studies have examined the impact of DT. For instance, DT can promote enterprise growth by decreasing information asymmetry (Li et al., 2024), bolstering supply chain resilience (Jiang & Wang, 2024), enhancing corporate performance (Zhai et al., 2022), and increasing total factor productivity (Guo et al., 2023). However, the adoption of DT can undermine managerial authority, stifle product innovation, and increase the risk of data breaches. Furthermore, DT will influence financial processes and structures through inter-sectoral linkages. Research has demonstrated that DT can reduce stock price crash risk by decreasing information opacity and improving internal governance (Jiang et al., 2022; LiangZhao, 2024; Wu et al., 2022). Additionally, DT reduces financing constraints, decreases short-term credit bias among financial system, and strengthens banking system stability (He et al., 2024; Wu et al., 2023).

While much literature suggests that DT contributes to financial stability (FS), it is crucial to examine whether the DT of all enterprises results in a positive impact on FS. From the perspective of FS, is it advisable to encourage all businesses to undergo DT? DT has shifted from single technology applications to comprehensive strategic reforms. Corporate competitiveness significantly impacts the success of transformation. DT is a long-term and resource-intensive process. Competitive enterprises possess greater financial resources and capabilities to support it effectively. In contrast, less competitive enterprises may encounter liquidity crises due to hasty or poorly planned transformations, which can exacerbate risk exposure (Carcary & Deherty, 2016) and diminish audit efficiency (Leng & Zhang, 2024). Therefore, DT outcomes differ significantly among enterprises with varying competitiveness.

Our investigates the Chinese market to determine how different levels of competitiveness in DT affect FS. Considering China's financial system, which is largely bank-oriented and

dependent on indirect financing, this study examines the role of banks in preserving FS. We aim to answer three questions: (1) Does DT enhance FS for enterprises with varying levels of competitiveness? (2) Do differences exist in the pathways through which the DT of enterprises with varying levels of competitiveness impacts FS? (3) How do market environments and enterprise characteristics influence the impact of DT on FS?

This study makes contributions in three areas. First, while previous studies have primarily concentrated on the internal impacts DT exerts on enterprises, this study investigates its cross-departmental effects, particularly on the financial system. Second, this study enriches the research on FS. Previous studies have concentrated on macro-level factors such as the leverage ratio (Calmes & Theoret, 2013; Wu et al., 2024), and climate change (Liu et al., 2024). In contrast, this study examines the impact of DT on FS from a micro-level perspective, thereby sharpening the focus of the research conclusions. Third, we expand the research on the spillover effects of enterprise competitiveness. Previous studies have focused on how DT boosts competitiveness by optimizing business integration (Ahmed et al., 2023), enhancing human capital (Sui et al., 2024), and increasing organizational flexibility (Chatterjee & Mariani, 2024). This study integrates the research on enterprise competitiveness and DT, investigating the moderating role of enterprise competitiveness in the relationship between DT and FS. Additionally, it provides more concrete and detailed application scenarios for the research findings.

The reminder of the article proceeds as follows. Section 2 reviews previous literature and establishes hypotheses, Section 3 delineates our sample and variable measurements and constructs the empirical models, while Section 4 presents and discusses the empirical findings. Section 5 summarizes the conclusions and proposes topics for further discussion.

2. LITERATURE REVIEW AND RESEARCH HYPOTHESES

2.1 Digital Transformation and Financial Stability

From the perspective of cross-sector research, the impact of DT on FS is mainly transmitted to the financial system through the household sector and the enterprise sector. Previous studies have demonstrated that the scale of employment, employees' salary, and information asymmetry are important factors influencing FS. (Wu et al., 2023; Wang & Luo, 2024; Liao et al., 2009). First, expanding employment opportunities helps to reduce the risk of unemployment, minimize social conflicts, and foster FS. Second, higher salary levels enhance residents' ability to repay debts, thereby reducing default risk and lowering the non-performing loan (NPL) ratio within the banking system. Thirdly, the information asymmetry between enterprises and their industrial chain partners, as well as financial system, impedes access to supply chain financing

and bank loans. This limitation increases business risks and diminishes the quality of banks' credit portfolios.

DT can significantly influence the aforementioned three aspects. DT enables enterprises to reduce production costs, enhance operational efficiency, expand production and services, and create new business opportunities, leading to increased employment scale (Sun et al., 2022; Liu et al., 2023; Zhao & Tang, 2024). In addition, DT enhances corporate performance, optimizes staff structures, and provides employees with opportunities to participate in corporate successes, thereby leading to increased salary. (Chen et al 2024; Li et al., 2023). Furthermore, DT facilitates information dissemination through the use of big data and cloud computing, thereby mitigating information asymmetry among enterprises, supply chain partners, and financial system. (Wei et al., 2021; Aben et al., 2021).

However, the outcomes of DT vary among enterprises based on their competitiveness, which in turn has distinct impacts on FS. Highly competitive enterprises emphasize innovation and efficiency, creating more high-quality job opportunities. They also tend to be more profitable, enabling higher investment in human capital and offering competitive salaries. Additionally, these enterprises focus on data governance and transparency to reduce information asymmetry. Thus, we have the following hypothesis:

H1a: The impact of DT on FS is significantly positive.

H1b: The impact of DT on promoting FS is more significant for highly competitive enterprises.

2.2 The Influence Mechanism of Digital Transformation on Financial Stability

2.2.1 The Enterprise Path Based on Employment Scale

Currently, DT has automated many human tasks, presenting new challenges for employment. Autor et al. (2003) were the first to identify that technology exerts both a creative effect and a substitution effect on labor demand. In terms of the substitution effect, DT enables enterprises to adopt automated equipment and intelligent systems. These technologies can efficiently manage repetitive production tasks, thereby reducing the need for human labor. Moreover, DT has prompted organizations to re-evaluate their business processes and streamline operations by eliminating redundant steps, which has resulted in job displacement. (Verhoef et al., 2021; Liu et al., 2011). Furthermore, DT enhances the speed and accuracy of information transmission, improves decision-making efficiency, and fosters flatter organizational structures, thereby reducing the need for management personnel. (George et al., 2018). Scholars have demonstrated the significant impact of DT on employment substitution through empirical research. For instance, Frey and Osborne (2017) found that 47% of U.S. jobs are at high risk of automation, predicting that significant layoffs could occur soon. Based on an analysis of economic panel

data from 68 countries, You et al. (2024) found that the employment substitution effect resulting from DT is more pronounced in developing countries compared to developed ones. In terms of the creation effect, DT has developed new production methods and business models, resulting in new employment opportunities. For instance, the widespread adoption of digital technologies, including broadband and the Internet, has given rise to new roles such as software developers and network maintenance technicians.(Akermanet et al., 2015). Besides, DT enhances production efficiency, reduces costs and prices, boosts consumer demand, expands production scale, and creates additional jobs (Han et al., 2024). Lower product prices will increase consumers' real salary, stimulate demand for products in other sectors, and subsequently increase employment scale in those sectors. Due to varying economic contexts and different metrics used to assess digitalization, existing studies show inconsistent conclusions about its impact on employment scale (Cirillo et al., 2021). Given that DT in China is still in its early stages, the labor-displacement effect of DT has not yet become pronounced, as seen in developed economies (Li et al.,2021). Consequently, DT creates more jobs than it replaces, increasing overall labor demand.

The implications of increased employment scale for FS are substantial. Higher levels of employment scale signify that enterprises are expanding their production capacities, thereby enhancing profitability, strengthening balance sheets, mitigating default risks, and promoting the resilience of the financial system. Additionally, the expansion of employment generates higher tax revenues, enhances the government's fiscal position, and offers greater policy flexibility to respond to economic fluctuations, thereby reinforcing the overall stability of the financial system. However, during the process of DT, enterprises with different competitiveness levels affect employment scale differently. Highly competitive enterprises attract and retain top talent through better career opportunities, giving them a significant market advantage. They also exhibit greater resilience to external shocks, protecting jobs more effectively. In contrast, less competitive enterprises face challenges such as weaker talent attraction, limited innovation, and insufficient capital, which hinder employment expansion. Thus, we hypothesize the following:

H2a: The impact of DT on FS is significantly positive through expanding employment scale.

