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Chapter: Advancing Digital Transformation through Information and Innovation Management

DOES DIGITAL TRANSFORMATION REDUCE CORPORATE FINANCIAL RISKS? A DUAL PERSPECTIVE OF INTERNAL DISCLOSURE AND EXTERNAL SUPERVISION

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Annotation. Digital technologies lead to a new wave of technological innovation and transformation. However, existing literature has not provided systematic theoretical insights into whether digital transformation can reduce corporate financial risks. To explore the relationship between digital transformation and corporate financial risks, based on resource-based theory and signaling theory, the impact of digital transformation on corporate financial risks was analyzed by using a sample of A-share listed companies in China from 2011 to 2022. Results show that from the perspectives of internal disclosure and external supervision, digital transformation mitigates financial risks primarily by increasing analyst following and enhancing information transparency. Further analysis reveals that the inhibitory effect of digital transformation on financial risks is more pronounced in non-high-tech and non-labor-intensive enterprises. The conclusions obtained from this study provide new empirical evidence on how digital transformation can mitigate corporate financial risks and offer theoretical guidance and strategic support for stakeholders to adopt location-specific digital transformation strategies based on their resource endowments and market environments.

Keywords: digital transformation, financial risk, analyst concerns, transparency of information.

JEL classification: M14, L25, C12.

Introduction

The rapid advancement of digital technologies drives the deep integration of digital innovations with traditional industries, showcasing substantial potential and transformative energy. In exploring the economic implications of enterprise digitalization, prior research grounded in resource-based theory suggests that the unique resources enterprises possess—such as technology, knowledge, and information—serve as sources of competitive advantage. Through technological enablement, digital

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transformation enhances an enterprise's ability to acquire and integrate information, thereby reinforcing competitive advantages and generating positive outcomes (Wang *et al.*, 2023). For instance, traditional corporate financial risk identification methods, which often rely on manual data collection, are typically reactive and fail to adapt to increasingly complex and dynamic economic conditions. Digital transformation addresses these challenges by improving real-time data acquisition and integration capabilities, providing managers with a comprehensive understanding of enterprise dynamics (Koman *et al.,* 2024). This advancement enhances the accuracy of market forecasting, the scientific rigor of decision-making, and the ability to seize market opportunities while mitigating risks. Such improvements form a solid foundation for reducing corporate financial risks From the perspective of platform economic theory, interconnection and value co-creation among enterprises have evolved into platform- and industry-based systems (Anthony, 2024; Elkrghli, Almansour, 2024). By integrating external information flows with internal data, advanced digital technologies enhance the connectivity and interaction of platform enterprises, reducing organizational path dependence and improving information transmission efficiency (Bohnsack *et al.*, 2021; Angelova *et al.,* 2023). These transformations optimize inter-enterprise collaboration models and strengthen the competitiveness of industrial ecosystems (Verhoef *et al.*, 2021). Furthermore, by advancing industrial structure optimization and investment in cutting-edge technologies, digital transformation enables seamless data sharing and interoperability across industries and regions. This significantly improves the efficiency of green supply chains (Li, Donta, 2023) and promotes low-carbon enterprise development (Ding *et al.*, 2024). These measures enhance production efficiency, reduce costs, and minimize resource waste, thereby bolstering enterprise resilience against corporate financial risks (Kharabsheh, Al-Qudah, 2024).

Despite its potential, some scholars question whether digital transformation consistently delivers positive outcomes for enterprises. Drawing on organizational inertia theory, researchers argue that the rigid structures within traditional enterprises can impede innovation and resource reallocation during the initial stages of digital transformation. This inflexibility can hinder the timely updating of operational processes, leading to sunk costs in legacy investments and potential deterioration in business performance, ultimately increasing corporate financial risks (Guo *et al.*, 2023). Moreover, over time, the value creation associated with digital transformation may diminish. Misalignment between the advanced architecture of digital technologies and organizational resources can result in higher internal learning costs, with the benefits of digital transformation offset by associated management costs (Zhang *et al.*, 2022). These complexities highlight the multifaceted impact of digital transformation on enterprises, warranting deeper exploration.

According to data from the Ministry of Industry and Information Technology, by December 2023, the national public service platform for the integration of digital and industrial systems had served 183,000 enterprises, with a digital R&D tool penetration rate of 79.6% and a numerical control rate of key processes at 62.2%. China's rapid digital economy development offers abundant data for studying the implications of digital transformation. Analyzing the digitalization of Chinese enterprises provides critical insights into the economic consequences of digital technologies on micro-enterprises and serves as a valuable reference for policymakers and business leaders worldwide in crafting digital economy strategies. Based on the above, this study aims to investigate the following questions: First, does digital transformation reduce corporate financial risks? Second, from the dual perspectives of internal disclosure and external supervision, are information transparency and analysts following effective mechanisms through which digital transformation can reduce corporate financial risks? Finally, for different types of enterprises, are there significant differences in the impact of digital transformation on corporate financial risks? To explore these questions, this study selects data from Chinese A-share listed companies from 2011 to 2022 to conduct an empirical analysis, examining the direct impact of digital transformation on corporate financial risks and its underlying mechanisms.

The marginal contributions of this study are as follows: (1) this study deepens the research on the economic consequences of digital transformation. By examining the microeconomic effects of digital transformation from a risk-aversion perspective, this paper sheds light on how digital transformation influences corporate financial risk, thereby providing a valuable theoretical supplement to the study of the microeconomic consequences of digital transformation. (2) This study enriches the research on the mechanisms through which digital transformation impacts corporate financial risk. Drawing on information asymmetry theory and the perspective of internal and external information supervision, this study investigates the roles of information transparency and analyst following as key elements in the mechanism of digital transformation, offering new evidence for pathways that alleviate corporate financial risks. (3) Existing literature inadequately addresses how digital transformation affects enterprises with varying attributes. This study explores the differentiated impacts across enterprises with distinct technological, ownership, and resource characteristics. The findings offer actionable recommendations for tailoring digital transformation strategies to enterprise-specific needs and help enterprises prevent financial risks more efficiently.

The structure of the study is organized as follows: Section 1 presents the theoretical analysis and hypothesis development, focusing on digital transformation's direct effects on corporate financial risks and the mediating roles of information supervision. Section 2 outlines the research design, including the variable definitions, and model specifications. Section 3 provides the empirical results, featuring descriptive statistics, correlation analysis, primary regression tests, and robustness tests. Section 4 focuses on the mechanism analysis, examining the mediating roles of information transparency and analyst following. Section 5 presents the heterogeneity analysis, focusing on technological attributes, ownership structures, and resource intensity. Section 6 discusses the findings, offering theoretical and practical insights. Finally, Section 7 makes conclusions and recommendations, presenting suggestions, limitations, and directions for future research.