H2b: In the process of DT, enterprises with highly competitiveness play a more significant role in promoting FS through the path of expanding employment scale.

2.2.2 The Enterprise Path Based on Employees' Salary

DT will affect employees' salary. Research indicates that DT affects employees' salary through two mechanisms: enterprise revenue distribution and employment structure adjustments. On one hand, DT enables enterprises to enhance their profitability. DT enhances the efficiency and quality of information dissemination while reducing costs across all links in the industrial chain. In procurement, enterprises optimize resource allocation by searching globally for specific suppliers. For R&D, software simulations provide timely data feedback, speeding up iterative debugging and shortening the R&D cycle. In sales, big data-driven marketing and improved consumer experiences enhance supply-demand alignment. Consequently, enhanced DT not only facilitates a larger market share and higher revenues but also increases the likelihood of employee participation in profit-sharing. On the other hand, DT affects the internal employee structure of enterprises (Qin et al., 2024). Automation equipment, such as industrial robots, replaces highly repetitive and low-creativity tasks. Conversely, skilled employees in knowledge-intensive and innovative roles benefit more from DT, as their work is less susceptible to automation and can continuously generate new value (Autor, 2015). DT will boost the demand for high-skilled labor, enhancing premium capabilities and wages. As this transformation progresses, the proportion of medium and low-skilled workers is expected to decrease. To remain competitive, the remaining medium and low-skilled workers may seek skill improvements, potentially increasing their wages.

Increased salary enhances FS in several ways. First, it improves the financial condition of individuals and households, boosting their ability to repay debts, reducing default risks, and lowering the non-performing loan (NPL) ratio. Second, higher salary boost consumer spending, which in turn stimulates business production and investment. Stable demand for consumption and investment assists financial system in maintaining asset quality and liquidity. Third, rising salary enable residents to build wealth and enhance their resilience to risk, decreasing the probability of large-scale fund withdrawals during recessions and mitigating the propagation of financial crises. However, enterprises with different competitiveness exhibit distinct effects on employee compensation during DT. Highly competitive enterprises are more proficient at translating technological advantages into business outcomes, thereby enhancing overall profitability. This increased profitability allows these enterprises to attract and retain top talent by providing higher wages. Furthermore, competitive enterprises may offer appealing compensation packages to encourage their employees to adopt new technologies and working methods swiftly, thereby maintaining their market leadership. Thus, we hypothesize the following:

H3a: The impact of DT on FS is significantly positive through raising employees' salary.

H3b: In the process of DT, enterprises with highly competitiveness play a more significant role in promoting FS through the path of raising employees' salary.

2.2.3 The Enterprise Path Based on Commercial Credit

China's financial system is characterized by its bank-oriented nature. Due to information asymmetry, scale-based discrimination, and ownership preferences, many enterprises face difficulties in obtaining the necessary funding. Commercial credit financing can assist in addressing this issue. Upon utilizing the WIND database, we discovered that between 2000 and 2020, the proportion of the aggregate of accounts payable, notes payable, and advance receipts of Chinese listed enterprises to assets increased from 10.01% to 13.24%. This trend underscores the increasing importance of commercial credit financing. DT can alleviate information asymmetry within the supply chain, benefiting enterprises, their partners, and financial system alike. Previous research has shown that enterprises strive to maintain competitiveness by securing commercial credit from suppliers and extending commercial credit to downstream customers.

From the perspective of enterprises and their suppliers, DT enhances the efficiency of information transmission and enables suppliers to obtain precise production data from enterprises. Moreover, DT will attract the attention of financial analysts. The analysis and interpretation of corporate information by these analysts can mitigate internal information fraud and improve the overall quality of corporate information disclosure (Chen et al., 2022). Therefore, by enhancing the speed and quality of information dissemination, we can reduce information asymmetry, thereby facilitating enterprises in securing business credit from suppliers more easily. From the perspective of enterprises and their downstream customers, commercial credit serves as both an alternative financing method and a business strategy. On the one hand, DT encourages enterprises to extend business credit to their customers. This practice fosters long-term trust, reduces the risk of customer attrition, and maximizes synergistic benefits (Fisman & Raturi, 2004; Bougheas et al., 2009). On the other hand, DT enhances enterprises' ability to provide business credit to their customers. According to the theory of redistribution, the volume of credit a enterprise acquires from financial system is positively correlated with its ability to provide trade credit to customers. Empirical evidence indicates that DT mitigates information asymmetry between enterprises and banks, facilitating greater access to bank credit (Yang & Masron, 2024; He et al., 2024). Therefore, DT will enable enterprises to offer more commercial credit to their downstream customers.

However, the increase in commercial credit financing poses a threat to FS. It heightens the risk of triangular debt, potentially triggering a domino effect of credit issues among enterprises and fueling market speculation. This disrupts financial market order. Additionally, it complicates the transmission of monetary policy and makes it more difficult for regulators to monitor and control financing, thereby weakening policy effectiveness. However, enterprises with varying levels of competitiveness differ significantly in their propensity and capacity for utilizing commercial credit. Highly competitive enterprises can secure commercial credit from suppliers and extend it to their customers. Enhanced competitiveness boosts an enterprise's status within the supply chain. According to buyer market theory, enterprises that hold a dominant buyer position and maintain a high credit rating can secure favorable commercial credit terms from suppliers. Consequently, they can achieve liquidity at a reduced cost (Fabbri & Menichini, 2010; Love et al., 2007). In addition, enterprises with strong competitiveness can generate free cash flow and secure external funding through debt or equity financing. As a result, they have access to a broader range of capital sources. To maximize their interests, these enterprises can decrease reliance on commercial credit from customers, thereby strengthening relationships and fostering long-term cooperation.Thus, we hypothesize the following:

H4a1: The impact of DT on FS is significantly negative through increasing commercial credit from supplier.

H4a2: In the process of DT, enterprises with highly competitiveness play a more significant role in deteriorating FS through the path of increasing commercial credit from supplier.

H4b1: The impact of DT on FS is significantly positive through decreasing commercial credit to customer.

H4b2: In the process of DT, enterprises with highly competitiveness play a more significant role in promoting FS through the path of decreasing commercial credit to customer.

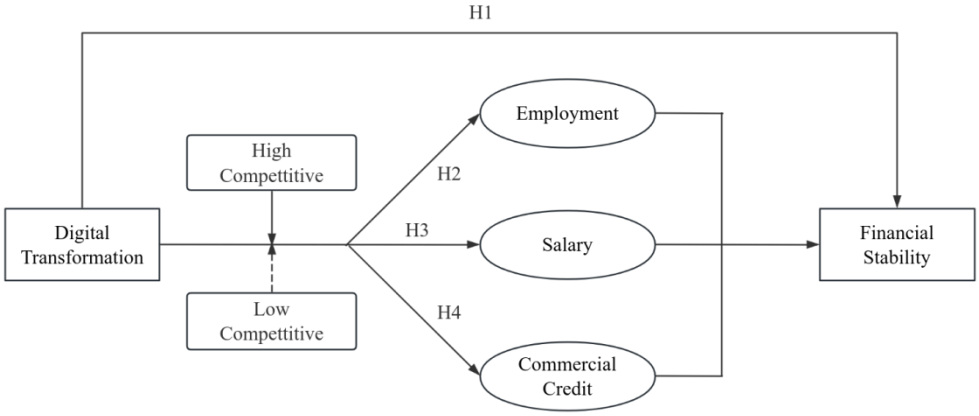

Fig. 1 - The influencing path diagrams from DT to FS. Source: own search

3. RESEARCH DESIGN

3.1 Sample Selection and Data Sources

This study uses A-share listed enterprises from 2007 to 2022 as its research sample, with data sourced from the WIND database, the People's Bank of China, and the National Bureau of Statistics of China. Building upon existing literature, the sample undergoes the following processing steps: (1) exclusion of listed enterprises with financial issues or other irregularities; (2) elimination of samples with incomplete data; (3) removal of listed enterprises from the financial system. Following this processing, a total of 22,400 observations were ultimately obtained.

3.2 Variable Definitions

3.2.1 Dependent Variable

Financial Stability Index (Stability): Illing and Liu (2003) constructed the financial stress index using Canadian banking and stock market data, providing a novel method for estimating FS. Subsequently, scholars developed financial stress indices from various dimensions to assess FS more accurately (Balakrishnan et al., 2011; Gardarelli et al., 2011). Based on previous research and China's bank-oriented financial structure, we developed a regional FS indicator framework, taking into account data availability. We applied the entropy weight method to assign weights to three key indicators of regional banks: the NPL ratio, the loan-to-deposit ratio, and the credit expansion ratio. We assessed each ratio following standardization. Each indicator possesses unique characteristics and necessitates a specific standardization approach, as illustrated in Table 1. In the formula, the 'i' and 't' in the formula represent the i index value in the t year.

The processing of positive indicators is depicted in formula ((3-2-1) :

$$r_{i,t} = [r_{i,t} - \min(r_{i,t})]/[\max(r_{i,t}) - \min(r_{i,t})] \quad (3\text{-}2\text{-}1)$$

The processing of the reverse index is depicted in equation (3-2-2) :

$$r_{i,t} = [\max(r_{i,t}) - r_{i,t}]/[\max(r_{i,t}) - \min(r_{i,t})] \quad (3\text{-}2\text{-}2)$$

The processing of moderate indicators is depicted in formula (3-2-3) :

$$r_{i,t} = \left|r_{i,t} - \overline{r_{i,t}}\right|/[\max(r_{i,t}) - \min(r_{i,t})] \quad (3\text{-}2\text{-}3)$$

Tab. 1 - Composition of Financial Stability Index. Source: own search

Name	Definition	Property
NPL ratio	Non-performing loans/total loan balance	-
Loan-to-deposit ratio	Deposit balance/loan balance	+
Rate of credit expansion	Credit growth rate /GDP growth rate	Neutral

3.2.2 Independent Variable

Digital Transformation Index (Digit): DT is a critical strategy for development. This information is evident in the annual reports of enterprises, which reflect their business philosophies and development paths. Therefore, assessing the degree of DT through word frequency analysis in these reports is both feasible and sound. Based on Wu et al. (2021), this study systematically gathers and organizes the annual reports of all A-share listed enterprises using Python's web crawling capabilities, and extracts all textual content utilizing the Java PDFBox library. Based on the feature words listed in Table 2, we conduct searches, matchings, and word frequency analyses. The word frequencies of key technological directions are subsequently categorized and aggregated to form a cumulative word frequency, which serves as an indicator for measuring the extent of DT. Due to the right-skewed distribution, a logarithmic transformation is applied as shown in the formula (3-2-4).

$$digit_{i,t} = \ln(AI + BC + CC + BD + DTA + 1) \quad (3\text{-}2\text{-}4)$$

Tab.2 - Composition of Digital Transformation Index. Source: own search

Index Category	Index Name
Artificial Intelligence (AI)	artificial intelligence, business intelligence, image understanding, Investment decision assistance systems, intelligent data analysis, intelligent robots, machine learning, deep learning, semantic search, biometric technology, facial

	recognition, speech recognition, identity verification, autonomous driving, natural language processing
Block-Chain (BC)	digital currency, smart contracts, distributed computing, decentralization, bitcoin, consortium block-chain, differential privacy technology, consensus mechanism
Cloud Computing (CC)	memory computing, cloud computing, stream computing, graph computing, Internet of Things, multi-party secure computing, neuromorphic computing, green computing, cognitive computing, fusion architecture, billion level concurrency, EB level storage, information physical system
Big Data (BD)	Big data, data mining, text mining, data visualization, heterogeneous data, credit reporting, augmented reality, hybrid reality, virtual reality
DT Application (DTA)	mobile Internet, industrial Internet, Internet medical, e-commerce, mobile payment, third-party payment, FC payment B2B, B2C, C2B, C2C, O2O, Internet connection, intelligent wear, intelligent agriculture, intelligent transportation, intelligent medical care, intelligent customer retail, Internet finance, digital finance, fintech, financial technology, quantitative finance, and open banking

3.2.3 Enterprise Competitiveness Variable

Enterprise Competitiveness Index (competitiveness): The competitiveness of an enterprise is influenced by market conditions, technological advancements, and various other factors. There is no consensus among academics on a standard definition, which has resulted in a variety of measurement approaches. Many scholars collect operational data from financial indicators of listed enterprises or through surveys to construct composite indices, which are used to analyze corporate competitiveness (Jin, 2003; Lewandowska et al., 2021; Sedliacikova et al., 2021; Xu et al., 2024). This study selects indicators from three dimensions: profitability, growth capability, and innovation capability. We use principal component analysis and the entropy weight method to determine indicator weights and construct the competitiveness index.

Tab. 3 - Composition of Enterprise Competitiveness Indicators. Source: own search

Name	Definition
Capacity for Profitability	Total operational income
	Total net profit
Capacity for Growth	The compound growth rate of operational income over the past three years
	The compound growth rate of net profit over the past three years

Capacity for Innovation	The quantity of patent invention applications

Tab. 4 - Definition of Variables. Source: own search

Variable Category	Variable Name	Measurement Metrics
Dependent Variable	Stability	The calculation process is explained in equations (3-2-1) through (3-2-3).
Independent variable	Digit	The natural log of word frequency.
Control Variables	Size	The natural log of total assets.
	LEV	The ratio of total liabilities to total assets.
	PPE	The ratio of fixed assets to total assets.
	ROA	The ratio of net income to total assets.
	Cash	The ratio of Net cash flow from operating activities to total assets.
	Boardsize	The natural log of the quantity of board members.
	Indboard	The ratio of independent directors to the board of directors.
	BM	The ratio of Stockholder's equity to Market value.
	Dual	The dummy variable equal 1 if the chairman and the general manager are the same person,0 otherwise.
	Age	Establishment years of the enterprise.

3.3 Empirical Model Design

3.3.1 Model for Testing the Impact of DT on FS

The following model is designed to test H1:

$$Stability_{i,t} = \alpha_0 + \alpha_1 Digit_{i,t} + \alpha_2 Controls_{i,t} + \sum Year + \varepsilon_{i,t} \quad (3\text{-}3\text{-}1)$$

In Model (1), DT and FS indexes are respectively denoted by digit and stability. If α1 > 0,it implies that DT exerts a positive impact on FS, and vice versa. In addition, we include control variables, such as Size, LEV, PPE, ROA, Cash, Boardsize, Indboard, BM, Dual and Age. We also add dummy variables to control for year effects. εi,t represents the random disturbance term.