1. Theoretical Analysis and Hypothesis Development

1.1 Digital Transformation and Corporate Financial Risks

From a resource-based perspective, digital transformation enables enterprises to establish integrated information systems that leverage data resources to collect, process, and store diverse operational and financial data in real-time. This process not only enriches the data resources available to enterprises but also enhances the timeliness and transparency of information flows (Pakkala, 2024). Moreover, by utilizing advanced data mining and intelligent analysis capabilities, enterprises can precisely identify potential risk points and anomalies, providing robust informational support for corporate financial risk management (Zhao *et al.*, 2024; Tobisova *et al.,* 2023). This data-driven decision-making model improves enterprises' responsiveness to market changes, accelerates reaction times, and promotes a more scientific approach to risk management. From the perspective of process reengineering, digital transformation reshapes internal operations and fosters seamless information sharing and collaboration across departments. Integrated information systems enable real-time communication and cross-departmental coordination, significantly enhancing overall risk management capabilities (Ye, 2024). By streamlining approval processes and improving operational efficiency, this reengineering reduces the likelihood of corporate financial risks arising from delayed information or miscommunication

(Hashemizadeh *et al.*, 2023). Additionally, the standardization and automation of processes ensure the accuracy and consistency of financial data, strengthening the foundation for effective corporate financial risk management. This also bolsters the reliability of internal information disclosure, facilitates the development of robust internal control systems (Huang *et al.*, 2023), and mitigates risks associated with internal mismanagement.

Furthermore, digital transformation equips enterprises with the agility to rapidly adopt innovative technologies and adapt to evolving market conditions (Rauniyar *et al.*, 2023). By establishing open industry data-sharing platforms, enterprises can access up-to-date information on external entities such as suppliers, customers, and competitors (Anthony, 2024). This enhances their ability to anticipate market trends and recalibrate business strategies accordingly, reducing exposure to market-related corporate financial risks (Jiang, Hao, 2024). Integrated information systems further enable real-time monitoring and analysis of financial and operational data, allowing enterprises to promptly identify and address potential risks. This capability substantially improves the efficiency and accuracy of risk oversight, ensuring stable and secure operations (Zhang, Jing, 2024). Based on the above analysis, this study proposes the following hypothesis.

Hypothesis 1: Digital transformation significantly reduces corporate financial risks.

1.2 Digital Transformation, Analyst Following and Corporate Financial Risks

From the perspective of external oversight, digital transformation plays a pivotal role in addressing information asymmetry between enterprises and the public. According to signal transmission theory, information asymmetry often results in the public experiencing delays or loss of corporate information. While digital transformation generates substantial information resources, it can also lead to information redundancy and overload, making it challenging for some investors to process data accurately. As a result, investors often rely on the insights and interpretations of external analysts (Srivastava, Dixit, 2023). Unlike general investors, analysts possess advanced theoretical knowledge and practical experience, enabling them to access and interpret information that is not readily available to the public (Roeder *et al.*, 2022). Before publishing research reports, analysts engage in prolonged tracking and monitoring of companies to ensure the authenticity of the information collected and the accuracy of their analyses. Through the publication of research reports, stock ratings, and earnings forecasts, analysts accurately and promptly communicate the true operational status of the company to parties with information disadvantages (Roeder *et al.*, 2022). In recent years, China's policy measures have actively encouraged enterprises to accelerate digital transformation, aiming to break free from traditional growth constraints and achieve significant productivity gains. The “spotlight effect” of digital transformation increases analysts’ following to enterprises, especially those adopting advanced digital technologies, thereby amplifying the governance role of analysts.

Moreover, digital transformation enhances enterprises’ capabilities in data collection, resource management, and analysis (Pakkala *et al.*, 2024). This improvement expands the volume and accuracy of information available to analysts, leading to more precise and reliable forecasts. According to market supervision theory, heightened analyst following strengthens external supervision, improving internal corporate governance by mitigating self-serving behaviors among shareholders and management. Such oversight reduces violations and enhances compliance (Liu *et al.*, 2024). Conversely, diminished analyst following weakens this supervisory effect, potentially increasing financing constraints and exacerbating corporate financial risks. Increased analyst focus also enables stakeholders to identify managerial actions that could harm creditors’ interests (Healy, Palepu, 2001). Concurrently, public and institutional scrutiny of enterprises intensifies, reducing the likelihood of defaults and stock price collapses while improving financial sustainability (Liang, Zhao, 2024). Based on the above analysis, this study proposes the following hypothesis.

Hypothesis 2: Digital transformation significantly inhibits corporate financial risks by increasing analyst following.

1.3 Digital Transformation, Information Transparency, and Corporate Financial Risks

First, from the perspective of internal disclosure, digital transformation plays a crucial role in mitigating corporate financial risks by enhancing information transparency. The integration of digital technologies, application scenarios, and business models during the digital transformation process helps eliminate information barriers within and outside the enterprise. This, in turn, improves the efficiency of financial information feedback and fosters a more transparent and efficient information environment (Abiodun *et al.*, 2023). Second, from the lens of agency theory, the creation of a transparent information environment can effectively alleviate principal-agent conflicts. Low transparency often enables management to obscure corporate violations for personal gain. However, enhanced transparency significantly curtails such opportunistic behaviors, thereby reducing credit risks (Bi *et al.*, 2024) and the likelihood of leverage manipulation. Third, viewed through investor protection theory, digital transformation enhances the accessibility of enterprise information, optimizes disclosure processes, and reduces supervision costs. This optimization strengthens the public's oversight role, curbing unlawful activities such as major shareholders' illegal reduction of holdings and narrowing the scope for corporate malfeasance (Qian *et al.*, 2017). Finally, based on information asymmetry theory, digital technologies enable enterprises to communicate internal information to investors more efficiently and rapidly, thereby reducing the cost of information acquisition and processing for external stakeholders (Hodapp, Hanelt, 2022). As a result, the degree of information asymmetry between enterprises and stakeholders such as investors, financial institutions, and regulatory agencies diminishes (Guo *et al.*, 2022). This alleviation of investor concerns not only lowers corporate financing costs but also broadens financing channels, creating a more favorable financing environment (Liu *et al*, 2024). These developments promote industrial upgrading, technological innovation, and resource optimization, contributing to the sustainable growth of enterprises (Nepal *et al.*, 2024). Based on the above analysis, this study proposes the following hypothesis.

Hypothesis 3: Digital transformation significantly reduces corporate financial risks by enhancing information transparency.

2. Methodology

2.1 Samples

This study uses China's A-share listed companies from 2011 to 2022 as the initial research sample. All relevant variable data are sourced from the CSMAR (China Stock Market & Accounting Research) database. The sample selection follows these principles: (1) excluding firms in the financial industry, (2) excluding ST enterprises, (3) removing observations with abnormal or missing data, and (4) winsorizing major continuous variables at the 1% and 99% levels to mitigate the influence of extreme values. After applying these criteria, the final sample consists of 19,571 observations.

2.2 Variable Definitions

2.2.1 Dependent Variables: Corporate Financial Risks (FRZ)

Considering that digital transformation brings comprehensive improvement to enterprises' risk perception, resource acquisition, and resource transformation ability. The Z-score risk model can provide a more comprehensive financial evaluation from many aspects, such as asset size, profitability, financial structure, solvency, asset utilization efficiency, etc. Thus, the Z-score model proposed by Altman (1968) is used to measure corporate financial risks. The formula is as follows: Z-score = (1.2 × working capital + 1.4 × retained earnings + 3.3 × EBIT + 0.6 × total stock market value + 0.999 × sales revenue) / total assets. A higher Z-score indicates lower corporate financial risks.