3.3.2 Model for Testing the Mediating Role

The following model is designed to test H2-H4:

$$Stability_{i,t} = \alpha_0 + \alpha_1 Digit_{i,t} + \alpha_2 Controls_{i,t} + \sum Year + \varepsilon_{i,t} \quad (3\text{-}3\text{-}2\text{-}1)$$

$$M_{i,t} = \pi_0 + \pi_1 Digit_{i,t} + \pi_2 Control_{i,t} + \sum Year + \vartheta_{i,t} \quad (3\text{-}3\text{-}2\text{-}2)$$

$$M(employ)_{i1,t} = \pi_{01} + \pi_{11} Digit_{i,t} + \pi_{21} Control_{i,t} + \sum Year + \vartheta_{i1,t} \quad (3\text{-}3\text{-}2\text{-}2\text{-}1)$$

$$M(salary)_{i2,t} = \pi_{02} + \pi_{12} Digit_{i,t} + \pi_{22} Control_{i,t} + \sum Year + \vartheta_{i2,t} \quad (3\text{-}3\text{-}2\text{-}2\text{-}2)$$

$$M(credit)_{i3,t} = \pi_{03} + \pi_{13} Digit_{i,t} + \pi_{23} Control_{i,t} + \sum Year + \vartheta_{i3,t} \quad (3\text{-}3\text{-}2\text{-}2\text{-}3)$$

$$Stability_{i,t} = \beta_0 + \beta_1 Dight_{i,t} + \omega_1 M_{i,t} + \beta_3 Control_{i,t} + \sum Year + \tau_{i,t} \quad (3\text{-}3\text{-}2\text{-}3)$$

$$Stability_{i1,t} = \beta_{01} + \beta_{11} Dight_{i,t} + \omega_{11} M(employ)_{i1,t} + \beta_{31} Control_{i,t} + \sum Year + \tau_{i1,t} \quad (3\text{-}3\text{-}2\text{-}3\text{-}1)$$

$$Stability_{i2,t} = \beta_{02} + \beta_{12} Dight_{i,t} + \omega_{12} M(salary)_{i2,t} + \beta_{32} Control_{i,t} + \sum Year + \tau_{i2,t} \quad (3\text{-}3\text{-}2\text{-}3\text{-}2)$$

$$Stability_{i3,t} = \beta_{03} + \beta_{13} Dight_{i,t} + \omega_{13} M(credit)_{i3,t} + \beta_{33} Control_{i,t} + \sum Year + \tau_{i3,t} \quad (3\text{-}3\text{-}2\text{-}3\text{-}3)$$

Theoretical analysis suggests that the spillover effect of DT on FS can be attributed to an increase in both employee numbers and average salaries, as well as improvements in business credit finance. Consequently, we conduct a detailed examination of the mediating effects of these variables. εt, θt, τt represent the random disturbance terms. Eq. (3-3-2-1), Eq. (3-3-2-2), and Eq. (3-3-2-3) are used in combination to test Mid (employ, salary, credit) acts as a mediator linking digit and stability. The most prevalent approach for testing the mediating effect is to examine the regression coefficients progressively (Baron & Kenny, 1986; Judd & Kenny, 1981), the model must meet the following requirements: ① The coefficient α1 is statistically significant. ② $\beta 1 < \alpha 1$, or β1 is not statistically significant. ③ Coefficients π1 and ω are statistically significant. Some scholars argue that the stepwise test, which requires 'the coefficient α1 being statistically significant' is unnecessary (MacKinnon et al., 2004). In the equation $\pi 1 * \omega + \beta 1 = \alpha_1$, the sign of coefficient π1*ω (indirect effect) may be opposite to the sign of coefficient β1 (direct effect). The coefficient α1 (total effect) therefore may not be statistically significant. Thus, to address this issue, the bootstrap method was also used to test the mediating effect model.

4. EMPIRICAL RESULTS

4.1 Benchmark Regression

4.1.1 Descriptive Statistics of the Main Variables

Table 5 presents the descriptive statistics for the main variables across the entire sample. The mean values for stability and digit are 0.0446 and 1.1895, respectively. The average size is 11.363 billion yuan, with a standard deviation of 63.1565 billion yuan, indicating significant variation in the total asset size among enterprises. Similarly, the mean age is 10.707 years, with a standard deviation of 7.8755 years, suggesting that the average establishment time for Chinese listed enterprises is approximately 11 years, and there has been a trend toward younger enterprises in recent years. The mean value of the dual is 0.3131, indicating that a substantial proportion of listed enterprises adopt a decentralized governance structure, thereby enhancing transparency and accountability in the decision-making process.

Tab. 5 - Descriptive Statistics of the Main Variables. Source: own search

Variable	N	Min	Max	Mean	Std. dev	Median
Stability	22400	0.0131	0.4525	0.0446	0.0310	0.0372
Digit	22400	0.6931	6.3801	2.1874	1.1895	1.9459
Size	22400	-0.1149	2891.0000	11.3630	63.1565	1.9780
LEV	22400	0.0084	1.5454	0.4108	0.2028	0.4020
PPE	22400	0.0000	0.9600	0.1857	0.1494	0.1503
ROA	22400	-.5654	0.7859	0.0392	0.0868	0.0415
Cash	22400	0.0006	0.9603	0.1793	0.1415	0.1384
Boardsize	22400	4.0000	18.0000	8.4586	1.6914	9.0000
Indboard	22400	14.2900	80.0000	37.7165	5.6059	36.3600
BM	22400	0.0187	1.5777	0.6146	0.2495	0.6101
Dual	22400	0.0000	1.0000	0.3131	0.4638	0.0000
Age	22400	1.0000	33.0000	10.7067	7.8755	9.0000

Upon examining the entire sample, this study categorizes the observations into a high-competition group (n=5600) and a low-competition group (n=5600). It does so by ranking enterprises based on their competitiveness and subsequently dividing them into the top and bottom quartiles. The Mann-Whitney U test is used for comparing the digit and stability among groups, as shown in Table 6. From a median perspective, the effect of DT in the high-competitiveness group is significantly higher than that in the low-competitiveness group, indicating substantial differences between the two groups. Conversely, the FS of enterprises within the high-competitiveness group is lower than that of those in the low-competitiveness group, yet the difference between the groups remains statistically significant. These findings

confirm statistically significant variations in key variables between the two groups, thereby enhancing the accuracy and reliability of subsequent grouped regression analyses.

Tab. 6 - Mann-Whitney U Test Results. Source: own search

	High	Low	U value	Z value	P Value
Digit	2.1972	1.7918	13379378	-13.4494	0.0001e-3***
Stability	3.6841e-2	3.6847e-2	15330218	-2.0446	0.0409**

The table presents the results of the Mann-Whitney U test concerning digit and stability for the high and low competition groups. ***, **, and * indicate coefficients significant at the 1%, 5%, and 10% levels, respectively.

4.1.2 Benchmark Regression and Robustness Test

Table 7 presents the regression results on the impact of DT on FS. Columns (1) to (3) show outcomes for the full sample, high-competition group, and low-competition group, respectively. Controlling for year fixed effects, the regression coefficients between digit and stability are 0.0004, 0.0009, and 0.0005, with t-values of −2.2969, −2.3568, and −1.2001. The full sample and the high-competition group are significant at the 5% level, whereas the low-competition group is not. This indicates that DT generally improves FS, with a more pronounced effect in the highly competitive group. In contrast, less competitive enterprises exhibit no significant impact. These findings support Hypothesis 1.

To evaluate the robustness of the research conclusions, we employ an alternative method to measure the independent variables. Specifically, we calculate the frequency of 99 digital-related terms across four dimensions: digital technology applications, internet business models, intelligent manufacturing, and modern information systems. Finally, the digit2 index is synthesized. The empirical results in columns (4) to (6) support our initial hypotheses and benchmark regression findings, confirming the robustness of our research.

Tab. 7 - Benchmark Regression and Robustness Tests. Source: own search

	Benchmark Regression(digit)			Robustness Test(digit2)		
	(1)	(2)	(3)	(4)	(5)	(6)
	Total-sample	High-Competitive	Low-Competitive	Total-sample	High-competitive	Low-competitive
	Stability	Stability	Stability	stability	stability	stability
Digit	0.0004**	0.0009**	0.0005	0.0007***	0.0011**	0.0004
	(-2.2969)	(-2.3568)	(-1.2001)	(-3.2498)	(-2.3106)	(-1.014)
Size	0.2121e-04***	0.1914e-04***	0.2297e-05	0.2098e-04***	0.1899***	0.7772e-05
	(-6.2785)	(-5.6831)	(-0.0166)	(-6.2087)	(-5.6369)	(-0.056)
LEV	0.0015	-0.0066**	0.0057**	0.0014	-0.0068**	0.0062**
	(-1.1935)	(-2.1970)	(-2.2275)	(-1.1002)	(-2.2754)	(-2.4259)
PPE	-0.0035**	0.0055*	-0.0051*	-0.0032**	0.0053	-0.0043

	(-2.2552)	(-1.6888)	(-1.6743)	(-2.0864)	(-1.6441)	(-1.4285)
ROA	-0.0102***	-0.0420***	-0.0011	-0.0103***	-0.0425***	-0.0001
	(-4.0718)	(-4.8589)	(-0.3098)	(-4.1000)	(-4.9234)	(-0.0328)
Cash	0.0093***	0.0098**	0.0131***	0.0093***	0.0099**	0.0138***
	(-5.4502)	(-2.4224)	(-3.5055)	(-5.4102)	(-2.449)	(-3.698)
Boardsize	0.0005***	0.0003	0.0006	0.0005***	0.0003	0.0007*
	(-3.1165)	(-1.2278)	(-1.576)	(-3.0336)	(-1.2287)	(-1.8516)
Indboard	0.0001**	0.0001*	0.0001	0.0001**	0.0001*	0.0001
	(-2.5413)	(-1.7178)	(-0.8593)	(-2.4636)	(-1.6954)	(-0.8823)
BM	-0.0048***	-0.0032*	-0.0025	-0.0048***	-0.0033*	-0.0038*
	(-5.2008)	(-1.6615)	(-1.2485)	(-5.2007)	(-1.7080)	(-1.9037)
Dual	-0.0007	-0.0020**	-0.0004	-0.0007	-0.0020*	-0.0006
	(-1.4881)	(-1.9865)	(-0.3651)	(-1.5249)	(-1.9489)	(-0.6257)
Age	0.0001***	-0.0001	0.0001**	0.0001***	-0.0001	0.0001*
	(-3.0084)	(-1.2654)	(-2.0628)	(-3.2849)	(-1.1632)	(-1.8511)
Constant	0.4327***	0.1798	0.8927***	0.5123***	0.267	0.0321***
	(-3.3932)	(-0.623)	(-3.1594)	(-3.8792)	(-0.9013)	(-5.131)
Year	yes	yes	yes	yes	yes	yes
N	22400	5600	5600	22400	5600	5600
Adjusted R^2	0.0072	0.0119	0.0056	0.0074	0.0119	0.0043

This table presents the benchmark regression and robustness test results of DT on FS. ***, **, and * indicate coefficients significant at the 1%, 5%,and 10% levels, respectively. T-statistics appear in parentheses below the coefficients.

4.2 Test the Mediating Role Model

4.2.1 The Mediating Role of Employment Scale

Table 8 presents the analysis of the mediating role of employment scale in the relationship between DT and FS. Columns (1) through (3) display the results for the high competition group, while columns (4) through (6) encompass the low competition group. Column (2) indicates that DT increases employment scale in highly competitive enterprises. (coefficient = 1.5426, $p < 0.01$). Column (3) shows that increased employment scale has a positive impact on FS (coefficient = 0.4158e-04, $p < 0.05$). These findings suggest that the DT of highly competitive enterprises has a positive impact on FS by increasing their employment scale. In contrast, for the low competition group, although DT helps to increase employment scale (coefficient = 0.1982, $p < 0.01$), it does not improve FS (Column 6, Boot CI 95% includes zero). Thus, these findings partially support Hypothesis 2. While DT increases employment scale across all enterprises, it promotes FS only in highly competitive enterprises through this pathway.

Tab.8 - Mediating Path Results Based on Employment Scale. Source: own search

	High-Competitive			Low-Competitive		
	(1)	(2)	(3)	(4)	(5)	(6)
	Stability	Employ	Stability	Stability	Employ	Stability

Digit	0.0009**	1.5426***	0.0008**	0.0005	0.1982***	0.0005
	(-2.3568)	(-5.7942)	(-2.1818)	(-1.2001)	(-4.1091)	(-1.1612)
Employ			0.4158-4e**			0.0001
			(-2.1838)			(-0.6741)
Controls	yes	yes	yes	yes	yes	yes
Constant	0.1798	1307.8439***	0.1254	0.8927***	148.0561***	0.8812***
	(-0.6230)	(-6.4512)	(-0.4331)	(-3.1594)	(-4.5173)	(-3.1129)
Year	yes	yes	yes	yes	yes	yes
N	5600	5600	5600	5600	5600	5600
Boot CI(95%)	0.0008 ~ 0.0054			-0.0006 ~ 0.0033		
Adjusted R^2	0.0119	0.6653	0.0126	0.0056	0.3191	0.0055

This table presents the estimated results of the mediating effect of employment scale on DT and FS. ***, **, and * indicate coefficients that are significant at the 1%, 5%, and 10% levels, respectively. The t-statistics appear in parentheses below the coefficients.

4.2.2 The Mediating Role of Employees' Salary

Table 9 presents the analysis of the mediating effect of employees' salaries on the relationship between DT and FS. Column (2) indicates that in highly competitive enterprises, DT has a positive impact on employees' salaries, with a coefficient of 0.5524 and a significance level of $p < 0.01$. Column (3) indicates that this transformation enhances FS by raising employee salaries, with a coefficient of 0.0001 and a significance level of $p < 0.01$. Similarly, enterprises characterized by low competition also witness an increase in average employee salary, with a coefficient of 0.4382 and a significance level of $p < 0.01$. Consequently, DT enhances employee salary and FS across enterprises, regardless of their level of competitiveness, thus supporting Hypothesis 3a.

Tab. 9 - Mediating Path Results Based on Employees' Salary. Source: own search

	High-Competitive			Low-Competitive		
	(1)	(2)	(3)	(4)	(5)	(6)
	Stability	Salary	Stability	Stability	Salary	Stability
Digit	0.0009**	0.5524***	0.0008**	0.0005	0.4382***	0.0004
	(-2.3568)	(-4.0521)	(-2.1532)	(-1.2001)	(-3.752)	(-1.0605)
Salary			0.0001***			0.0001***
			(-3.7496)			(-2.7687)
Controls	yes	yes	yes	yes	yes	yes
Constant	0.1798	-1875.4886***	0.4411	0.8927***	-1226.9115***	1.0544***
	(-0.623)	(-18.0680)	(-1.4872)	(-3.1594)	(-15.4572)	(-3.6565)
Year	yes	yes	yes	yes	yes	yes
N	5600	5600	5600	5600	5600	5600
BootCI (95%)	0.0008 ~ 0.0054			-0.0006 ~ 0.0033		
Adjusted R^2	0.0119	0.0956	0.0142	0.0056	0.1109	0.0068

This table presents the estimated results of the mediating effect of employees' salary on DT and FS. ***, **, and * indicate coefficients that are significant at the 1%, 5%, and 10% levels, respectively. The t-statistics appear in parentheses below the coefficients.

4.2.3 The Mediating Role of Commercial Credit

Tables 10 and 11 illustrate the intermediary role of commercial credit in DT and FS, considering the perspectives of suppliers and customers.

Credit-s = (Accounts payable + Notes payable - Prepayment) / Total assets

Credit-c = (Accounts received in advance - Accounts receivable - Notes receivable) / Total assets.

From the supplier's perspective, columns (2), (3), (5), and (6) in Table 10 indicate that the regression coefficients for digit, credit-s, and stability are insignificant in both competition groups. The 95% Boot CI values all include zero, suggesting that DT does not enhance FS through this channel. From the customer's perspective, we can observe that only highly competitive enterprises improve FS by reducing commercial credit to customers. These findings partially support Hypothesis 4.

Tab. 10 - Mediating Path Results Based on Commercial Credit from Suppliers. Source: own search

	High-Competitive			Low-Competitive		
	(1)	(2)	(3)	(4)	(5)	(6)
	stability	Credit-s	stability	stability	Credit-s	stability
Digit	0.0009**	-0.0013	0.0009**	0.0005	0.0001	0.0005
	(-2.3568)	(-0.9771)	(-2.3688)	(-1.2001)	(-0.0829)	(-1.199)
Credit-s			0.0037			0.0046
			(-0.9314)			(-0.9534)
Controls	yes	yes	yes	yes	yes	yes
Constant	0.1798	7.1057***	0.1538	0.8927***	5.1203***	0.8694***
	(-0.623)	(-7.2306)	(-0.5304)	(-3.1594)	(-6.4715)	(-3.0654)
Year	yes	yes	yes	yes	yes	yes
N	5600	5600	5600	5600	5600	5600
Boot CI (95%)	-0.0022 ~ 0.0002			-0.0008 ~ 0.0008		
Adjusted R^2	0.0119	0.1548	0.0119	0.0056	0.1348	0.0056

This table presents the estimated results of the mediating effect of commercial credit from suppliers on DT and FS. ***, **, and * indicate coefficients that are significant at the 1%, 5%, and 10% levels, respectively. The t-statistics appear in parentheses below the coefficients.