2.2.2 Independent Variables: Digital Transformation (DGG)

Referring to the study of Zhai *et al.* (2022), this study uses the digital transformation indicators provided by the CSMAR digital economy database to define digital transformation. This index covers five aspects: artificial intelligence, blockchain, cloud computing, big data, and digital technology applications. The more keywords related to these five aspects appear in the annual report, the higher the company's attention to digital transformation that year, indicating a higher level of digitalization. This measurement method aligns with the research by Wu *et al.* (2021). Thus, this study uses the sum and logarithmic values based on the digital transformation indicators provided by CSMAR (China Stock Market Accounting Research) to measure the degree of digital transformation in enterprises.

2.2.3 Mediator Variable

Analyst Following (*Ana*). Referring to the studies by He, Tian (2013), this study defines analyst following as the natural logarithm of the number of analysts (or teams) tracking a listed company in the current year, after adding one, represented as Ana. This index effectively quantifies the market's attention to an enterprise: a higher Ana value indicates a greater analyst following.

Information Transparency (*Info*). Referring to the studies by Sun and Xin (2023), this study utilizes the evaluation results of information disclosure of listed companies by the exchange, as provided by the CSMAR database, and represents these results with Info. Specifically, a higher Info value indicates more comprehensive information disclosure and greater transparency.

2.2.4 Control Variables

To ensure the explanatory power of the regression model and prevent interference from other variables, by referring to the studies of Luo, Liu (2024) *et al.*, this study controls the variables related to internal governance and external market that may affect corporate financial risks in this model. The control variables selected are: enterprise size (*SIZE*), asset-liability ratio (*LEV*), return on equity (*ROE*), board size (*BS*), interest coverage ratio (*ICR*), investment growth rate (*IGR*), current ratio (*CR*), equity concentration (*OC*), equity balance (*Rind*), and stock return (*SR*). The detailed data structure of variables is presented in *Table 1*.

Table 1. Symbols and definitions of variables

Variables	Name	Symbol	Definitions
Dependent variable	Degree of digital transformation	*DGG*	Word frequency related to digital transformation in the annual report is obtained through the CSMAR database, which is summarized and logarithmically processed.
Independent variable	Corporate financial risks	*FRZ*	(1.2 × working capital + 1.4 × retained earnings + 3.3 × EBIT + 0.6 × total stock market value + 0.999 × sales revenue)/total assets
Mediator Variables	Analyst following	*Ana*	LN (Number of analysts (or team) covering a public company that year +1)
	Information transparency	*Info*	The CSMAR database provides the evaluation results of the exchange's information disclosure of listed companies.
Control variables	Business size	*SIZE*	The natural logarithm of the total annual market value of a business.
	Asset-liability ratio	*LEV*	Total liabilities/total assets
	Return on equity	*ROE*	Net profit/net worth
	Board size	*BS*	LN (Number of directors + 1)
	Interest coverage ratio	*ICR*	Ebit/finance expense
	Investment growth rate	*IGR*	(Cash paid by enterprises for the purchase and construction of fixed assets, intangible assets, and other long-term assets - cash recovered from the disposal of fixed assets, intangible assets, and other long-term assets)/total assets
	Current ratio	*CR*	Current assets/current liabilities
	Ownership concentration	*OC*	Percentage of the largest shareholder's holdings.
	Equity balance degree	*Rind*	Shares held by the 2nd to 5th largest shareholders/shares held by the 1st largest shareholders
	Stock returns	*SR*	Consider the annual individual stock return on cash dividends reinvested.

Source: authors' own results.

2.3 Regression Model

This study employs a two-way fixed-effect model to investigate the impact of digital transformation on corporate financial risks. To account for potential bias caused by the heterogeneity of subdivided industries, the "industry-year" effect is controlled. Based on these assumptions, the following fixed-effect model equation is constructed:

$$FRZ_{it} = \alpha_0 + \alpha_1 DGG + \sum \alpha_k Control_{it} + \sum Year_t + \sum Ind_j + \varepsilon_{it} \tag{1}$$

To further examine the mechanism by which digital transformation affects corporate financial risks, specifically whether it does so by increasing analysts' following or improving information transparency, this study establishes the following three regression models based on the operational suggestions for mediation effect analysis by Wen *et al.* (2022)

$$FRZ_{it} = \alpha_0 + \alpha_1 DGG + \sum \alpha_k Control_{it} + \sum Year_t + \sum Ind_j + \varepsilon_{it} \tag{2}$$

$$Mediator_{it} = \beta_0 + \beta_1 DGG + \sum \beta_k Control_{it} + \sum Year_t + \sum Ind_j + \varepsilon_{it} \tag{3}$$

$$FRZ_{it} = \gamma_0 + \gamma_1 DGG + \gamma_2 Mediators_{it} + \sum \gamma_k Control_{it} + \sum Year_t + \sum Ind_j + \varepsilon_{it} \tag{4}$$

In the above equations, *i* and *t* represent the enterprise and year, respectively; *FRZ* is the explained variable, indicating corporate financial risks; *DGG* is the explanatory variable, representing the degree of digital transformation; *Control* comprises the control variables of the model; *Mediator* is the mediator variable; *Year* denotes the time fixed effect; *Ind* signifies the fixed effect of industry; and ε represents the random error term.

3. Results Analysis

3.1 Descriptive Analysis

Table 2 presents the descriptive statistics. *FRZ* exhibits a maximum value of 3.631 and a minimum value of -2.483, indicating a substantial range. The standard deviation of 0.782 highlights a considerable dispersion in corporate financial risk levels, reflecting significant differences in their risk-taking capacities. DGG has a maximum value of 5.468 and a minimum value of 0, revealing notable variability in the extent of digital transformation across listed companies. The standard deviation of 1.432 further emphasizes this variability. Notably, some enterprises do not mention digital transformation in their annual reports, suggesting significant disparities in their understanding of and investment in digital transformation strategies. This indicates that digital transformation is not universally adopted among enterprises. To ensure a robust analysis, this study incorporates a range of control variables that may influence corporate financial risks and digital transformation. This comprehensive approach helps mitigate potential confounding factors, enabling a more precise exploration of the relationship between these variables and enhancing the reliability of the findings.

Table 2. Descriptive statistics of main variables

Variables	N	Mean	SD	Min	p25	p50	p75	Max
FRZ	19571	1.178	0.782	2.483	0.765	1.179	1.617	3.631
DGG	19571	1.383	1.432	0	0	1.099	2.303	5.468
SIZE	19571	15.69	0.925	13.69	15.01	15.56	16.23	19.06
LEV	19571	0.459	0.193	0.0800	0.310	0.452	0.599	0.935
ROE	19571	0.0360	0.187	2.175	0.0200	0.0600	0.105	0.409
BS	19571	2.240	0.172	1.792	2.079	2.303	2.303	2.773
ICR	19571	11.40	39.26	91.63	0	2.702	8.716	642.8
IGR	19571	0.0450	0.0450	0.0420	0.0130	0.0320	0.0630	0.269
CR	19571	1.919	1.415	0.221	1.088	1.524	2.238	10.21
OC	19571	32.15	14.27	6.789	21.10	29.95	41.51	76.44
Rind	19571	3.643	0.140	0	3.536	3.621	3.781	4.331
SR	19571	0.125	0.560	0.822	0.228	0	0.324	15.21

Source: authors' own results.

3.2 Correlation Matrix

Table 3 presents the correlation analysis results for the study variables. The correlation coefficient between *FRZ* and *DGG* is 0.068, which is statistically significant at the 1% level. This indicates that higher levels of digital transformation are associated with reduced corporate financial risks. Additionally, the correlation coefficients between the main variables and the control variables are all below 0.8, suggesting that multicollinearity is not a concern in the regression model. This ensures the reliability of the subsequent regression analysis.