Tab. 11 - Mediating Path Results Based on Commercial Credit from clients. Source: own search

	High-Competitive			Low-Competitive		
	(1)	(2)	(3)	(4)	(5)	(6)
	stability	Credit-c	stability	stability	Credit-c	stability
digit	0.0009**	-0.0050***	0.0009**	0.0005	-0.0009	0.0005
	(-2.3568)	(-3.1661)	(-2.2645)	(-1.2001)	(-0.5851)	(-1.181)
Credit-c			-0.0069**			-0.0092**
			(-2.1509)			(-2.5059)
Controls	yes	yes	yes	yes	yes	yes
Constant	0.1798	-10.2632***	0.1086	0.8927***	2.4498**	0.9151***
	(-0.623)	(-8.5786)	(-0.3738)	(-3.1594)	(-2.3696)	(-3.2387)
Year	yes	yes	yes	yes	yes	yes
N	5600	5600	5600	5600	5600	5600
Boot CI(95%)	-0.0001 ~ 0.0028			-0.0006 ~ 0.0011		
Adjusted R^2	0.0119	0.1225	0.0125	0.0056	0.1542	0.0066

This table presents the estimated results of the mediating effect of commercial credit from clients on DT and FS. ***, **, and * indicate coefficients that are significant at the 1%, 5%, and 10% levels, respectively. The t-statistics appear in parentheses below the coefficients.

4.3 Heterogeneity Discussion

4.3.1 Digital Economy Environment Heterogeneity

The development of the regional digital environment can facilitate DT by optimizing their production and management models, stimulating technological innovation, and enhancing market competition. Ning et al. (2022) discovered a positive correlation between regional digital economy development and DT. This study delves deeper into whether the impact of DT on FS varies among enterprises with differing levels of competitiveness across different regions. Referring to Liu et al. (2020), this study evaluates the development level of the digital economy from two perspectives: Internet development and digital financial inclusion. The assessment is conducted using provincial-level data where pertinent information is available. To measure Internet development, we employ the methodology proposed by Huang et al. (2019), which focuses on four key indicators: Internet penetration rate, employment in relevant sectors, output of relevant industries, and mobile phone penetration rate. Data are sourced from the China City Statistical Yearbook. For assessing the development of digital finance, we use the China Digital Inclusive Finance Index, a joint initiative by Peking University's Institute of Digital Finance and Ant Financial Group (Guo et al., 2020). Principal component analysis is used to standardize and reduce the data, thereby deriving a comprehensive digital economy index. Details of the indicators are provided in Table 12.

Tab. 12 - Index of Digital Economy Environment. Source: own search

Variable Name	Measurement Metrics
Internet penetration ratio	Number of Internet users per 100 people
Number of Internet-related employees	Proportion of computer services and software employees
Internet-related output	Total amount of telecommunications services per capita
Number of mobile Internet users	Number of mobile phone users per 100 people
Comprehensive development of digital finance	China Digital Inclusive Financial Index

Columns (1) and (2) of Table 13 present the regression results for digit and stability in high-competition and low-competition enterprises when regional digital economy development is high. The results indicate that DT improves FS, especially in less competitive enterprises. Conversely, when regional digital economy development is low, DT does not enhance FS in either group. Consequently, establishing a robust regional digital economic environment is crucial, as it significantly facilitates DT, thereby positively contributing to FS.

Tab. 13 - Regression Results Based on the Level of Digital Economy Development. Source: own search

	Digital Economy Development-High		Digital Economy Development-Low	
	High-Competitive	Low-Competitive	High-competitive	Low-Competitive
	Stability	Stability	Stability	Stability
Digit	0.0019***	0.0022***	-0.3248e-04	-0.0020
	(-3.4036)	(-3.4824)	(-0.0445)	(-1.4837)
Controls	yes	yes	yes	yes
Constant	-0.2504	-0.4847	-0.3596	0.3830
	(-0.4749)	(-0.8373)	(-0.5689)	(-0.3705)
Year	yes	yes	yes	yes
N	1400	1400	1400	1400
Adjusted R^2	0.0537	0.0268	0.003	0.0089

This table presents the regression results of DT on FS based on different level of digital economy development. ***, **, and * indicate coefficients significant at the 1%, 5%, and 10% levels, respectively. T-statistics appear in parentheses below the coefficients.

4.3.2 Ownership Heterogeneity

In China, enterprises with various ownership structures possess distinct resources, goals, and operational constraints (Ruan & Liu, 2021). Scholars hold differing opinions on the

effectiveness of DT across different ownership types. Several empirical studies have demonstrated that state-owned enterprises (SOEs) benefit from the support of national reputation, enjoy a more favorable financing environment, can access additional government resources, possess stronger strategic planning capabilities, and achieve more substantial outcomes in DT (Zahid et al., 2023; Che & Wang, 2023). Others contend that SOEs, due to their dominant position within the industrial chain, consistently secure higher profits. This advantage diminishes their inclination to implement certain changes (Wu et al., 2021a). Conversely, non-state-owned enterprises (non-SOEs) demonstrate a greater propensity for self-optimization in response to market competition, leading to more pronounced DT outcomes (Liu et al., 2021). Moreover, scholars have explored how mixed-ownership enterprises, especially SOEs, can improve supervisory and incentive mechanisms by introducing SOEs. This may stimulate innovation and enhance DT (Ren et al., 2024). From the perspective of enterprise competitiveness, this study examines whether the effectiveness of DT varies among enterprises with different levels of competitiveness and ownership structures compared to previous studies. Table 14 demonstrates that only highly competitive non-SOEs exhibit a positive impact on FS through DT, suggesting that property rights significantly influences the effectiveness of DT. This finding indicates that DT in private enterprises has a more pronounced effect on promoting FS.

Tab. 14 - Regression Results Based on the Enterprise Ownership. Source: own search

	High-competitive			Low-competitive		
	(1)	(2)	(3)	(1)	(2)	(3)
	state-owned	non-state-owned	mixed-ownership	state-owned	non-state-owned	mixed-ownership
	Stability	Stability	Stability	Stability	Stability	Stability
Digit	0.0012	0.0009**	-0.0004	-0.0026	0.0007	0.0020
	(0.7927)	(2.2566)	(-0.1412)	(-1.259)	(1.6137)	(0.2453)
Controls	yes	yes	yes	yes	yes	yes
Constant	0.4242	0.0644	-0.2727	1.7181	0.8209	-1.0581
	(0.51101)	(0.2011)	(-0.0004)	(1.7508)	(2.7140)	(-0.2750)
Year	yes	yes	yes	yes	yes	yes
N	740	4655	205	391	5176	33
R^2	0.01685	0.0179	0.0682	0.0667	0.0074	0.4211
Adjusted R^2	0.0006	0.01534	0.01511	0.03708	0.00500	0.0737

This table presents the regression results of DT on FS based on different level of digital economy development. ***, **, and * indicate coefficients significant at the 1%, 5%, and 10% levels, respectively. T-statistics appear in parentheses below the coefficients.

4.3.3 Scale and Salary Heterogeneity

This confirms that enterprises with varying levels of competitiveness differ in their promotion of FS through employment scale and salary during DT. However, some questions remain unanswered: How do internal employment scale and salary structures change during this process? Do these changes affect FS differently? This study explores these issues further.