Table 3. Correlation matrix

	FRZ	***DGG***	***SIZE***	***LEV***	***ROE***	***BS***	***ICR***	***IGR***	***CR***	***OC***	***Rind***	***SR***
FRZ	1											
DGG	0.068***	1										
SIZE	0.175***	0.169***	1									
LEV	0.369***	0.104***	0.024***	1								
ROE	0.582***	0.035***	0.242***	0.218***	1							
BS	0.019***	0.111***	0.136***	0.134***	0.063***	1						
ICR	0.219***	0.00900	0.090***	0.143***	0.214***	0.0100	1					
IGR	0.029***	0.098***	0.087***	0.077***	0.114***	0.037***	0.025***	1				
CR	0.333***	0.089***	0.014*	0.671***	0.118***	0.121***	0.095***	0.060***	1			
OC	0.141***	0.168***	0.134***	0.094***	0.130***	0.041***	0.020***	0.046***	0.046***	1		
Rind	0.037***	0.080***	0.022***	0.025***	0.026***	0.520***	0.00700	0.00900	0.021***	0.013*	1	
SR	0.050***	0.00400	0.226***	0.029***	0.106***	0.023***	0.034***	0.00700	0.026***	0.00700	0.0110	1

Note: ***, * *, and * respectively represent significant levels at 1%, 5%, and 10%.

Source: authors' own results.

3.3 Baseline Results

Table 4 presents the regression results of the "Digital Transformation - Corporate Financial Risks" benchmark framework. Following the processing of missing values and indentation to ensure data validity and robustness, the relationship between *DGG* and *FRZ* is examined, both with and without including control variables. In column (1) of Table 4, only the core independent variable, *DGG*, is included to identify its basic relationship with the dependent variable, *FRZ*. The regression results indicate that the coefficient of *DGG* is positive and significant at the 1% level, suggesting that digital transformation has an inhibitory effect on corporate financial risks. In column (2), control variables are added in addition to digital transformation. The regression results again show that the coefficient of *DGG* is positive and significant at the 1% level. This finding further supports *Hypothesis 1*.

Table 4. The main effect of digital transformation on corporate financial risks

Variables	**(1)** ***FRZ***	**(2)** ***FRZ***
DGG	0.0649*** (0.00497)	0.0424*** (0.00365)
SIZE		0.0772*** (0.00537)
LEV		0.671*** (0.0382)
ROE		1.998*** (0.0548)
BS		0.00318 (0.0281)
ICR		0.00126*** (0.000115)
IGR		0.757*** (0.0888)
CR		0.0863*** (0.00453)
OC		0.00573*** (0.000287)
Rind		0.199*** (0.0340)

Table 4 (*continuation*). The main effect of digital transformation on corporate financial risks

Variables	(1) *FRZ*	(2) *FRZ*
SR		0.0331*** (0.0105)
Constant	1.148*** (0.0474)	0.582*** (0.176)
Year	YES	YES
Ind	YES	YES
Observations	19571	19571
R-squared	0.095	0.516

Note: ***, * *, and * respectively represent significant levels at 1%, 5%, and 10%.

Source: authors' own results.

3.4 Robustness Test

3.4.1 Alternative Explanatory Variables

This study employs alternative methods to re-measure the explanatory variables to mitigate potential bias stemming from the use of a single measurement approach.

Firstly, to address the bias introduced by using word frequency as a measure of digital transformation, this study follows the approach of Li and Zhou (2024) and replaces the continuous variable *(DGG)* with a binary variable (*DGG1*). In this case, a value of 1 indicates that digital transformation has occurred, while a value of 0 indicates that it has not. Secondly, to minimize the impact of subjective reporting on the word frequency statistics for digital transformation, this study adopts the methodology of Zhao *et al.* (2021), employing text analysis and expert scoring to construct a digital transformation index (*DGG2*) specifically for manufacturing enterprises. Lastly, to reduce the influence of a single data source on the measurement of digital transformation, this study draws upon the approach of Zhen *et al.* (2023), using the enterprise digital transformation index provided by the CSMAR database (*DGG3*) to assess the level of digital transformation.

The regression results presented in columns (1), (2), and (3) of *Table 5*, show significant positive coefficients at the 1% level for all three alternative measurements, confirming the robustness of the core conclusion.

3.4.2 Alternative Explained Variable

The Naive model proposed by Bharath and Shumway (2008) is used to calculate default risk distance (DD) as the dependent variable. The regression results, shown in column (4) of *Table 5*, are significantly positive at 10%. It further indicates that our core conclusion is valid.

Table 5. Alternative indicators

Variables	(1) *FRZ*	(2) *FRZ*	(3) *FRZ*	(4) *DD*
DGG1	0.0727*** (0.00927)			
DGG2		0.322*** (0.0365)		
DGG3			0.00351*** (0.000468)	

Table 5 (*continuation*). Alternative indicators

Variables	**(1)** ***FRZ***	**(2)** ***FRZ***	**(3)** ***FRZ***	**(4)** ***DD***
DGG				0.00467* (0.00258)
SIZE	0.0832*** (0.00534)	0.0811*** (0.00536)	0.0800*** (0.00540)	0.0374*** (0.00397)
LEV	-0.675*** (0.0384)	-0.672*** (0.0383)	-0.674*** (0.0383)	-1.500*** (0.0246)
ROE	1.993*** (0.0546)	1.998*** (0.0547)	1.999*** (0.0548)	0.0362* (0.0213)
BS	-0.00210 (0.0281)	-0.00258 (0.0280)	0.000910 (0.0281)	-0.00324 (0.0202)
ICR	0.00125*** (0.000114)	0.00126*** (0.000115)	0.00126*** (0.000115)	0.000633*** (8.32e-05)
IGR	-0.781*** (0.0890)	-0.765*** (0.0891)	-0.770*** (0.0891)	-0.471*** (0.0646)
CR	0.0867*** (0.00456)	0.0872*** (0.00453)	0.0863*** (0.00454)	0.0387*** (0.00289)
OC	0.00558*** (0.000287)	0.00550*** (0.000285)	0.00560*** (0.000286)	0.000980*** (0.000216)
Rind	-0.193*** (0.0339)	-0.198*** (0.0336)	-0.197*** (0.0339)	-0.0934*** (0.0230)
SR	-0.0352*** (0.0106)	-0.0328*** (0.0106)	-0.0342*** (0.0106)	0.120*** (0.0107)
Constant	0.471*** (0.175)	0.540*** (0.174)	0.457*** (0.175)	3.650*** (0.124)
Year	YES	YES	YES	YES
Ind	YES	YES	YES	YES
Observations	19,571	19,571	19,571	19,571
R-squared	0.514	0.514	0.514	0.474

Note: ***, * *, and * respectively represent significant levels at 1%, 5%, and 10%.

Source: authors' own results.

3.4.3 Influence of Different Types of Enterprise Digitization on Corporate Financial Risks

This study decomposes the digital transformation index into five components: artificial intelligence technology (*AI*), blockchain technology (*BCT*), cloud computing technology (*CCT*), big data technology (*BDT*), and digital technology applications (*DTA*). The empirical results, shown in *Table 6*, indicate that all five components have a positive impact on reducing corporate financial risks, with significance levels at 1% and 5%, respectively. These results further support our theoretical hypothesis.

Table 6. Classification test of digital transformation

Variables	**(1)** ***FRZ***	**(2)** ***FRZ***	**(3)** ***FRZ***	**(4)** ***FRZ***	**(5)** ***FRZ***
AI	0.0168*** (0.00607)				
BCT		0.0549** (0.0270)			
CCT			0.0400*** (0.00510)		

Table 6 (*continuation*). Classification test of digital transformation

Variables	(1) *FRZ*	(2) *FRZ*	(3) *FRZ*	(4) *FRZ*	(5) *FRZ*
BDT				0.0189*** (0.00542)	
DTA					0.0570*** (0.00432)
SIZE	0.0853*** (0.00539)	0.0867*** (0.00534)	0.0831*** (0.00535)	0.0846*** (0.00537)	0.0775*** (0.00535)
LEV	0.676*** (0.0384)	0.678*** (0.0384)	0.676*** (0.0383)	0.676*** (0.0384)	0.672*** (0.0382)
ROE	1.997*** (0.0547)	1.997*** (0.0547)	1.994*** (0.0548)	1.998*** (0.0548)	2.001*** (0.0546)
BS	0.00306 (0.0280)	0.00388 (0.0280)	0.00161 (0.0280)	0.00300 (0.0280)	0.000535 (0.0282)
ICR	0.00125*** (0.000115)	0.00125*** (0.000114)	0.00126*** (0.000115)	0.00126*** (0.000115)	0.00125*** (0.000114)
IGR	0.786*** (0.0892)	0.785*** (0.0893)	0.788*** (0.0891)	0.778*** (0.0892)	0.745*** (0.0886)
CR	0.0865*** (0.00455)	0.0866*** (0.00455)	0.0864*** (0.00453)	0.0867*** (0.00455)	0.0867*** (0.00454)
OC	0.00555*** (0.000288)	0.00551*** (0.000288)	0.00563*** (0.000288)	0.00556*** (0.000288)	0.00568*** (0.000287)
Rind	0.188*** (0.0336)	0.187*** (0.0336)	0.197*** (0.0336)	0.190*** (0.0336)	0.198*** (0.0340)
SR	0.0343*** (0.0106)	0.0350*** (0.0107)	0.0344*** (0.0106)	0.0342*** (0.0106)	0.0337*** (0.0106)
Constant	0.445** (0.174)	0.421** (0.174)	0.494*** (0.174)	0.460*** (0.174)	0.582*** (0.176)
Year	YES	YES	YES	YES	YES
Ind	YES	YES	YES	YES	YES
Observations	19571	19571	19571	19571	19571
R-squared	0.513	0.513	0.514	0.513	0.518

Note: ***, * *, and * respectively represent significant levels at 1%, 5%, and 10%.

Source: authors' own results.

3.4.4 PSM-DID.

At the end of 2015, the Ministry of Industry and Information Technology selected 25 cities, including Beijing and Tianjin, as information consumption demonstration cities based on an evaluation index system. In 2016, the Ministry launched the "National Information Consumption Demonstration City Construction Guide" (hereafter referred to as the Guide), which called for these cities to accelerate the upgrading of information infrastructure, enhance the digital and intelligent capacity of public services, and foster innovation in information technology. Following these directives, enterprises in the demonstration cities began to take the lead in digital transformation efforts starting in 2016, driven by central government policies. This provides a crucial time point for constructing a difference-in-differences model to explore the causal relationship between digital transformation and corporate financial risks.

Based on the classification method of Ma *et al.* (2023), this study designates enterprises in the demonstration cities as the treatment group and those outside as the control group. The indicator for group classification is defined as "*Treat.*" The introduction of the Guide serves as the policy intervention point, marked as "*Post*." The interaction term (*did*) between "*Treat*" and "*Post*" is used to capture the policy's effect. The model is specified as follows:

$$FRZ_{it} = \alpha_0 + \alpha_1 Treat_{it} * Post_{it} + \sum Control_{it} + \sum Year_t + \sum Ind_j + \varepsilon_{it} \quad (5)$$

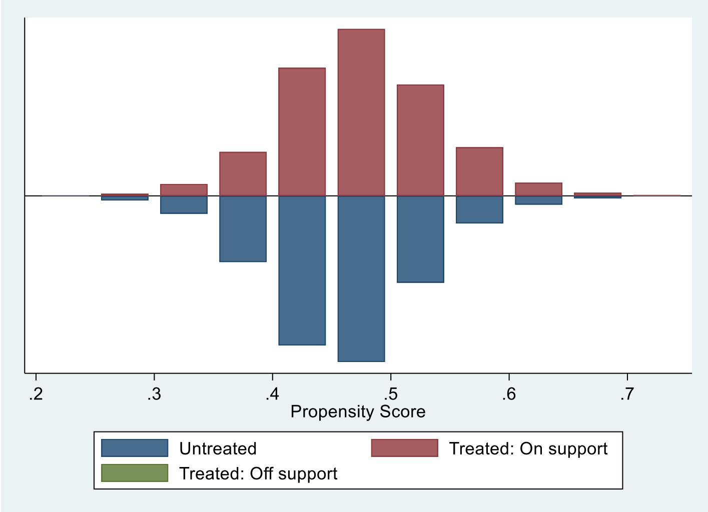
In this equation, $Treat_{it}$ is the identification for the experimental group, with a *Treat* value of 1 for the experimental group and 0 for the control group. $Post_{it}$ is a time-point variable, with a value of 1 in 2016 and beyond, and 0 before 2016. $Year_t$ and Ind_j represent fixed effects for year and industry, respectively.

Table 7. Balance test

Variables	Unmatched	Mean		%reduct		t-test	
	Matched	Treated	Control	%bias	|bias|	t	p>|tl
SIZE	U	15.733	15.643	9.7		6.81	0.000
	M	15.733	15.751	1.9	80.1	1.28	0.200
LEV	U	46318.	45496.	4.3		2.97	0.003
	M	46328.	46424.	0.5	88.3	0.33	0.744
ROE	U	0352.	03576.	0.3		0.21	0.834
	M	0352.	03698.	0.9	217.2	0.62	0.532
BS	U	2.2315	2.2479	9.5		6.65	0.000
	M	2.2315	2.232	0.3	97.0	0.19	0.851
ICR	U	11.365	11.424	0.1		0.10	0.917
	M	11.365	11.617	0.6	329.7	0.43	0.667
IGR	U	04098.	04812.	15.9		11.04	0.000
	M	04098.	04128.	0.7	95.8	0.47	0.635
CR	U	1.9894	1.8581	9.3		6.48	0.000
	M	1.9871	1.9722	1.0	88.7	0.67	0.504
OC	U	32.433	31.899	3.7		2.61	0.009
	M	32.431	32.415	0.1	97.0	0.08	0.940
Rind	U	3.6479	3.6389	6.5		4.52	0.000
	M	3.6479	3.6471	0.6	90.9	0.39	0.700
SR	U	13001.	12054.	1.7		1.18	0.238
	M	13008.	12667.	0.6	64.0	0.41	0.682

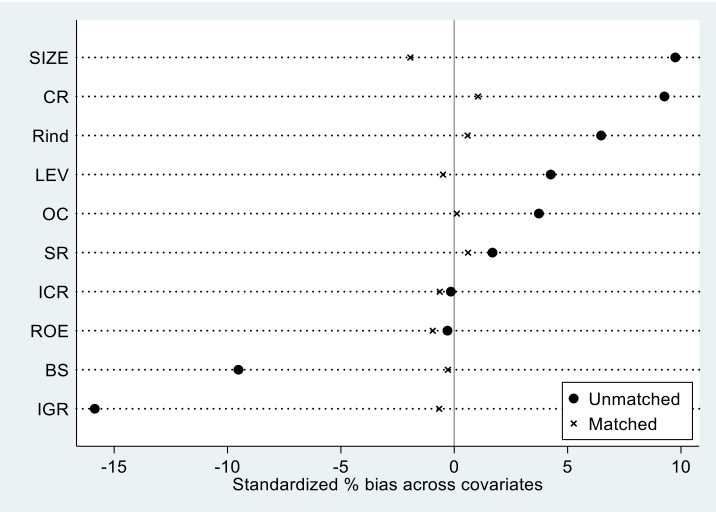
Source: authors' own results.