DT is accelerating the transition from labor-intensive to technology-intensive industries, imposing stricter skill requirements on workers and driving changes in employment structures (Huang, 2024). Previous shows that DT increases the demand for highly educated labor by integrating high-quality knowledge and human capital into production processes (Dou et al., 2023). It also replaces routine, repetitive, and low-skilled labor tasks (Dengler & Matthes, 2023). Consequently, this study examines the employment structure effects of DT and its impact on FS. We classify employees based on their education level: those with a bachelor's degree or higher are categorized as the high-education group, while those with a high school diploma or less are categorized as the low-education group. Empirical evidence indicates that highly competitive enterprises enhance FS by expanding both employee groups, with a more pronounced effect on the low-education group. In contrast, for less competitive enterprises, FS is improved primarily by increasing the number of highly educated employees. This suggests that DT primarily boosts FS through job creation for highly educated individuals.

Furthermore, our analysis reveals that DT can significantly raise employee salaries in both highly competitive and less competitive groups, thereby promoting FS. However, according to principal-agent theory, senior executives have the incentive to appropriate corporate profits to maximize their personal returns. Consequently, the positive impact of DT on wage levels may disproportionately benefit senior management rather than ordinary employees. This phenomenon, known as executive predation, becomes increasingly evident as a enterprise's profitability enhances. We aim to investigate the existence of this phenomenon and examine the differential performance among enterprises with varying levels of competitiveness. Therefore, we determine the average compensation for managers by dividing their total remuneration by their count. For ordinary employees, we calculate the average salary by dividing the remaining total salary (after deducting the managers' salary) by the number of ordinary employees. We then evaluated the impact of DT on both groups. The results indicate that in the low-competition group, DT raises salaries for both managers and ordinary employees, thereby enhancing FS. In the high-competition group, only ordinary employees are significantly impacted. This suggests there is no "executive predation" during DT, aligning with Ye et al., (2022). Detailed empirical results are provided in the appendix.

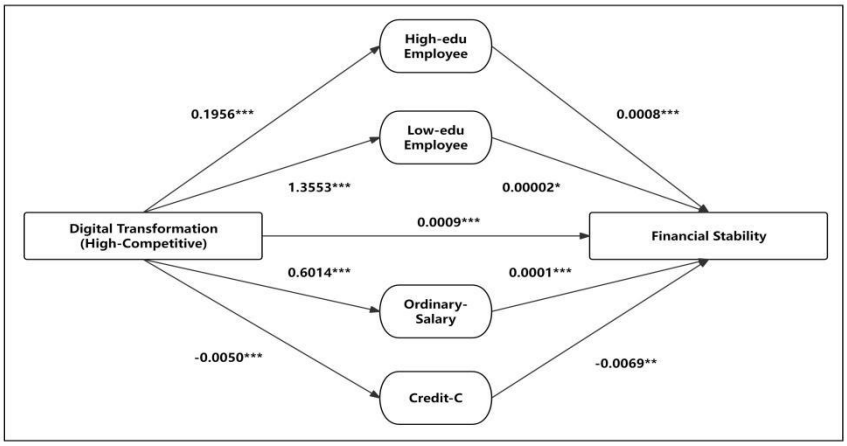

Fig.2 - Empirical Results for High Competition Group. Source: own search

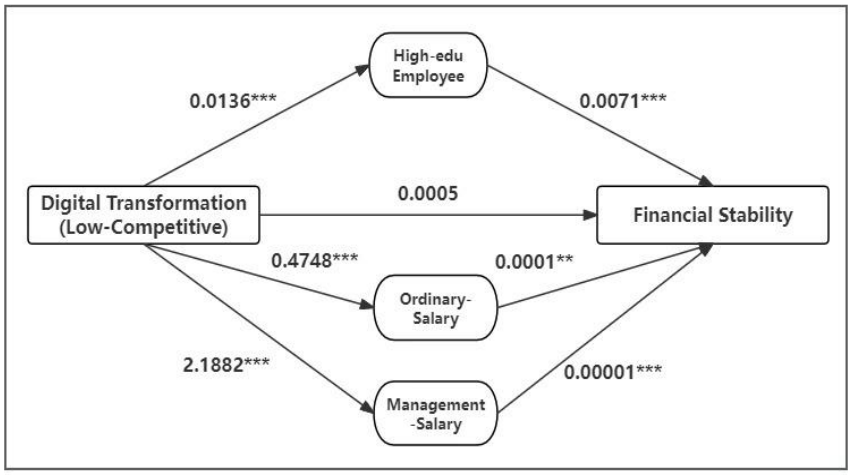

Fig.3 - Empirical Results for Low Competition Group. Source: own search

5. CONCLUSIONS AND DISCUSSIONS

Based on A-share listed enterprises in China from 2007 to 2022, we examine the impact mechanism and effects of DT on FS across enterprises with different competitiveness levels. The benchmark regression analysis reveals that DT has a positive effect on FS for both the full sample and the high-competition group, but not for the low-competition group. While DT generally has positive spillover effects, its success depends heavily on a enterprise's resource endowment. With the rapid development of science and technology, DT has become an inevitable choice for enterprise development. However, this process is both lengthy and resource-intensive. For less competitive enterprises, indiscriminate adoption of DT may not yield anticipated outcomes. It is crucial to remain vigilant about the potential exacerbation of the "digital divide", which could intensify the Matthew effect.

The findings from the mechanism indicate that high-competition enterprises influence FS through three channels: by expanding employment scale for all employees, by increasing salary for ordinary employees, and by reducing commercial credit extended to customers. While DT in low-competition enterprises does not directly enhance FS, it indirectly supports it by increasing the proportion of highly educated employees and raising overall employee salary. These findings have several implications. First, automation and technological progress will not necessarily render low-skilled labor obsolete, thereby alleviating concerns about DT fully replacing human workers. Highly competitive enterprises excel at reallocating tasks and providing targeted training, ensuring that less-educated employees remain valuable in their specific roles. This observation is consistent with findings from previous research (Akerman et al., 2015; Han et al., 2024; Acemoglu & Restrepo, 2016). Second, in addition to bolstering corporate profitability, DT can also promote a more equitable distribution of benefits. This

ensures that employees at all levels within the organization can fairly share in the advantages derived from corporate development, thereby preventing phenomena such as "executive predation." This underscores the inclusiveness and universality of DT. (Ye et al., 2022; Fang et al., 2022). Thirdly, Chinese enterprises are still in the nascent stages of DT, with its impact thus far being limited. Specifically, less competitive enterprises are finding it difficult to secure credit from suppliers and banks through digital channels, which hampers their capacity to manage and support downstream customers.

In the analysis of heterogeneity, regions characterized by advanced digital economies demonstrate that DT enhances FS, particularly for less competitive enterprises. Conversely, in regions with underdeveloped digital economies, this effect is negligible. These findings underscore the significance of regional digital economy development for successful DT (Ning et al., 2022; Nambisan et al., 2019). This outcome has implications for countries with underdeveloped digital infrastructures. When enterprises within these regions exhibit markedly insufficient competitiveness, fostering a supportive external environment may facilitate their DT and enhance operational efficiency. In addition, in the analysis of enterprise property rights, it was found that the DT of non-SOEs significantly promotes FS compared to state-owned and mixed-ownership enterprises. This finding aligns with the research conclusions of Wu et al. (2021) and Liu et al. (2021). This may indicate that SOEs face institutional challenges that render their DT efforts superficial, with little substantive progress. Ownership reforms have had minimal impact. In contrast, non-SOEs excel in DT due to their market sensitivity and strong innovation capabilities.

This study has some limitations. First, the measure of FS is concentrated solely on the banking sector and overlooks the capital market. This could result in a distorted assessment of overall FS, despite China's bank-oriented structure. Future assessments should include both sectors for a more comprehensive evaluation. Second, the evaluation of corporate competitiveness and regional digital economy development indicators includes subjective elements. To improve the robustness and comprehensiveness of our analysis, future research will employ an integrated approach that combines qualitative and quantitative methodologies, thus offering a more objective assessment of these indicators. Third, this study concentrates on the Chinese market, thereby limiting its geographical scope. Differences in resources, culture, and institutions among countries may influence how enterprise competitiveness impacts DT and FS. As a result, this constrains the international applicability of the findings. Future research should encompass a broader range of countries to enhance generalizability and robustness.