Table 7 presents the balance test results, showing that after matching the experimental and control groups with 10 covariates, the absolute bias values for all covariates are less than 10% and significantly lower than the %bias before matching. The absolute values of %bias decreased significantly by 64.0% to 97.0% compared to those before matching. After matching, the P-value of all covariates is greater than 0.05, indicating that all covariates do not reject the null hypothesis that "there is no systematic bias in the value of covariates between the two groups." *Figure 1* illustrates the regression results before and after matching, where "Unmatched" represents the regression result before matching and "Matched" represents the regression model after matching. The pseudo-R square in the regression result after matching is significantly smaller, indicating minimal differences in the values of all covariates between the two groups after matching, thereby reducing their explanatory power regarding changes in the dependent variables, which meets the test requirements. *Figure 2* shows that most samples from the experimental and control groups fall within the common range of values, with samples outside this range exhibiting more extreme propensity scores. In summary, the processed data are suitable for further analysis.



Source: authors' own results.

Figure 1. **Distribution of Propensity Score Values**



Source: authors' own results.

Figure 2. **Standardized Deviation Plot of Covariates**

Table 8 presents the empirical results after propensity score matching (PSM). Columns (1) to (4) report the results of fixed-effects regression, sample regression with non-empty weights, sample regression meeting the common support hypothesis, and frequency-weighted regression, respectively. In all four regressions, the core independent variables are significantly positive, and the coefficients in columns (2), (3), and (4) are similar to those in column (1). These findings indicate that the regression results remain robust after addressing partial sample selection bias.

Table 8. PSM-DID

Variables	(1) *FE*	(2) *Weight!=.*	(3) *On_Support*	(4) *Weight_Reg*
did	0.0279*** (0.0104)	0.0337*** (0.0117)	0.0280*** (0.0104)	0.0299*** (0.00992)
SIZE	0.0865*** (0.00535)	0.0917*** (0.00602)	0.0867*** (0.00535)	0.107*** (0.00464)
LEV	0.679*** (0.0384)	0.693*** (0.0429)	0.676*** (0.0385)	0.856*** (0.0337)
ROE	1.998*** (0.0547)	1.975*** (0.0598)	1.998*** (0.0547)	1.890*** (0.0438)
BS	0.00197 (0.0281)	0.00185 (0.0314)	0.00282 (0.0281)	0.0434* (0.0238)
ICR	0.00125*** (0.000115)	0.00123*** (0.000127)	0.00125*** (0.000115)	0.00131*** (9.73e-05)
IGR	0.788*** (0.0893)	0.723*** (0.102)	0.789*** (0.0893)	0.600*** (0.0812)
CR	0.0864*** (0.00456)	0.0872*** (0.00508)	0.0871*** (0.00457)	0.0752*** (0.00384)
OC	0.00550*** (0.000288)	0.00564*** (0.000324)	0.00550*** (0.000288)	0.00622*** (0.000252)
Rind	0.188*** (0.0335)	0.223*** (0.0382)	0.188*** (0.0335)	0.180*** (0.0275)
SR	0.0349*** (0.0106)	0.0416*** (0.0123)	0.0351*** (0.0106)	0.0556*** (0.00990)
Constant	0.425** (0.174)	0.472** (0.196)	0.424** (0.174)	0.00712 (0.143)
Year	YES	YES	YES	YES
Ind	YES	YES	YES	YES
Observations	19571	15369	19567	25749
R-squared	0.513	0.519	0.513	0.529

Note: ***, * *, and * respectively represent significant levels at 1%, 5%, and 10%.

Source: authors' own results.

3.4.5 Instrumental Variable

The average level of digital transformation within the same industry and region is chosen as the instrumental variable. Drawing on existing literature (Xiao *et al.*, 2022), this study uses the average digital transformation level of enterprises in the same industry and region (*DGG_AVE*) as the instrumental variable, adjusting for the enterprise's digital level in the previous period. The IV-2SLS method is then applied for re-estimation.

Table 9 reports the results of the 2SLS regression. In the first-stage regression, the coefficient for *DGG_AVE* is significantly positive at the 1% level, indicating that the chosen instrumental variables meet the correlation condition. Additionally, the P-value for the unidentifiable test in the first stage is 0, and the F-statistic is substantially higher than the empirical rule of 10, suggesting that the instrumental variables are sufficiently recognized and not weak, thus supporting the validity of the chosen instrumental variables.

Table 9. Regression of instrumental variables

Variables	First stage *DGG*	IV Exclusivity *FRZ*	Second stage *FRZ*
DGG		0.0544*** (0.0148)	0.0346*** (0.00415)
DGG_AVE	0.472*** (0.0136)		0.00936 (0.00745)
SIZE	0.235*** (0.0110)	0.0625*** (0.00665)	0.0671*** (0.00574)
LEV	0.0254 (0.0673)	0.630*** (0.0409)	0.631*** (0.0410)
ROE	0.105* (0.0553)	2.048*** (0.0606)	2.046*** (0.0607)
BS	0.132** (0.0616)	0.0281 (0.0311)	0.0255 (0.0311)
ICR	0.000195 (0.000228)	0.00114*** (0.000117)	0.00114*** (0.000116)
IGR	1.263*** (0.189)	0.834*** (0.0948)	0.859*** (0.0934)
CR	0.00626 (0.00814)	0.0876*** (0.00458)	0.0877*** (0.00458)
OC	0.00400*** (0.000607)	0.00511*** (0.000314)	0.00504*** (0.000306)
Rind	0.0965 (0.0725)	0.205*** (0.0382)	0.203*** (0.0379)
SR	0.0626*** (0.0190)	0.0264** (0.0112)	0.0276** (0.0112)
Constant	3.845*** (0.369)	0.619*** (0.208)	0.543*** (0.197)
Year	YES	YES	YES
Ind	YES	YES	YES
Kleibergen-Paap rkLM P value	0.000		
Kleibergen-Paap rk Wald F	1204.69		
Observations	16488	16488	16488
R-squared	0.468	0.517	0.518

Note: ***, * *, and * respectively represent significant levels at 1%, 5%, and 10%.

Source: authors' own results.

Furthermore, after directly introducing *DGG_AVE* into the benchmark regression equation, the influence coefficient of this instrumental variable on *FRZ* does not reject the null hypothesis. This demonstrates that the instrumental variable is not related to the error term of the benchmark regression equation and does not affect *FRZ* through any channel other than its influence on *DGG*. Hence, the instrumental variable meets the exclusion restriction condition.

The second-stage regression results show that the semi-elastic estimate of *FRZ* for *DGG* is 0.0544, rejecting the null hypothesis at the 1% significance level. This indicates that, all else being equal, for the sample of firms effectively influenced by the instrumental variables, a 1 standard deviation (0.0148) increase in *DGG* will, on average, increase *FRZ* by 0.0805%.

3.4.6 Alternative Model

To further address the issue of endogeneity, multidimensional fixed effects are employed to minimize biases arising from omitted variables. This study utilizes a more stringent fixed effects model for regression, including both province-time dual fixed effects and time-province-industry triple fixed effects (Xu, 2018). *Table 10* presents the test results, demonstrating that digital transformation continues to reduce corporate financial risks effectively.

Table 10. Robustness tests: Alternative model

Variables	(1) *FRZ*	(2) *FRZ*	(3) *FRZ*
DGG	0.0101** (0.00454)	0.0369*** (0.00338)	0.0378*** (0.00365)
SIZE	0.118*** (0.00918)	0.0663*** (0.00559)	0.0779*** (0.00534)
LEV	0.952*** (0.0508)	0.607*** (0.0360)	0.615*** (0.0379)
ROE	1.450*** (0.0442)	2.020*** (0.0550)	1.979*** (0.0535)
BS	0.0416 (0.0383)	0.00899 (0.0304)	0.0374 (0.0279)
ICR	0.000814*** (7.62e-05)	0.00136*** (0.000118)	0.00124*** (0.000112)
IGR	0.471*** (0.0815)	0.877*** (0.0889)	0.815*** (0.0879)
CR	0.0699*** (0.00458)	0.0925*** (0.00440)	0.0902*** (0.00444)
OC	0.00457*** (0.000630)	0.00516*** (0.000304)	0.00568*** (0.000285)
Rind	0.0511 (0.0348)	0.214*** (0.0389)	0.194*** (0.0338)
SR	0.0233*** (0.00740)	0.0351*** (0.0107)	0.0372*** (0.0105)
Constant	1.171*** (0.258)	0.845*** (0.195)	0.478*** (0.175)
Year	YES	YES	YES
Code	YES	NO	NO
Prov	NO	YES	YES
Ind	NO	NO	YES
Observations	19571	19571	19571
R-squared	0.852	0.469	0.533

Note: ***, * *, and * respectively represent significant levels at 1%, 5%, and 10%.

Source: authors' own results.

4. Mechanism Analysis

4.1 Analyst Following

Table 11 presents the identification test results of the mediation effect test on analyst following. The data indicate that *DGG* has a significant positive impact on Ana, with a coefficient of 0.0547, which is significant at the 1% level and passing the Sobel test. This finding demonstrates that analyst following partially mediates the relationship between digital transformation and corporate financial risks. Based on the above analysis, it can be concluded that digital transformation can improve analyst following, enhance the supply efficiency of professional financial information, and increase public scrutiny of firms. This heightened scrutiny, in turn, encourages firms to improve internal governance and mitigate corporate financial risks. This finding supports the core mechanism that digital transformation impacts corporate financial risks through external information channels. Therefore, companies should actively consider the suppressive effect of efficient and objective reporting by analysts on financial risks after undergoing digital transformation.

Table 11. The mediation effect test that analysts following

Variables	**(1)** ***Ana***	**(2)** ***FRZ***
DGG	0.0547*** (0.00548)	0.0363*** (0.00358)
Ana		0.113*** (0.00462)
SIZE	0.799*** (0.00709)	0.0128** (0.00629)
LEV	0.234*** (0.0474)	0.645*** (0.0375)
ROE	0.689*** (0.0425)	1.920*** (0.0531)
BS	0.0383 (0.0430)	0.00749 (0.0274)
ICR	0.00113*** (0.000174)	0.00113*** (0.000109)
IGR	3.754*** (0.142)	1.179*** (0.0884)
CR	0.00192 (0.00621)	0.0865*** (0.00439)
OC	0.00335*** (0.000449)	0.00611*** (0.000284)
Rind	0.191*** (0.0537)	0.178*** (0.0325)
SR	0.105*** (0.0135)	0.0213** (0.0105)
Constant	9.753*** (0.271)	1.680*** (0.173)
Year	YES	YES
Ind	YES	YES
Sobel test	0.000***(Z=9.326)	
Observations	19571	19571
R-squared	0.499	0.531

Note: ***, * *, and * respectively represent significant levels at 1%, 5%, and 10%.

Source: authors' own results.

4.2 Information Transparency

Table 12 presents the identification test results of the mediation effect test on information transparency. The data reveal that *DGG* significantly impacts Info, with a coefficient of 0.0534, significant at the 1% level, and passing the Sobel test. This confirms that information transparency is an effective intermediary variable, partially mediating the relationship between digital transformation and corporate financial risks.

Table 12. The mediating effect of information transparency

Variables	(1) *Info*	(2) *FRZ*
DGG	0.0534*** (0.00685)	0.0400*** (0.00362)
Info		0.0458*** (0.00341)
SIZE	0.0387*** (0.0109)	0.0789*** (0.00535)
LEV	0.872*** (0.0667)	0.631*** (0.0380)
ROE	0.671*** (0.0423)	1.967*** (0.0544)
BS	0.139** (0.0608)	0.00955 (0.0280)
ICR	0.000621*** (0.000197)	0.00123*** (0.000114)
IGR	3.526*** (0.193)	0.918*** (0.0885)
CR	0.0396*** (0.00791)	0.0844*** (0.00451)
OC	0.00133** (0.000654)	0.00567*** (0.000287)
Rind	0.0640 (0.0678)	0.196*** (0.0338)
SR	0.0987*** (0.0188)	0.0377*** (0.0107)
Constant	2.557*** (0.375)	0.465*** (0.175)
Year	YES	YES
Ind	YES	YES
Sobel test	0.000***(Z=6.341)	
Observations	19571	19571
R-squared	0.252	0.521

Note: ***, * *, and * respectively represent significant levels at 1%, 5%, and 10%.

Source: authors' own results.

Based on this analysis, it can be concluded that by enhancing information transparency, digital transformation reduces internal information asymmetry and mitigates the sudden release of negative news. This helps alleviate corporate financial risks related to factors such as agency costs and stock price crashes. Therefore, digital transformation enables enterprises to reduce the accumulation of negative information, effectively controlling their corporate financial risks.

5. Heterogeneity Test

5.1 Technological Attributes

Considering the resource endowment of digital transformation, the technological attributes of enterprises significantly influence their impact on corporate financial risks, resulting in notable differences between high-tech and non-high-tech enterprises. Non-high-tech enterprises typically follow an extensive growth model, driving economic growth through increased inputs of production factors such as land, labor, and raw materials. However, this growth model consumes substantial resources and often fails to improve product quality or enhance economic benefits, making it difficult to achieve significant competitive advantages. Therefore, when non-high-tech enterprises undergo digital transformation, it is more likely to unlock their development potential and effectively reduce corporate financial risks. Based on this reasoning, digital transformation is expected to have a more pronounced effect on reducing corporate financial risks in non-high-tech enterprises.