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Appendix A

Tables 1-4 present the detailed outcomes of the further analysis detailed in the main text. Table 1 illustrates whether DT can improve FS by increasing the number of highly educated employees. The results from (1) - (3) and (4) - (6) represent the regression outcomes for the high competition group and the low competition group, respectively. It is evident that the intermediary effects for both the high competition group and the low competition group are significantly positive at the 1% level, suggesting that DT, regardless of its level of competitiveness, can positively influence FS by expanding its workforce of highly educated employees.

Tab.1 - Mediating Path Results Based on High-Education Level. Source: own search

	High-Competitive			Low-Competitive		
	(1)	(2)	(3)	(4)	(5)	(6)
	Stability	High-Education	Stability	Stability	High-Education	Stability
Digit	0.0009**	0.1956***	0.0007*	0.0005	0.0136***	0.0004
	(-2.3568)	(-8.8431)	(-1.9186)	(-1.2001)	(-6.1737)	(-0.9644)
High-Education			0.0008***			0.0071***
			(-3.6129)			(-2.8219)
Controls	yes	yes	yes	yes	yes	yes
Constant	0.1798	-34.6761**	0.2085	0.8927***	-7.1612***	0.9438***
	(-0.6230)	(-2.0587)	(-0.7229)	(-3.1594)	(-4.7899)	(-3.3354)
Year	yes	yes	yes	yes	yes	yes

N	5600	5600	5600	5600	5600	5600
Boot CI (95%)	0.0027 ~ 0.0095			0.0007 ~ 0.0110		
Adjusted R^2	0.0119	0.3829	0.014	0.0056	0.0963	0.0069

This table presents the estimated results of the mediating effect of high-education level on DT and FS. ***, **, and * indicate coefficients that are significant at the 1%, 5%, and 10% levels, respectively. The t-statistics appear in parentheses below the coefficients.

Table 2 shows whether DT can promote FS by increasing the number of low-educated employees. The regression coefficient of digit and low-education in Column (2) is 1.3553, significant at the level of 1%,and the regression coefficient of low-education and stability in Column (3) is 0.00002, significant at the level of 10%. This shows that DT in the high competition group can promote FS by expanding the number of low-educated employees. In the low competition group, the regression coefficient of digit and Low-education in Column (5) is 0.1847, which is significant at the level of 1%, but the regression coefficient of low-education and stability in column (6) is not significant, and the BootCI (95%) value includes 0. This shows that although DT in the low-competition group can increase the number of low-educated employees, the path of the second half of the intermediary is not significant, so the path of the low-competition group promoting FS by increasing the number of low-educated employees is ineffective.

Tab.2 - Mediating Path Results Based on Low-Education Level. Source: own search

	High-Competitive			Low-Competitive		
	(1)	(2)	(3)	(4)	(5)	(6)
	Stability	Low-Education	Stability	Stability	Low-Education	Stability
Digit	0.0009**	1.3553***	0.0008**	0.0005	0.1847***	0.0005
	(-2.3568)	(-5.2560)	(-2.2154)	(-1.2001)	(-3.8560)	(-1.1701)
Low-Education			0.0002e-01*			0.0001
			(-1.9425)			(-0.5493)
Controls	yes	yes	yes	yes	yes	yes
Constant	0.1798	1347.7269***	0.1283	0.8927***	155.1372***	0.8828***
	(-0.623)	(-6.8636)	(-0.4429)	(-3.1594)	(-4.7669)	(-3.1179)
N	5600	5600	5600	5600	5600	5600
Boot CI (95%)	0.0005 ~ 0.0046			-0.0006 ~ 0.0030		
Adjusted R^2	0.0119	0.6592	0.0124	0.0056	0.3142	0.0055

This table presents the estimated results of the mediating effect of low-education level on DT and FS. ***, **, and * indicate coefficients that are significant at the 1%, 5%, and 10% levels, respectively. The t-statistics appear in parentheses below the coefficients.

Table 3 reveals whether DT can enhance FS by raising salary of ordinary employees. The regression coefficient of digit and ordinary-salary in Column (2) is 0.6014, which is statistically significant at the 1% level; the regression coefficient of ordinary-salary and stability in column (3) is 0.0001,which is also statistically significant at the 1% level. This indicates that DT in the high competition group can promote FS by increasing the per capita salary of ordinary employees. The enterprise path is also significant in the low competition group. This

demonstrates that DT with different competitiveness can positively contribute to FS by increasing salary of ordinary employees.

Tab. 3 - Mediating Path Results Based on Ordinary Employee Salary. Source: own search

	High-Competitive			Low-Competitive		
	(1)	(2)	(3)	(4)	(5)	(6)
	Stability	Ordinary-Salary	Stability	Stability	Ordinary-Salary	Stability
Digit	0.0009**	0.6014***	0.0008**	0.0005	0.4748***	0.0004
	(-2.3568)	(-4.415)	(-2.1363)	(-1.2001)	(-4.0449)	(-1.0603)
Ordinary-Salary			0.0001***			0.0001**
			(-3.7168)			(-2.5647)
Controls	yes	yes	yes	yes	yes	yes
Constant	0.1798	-1818.7504***	0.4312	0.8927***	-1105.9770***	1.0271***
	(-0.623)	(-17.5325)	(-1.456)	(-3.1594)	(-13.8644)	(-3.5757)
Year	yes	yes	yes	yes	yes	yes
N	5600	5600	5600	5600	5600	5600
Boot CI (95%)	0.0015 ~ 0.0068			0.0005 ~ 0.0075		
Adjusted R^2	0.0119	0.093	0.0142	0.0056	0.098	0.0066

This table presents the estimated results of the mediating effect of ordinary employee salary on DT and FS. ***, **, and * indicate coefficients that are significant at the 1%, 5%, and 10% levels, respectively. The t-statistics appear in parentheses below the coefficients.

Table 4 demonstrates whether corporate DT can enhance FS by raising salary of senior executives. The regression coefficient of digit and management-salary in Column (2) is 5.0096, which is statistically significant at the 1% level. The regression coefficient of management-salary and stability in Column (3) is insignificant, and the BootCI (95%) value encompasses 0. This indicates that DT in the high competition group is unable to promote FS by expanding salary of executives. In the low competition group, the enterprise path is significant. This reveals that DT with low competitiveness can positively boost FS by increasing the salary of senior executives.

Tab. 4 -1Mediating Path Results Based on Managerial Employee Salary. Source: own search

	High-Competitive			Low-Competitive		
	(1)	(2)	(3)	(4)	(5)	(6)
	Stability	Managerial-Salary	Stability	Stability	Managerial-Salary	Stability
Digit	0.0009**	5.0096***	0.0009**	0.0005	2.1882***	0.0004
	(-2.3568)	(-3.0924)	(-2.3392)	(-1.2001)	(-2.9875)	(-1.0749)
Managerial-Salary			0			0.0001e-01***
			(-0.3738)			(-3.1332)
Controls	yes	yes	yes	yes	yes	yes
Constant	0.1798	-24025.4682***	0.2079	0.8927***	-10717.3473***	1.1475***
	(-0.623)	(-19.4762)	(-0.697)	(-3.1594)	(-21.5306)	(-3.9057)
Year	yes	yes	yes	yes	yes	yes

N	5600	5600	5600	5600	5600	5600
Boot CI (95%)	-0.0011 ~ 0.0015			0.0007 ~ 0.0031		
Adjusted R^2	0.0119	0.1244	0.0117	0.0056	0.1704	0.0072

This table presents the estimated results of the mediating effect of managerial employee salary on DT and FS. ***, **, and * indicate coefficients that are significant at the 1%, 5%, and 10% levels, respectively. The t-statistics appear in parentheses below the coefficients.

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