Table 13. Heterogeneity test: Technology attributes

Variables	**(1) Non-high-tech** ***FRZ***	**(2) High and new tech** ***FRZ***
DGG	0.0809*** (0.00719)	0.0231*** (0.00421)
SIZE	0.0907*** (0.00918)	0.0682*** (0.00663)
LEV	0.710*** (0.0591)	0.619*** (0.0504)
ROE	1.726*** (0.0769)	2.195*** (0.0758)
BS	0.0511 (0.0455)	0.0263 (0.0361)
ICR	0.00172*** (0.000217)	0.00105*** (0.000129)
IGR	0.458*** (0.154)	0.974*** (0.105)
CR	0.105*** (0.0101)	0.0820*** (0.00519)
OC	0.00535*** (0.000475)	0.00589*** (0.000354)
Rind	0.159*** (0.0531)	0.235*** (0.0441)
SR	0.0609*** (0.0192)	0.0204 (0.0126)
Constant	0.249 (0.279)	1.078*** (0.222)
Year	YES	YES
Ind	YES	YES
Observations	7818	11753
R-squared	0.510	0.529
Coefficient group difference test P-value	0.000	

Note: ***, * *, and * respectively represent significant levels at 1%, 5%, and 10%. The P-value of the inter-group difference test of coefficients for heterogeneity analysis is calculated using the Fischer combination test (sampling 5000 times).

Source: authors' own results.

To further explore this difference, this study follows the classification methods of Wang *et al.* (2023), categorizing enterprises into high-tech and non-high-tech industries for heterogeneity analysis. The results, shown in *Table 13*, indicate that digital transformation significantly reduces corporate financial risks in both high-tech and non-high-tech enterprises. However, the coefficient difference test between groups is significant at the 1% level, suggesting that digital transformation substantially reduces corporate financial risks for non-high-tech enterprises compared to high-tech enterprises. This discrepancy can be attributed to the inherent familiarity of high-tech enterprises with advanced digital concepts, which already enhance their operational efficiencies before digital transformation. In contrast, non-high-tech enterprises often lack prior exposure to digital technologies and experience greater flexibility and benefits from digital adoption.

This insight is crucial for enterprise decision-makers. Although high-tech enterprises may have certain advantages in digital technology, further deepening their digital transformation still has a restraining effect on corporate financial risks. Therefore, the necessity of further advancing digital transformation should not be overlooked, despite the existing foundation. On the other hand, non-high-tech enterprises must recognize their digital technology shortcomings, introduce and apply digital technology in a targeted manner, and gradually build and improve their digital systems.

5.2 Factor Intensive

Industry-specific factors lead to varying impacts of digital transformation on corporate financial risks. For capital- and technology-intensive firms, development relies more on data-driven approaches. By integrating emerging digital technologies, these enterprises can significantly enhance the responsiveness of their industrial chain's front-end, mid-end, and back-end (Wang *et al.*, 2024), thereby boosting overall enterprise value. In contrast, labor-intensive industries rely less on technological innovation, leading to a weaker demand for digital technologies in their development process.

Table 14. Heterogeneity test: factor intensive

Variables	(1) Non-labor *FRZ*	(2) Labor *FRZ*	(3) Non-capital *FRZ*	(4) Capital *FRZ*	(5) Non-technology *FRZ*	(6) Technical *FRZ*
DGG	0.0456*** (0.00375)	0.00547 (0.0163)	0.0583*** (0.00557)	0.0305*** (0.00474)	0.0583*** (0.00557)	0.0305*** (0.00474)
SIZE	0.0650*** (0.00544)	0.226*** (0.0235)	0.0676*** (0.00741)	0.0937*** (0.00788)	0.0676*** (0.00741)	0.0937*** (0.00788)
LEV	0.639*** (0.0390)	1.097*** (0.183)	0.703*** (0.0498)	0.615*** (0.0581)	0.703*** (0.0498)	0.615*** (0.0581)
ROE	1.996*** (0.0554)	1.977*** (0.307)	1.892*** (0.0635)	2.196*** (0.106)	1.892*** (0.0635)	2.196*** (0.106)
BS	0.0182 (0.0291)	0.237** (0.107)	0.0510 (0.0365)	0.0938** (0.0433)	0.0510 (0.0365)	0.0938** (0.0433)
ICR	0.00125*** (0.000120)	0.00123*** (0.000355)	0.00136*** (0.000153)	0.00109*** (0.000172)	0.00136*** (0.000153)	0.00109*** (0.000172)
IGR	0.907*** (0.0895)	1.110*** (0.415)	0.555*** (0.121)	1.081*** (0.120)	0.555*** (0.121)	1.081*** (0.120)
CR	0.0882*** (0.00455)	0.0627** (0.0275)	0.101*** (0.00728)	0.0764*** (0.00566)	0.101*** (0.00728)	0.0764*** (0.00566)
OC	0.00549*** (0.000287)	0.00865*** (0.00155)	0.00547*** (0.000384)	0.00604*** (0.000410)	0.00547*** (0.000384)	0.00604*** (0.000410)

Note: ***, * *, and * respectively represent significant levels at 1%, 5%, and 10%. The P-value of the inter-group difference test of coefficients for heterogeneity analysis is calculated using the Fischer combination test (sampling 5000 times).

Source: authors' own results.

To further discuss this issue, this study follows the research method of Liang and Sun (2024), classifying sample firms according to the factor intensity of the two-digit subdivisions of the manufacturing industry, based on the Guidance on Classification of Listed Companies issued by the China Securities Regulatory Commission in 2012. The classifications include labor-intensive, capital-intensive, and technology-intensive industries. *Table 14* presents the regression results of factor-intensive heterogeneity. Column (1) represents non-labor-intensive, column (2) labor-intensive, column (3) non-capital-intensive, column (4) capital-intensive, column (5) non-technology-intensive, and column (6) technology-intensive enterprises. The empirical analysis results indicate that digital transformation significantly reduces corporate financial risks for capital-intensive and technology-intensive enterprises (significant at the 1% level in column [1]), but not for labor-intensive enterprises (column [2]). The regression and Sobel test results in columns (3) to (6) further support this conclusion. However, digital transformation does not significantly impact corporate financial risks for labor-intensive firms. This may be because companies in technology- and capital-intensive industries mainly export products, and digital transformation helps them more accurately understand customer needs, enhancing corporate performance and effectively reducing corporate financial risks. In contrast, digital transformation may not significantly improve the human resource structure of labor-intensive enterprises, as they primarily rely on low-skilled labor. Therefore, targeted digital transformation strategies should be adopted for different factor-intensive enterprises. For labor-intensive enterprises, digital transformation can focus on re-engineering and optimizing business processes, improving overall operational efficiency by introducing digital management systems. For technology-intensive and capital-intensive enterprises, advanced technologies such as big data and artificial intelligence can deepen insights into customer needs and market trends, enhancing competitiveness and reducing corporate financial risks.

6. Discussions

As governments and firms increasingly prioritize digital transformation, it is seen as an effective means for resource acquisition and transformative innovation. They expect digital transformation to enhance corporations' capacity to resist risks. The empirical results of this study show that digital transformation can effectively reduce corporate financial risks, with the pathway being facilitated through increased analyst following and improved information transparency. In non-high-tech and non-labor-intensive enterprises, digital transformation has a more pronounced inhibitory effect on corporate financial risks. The key findings discussed in this study can be summarized as follows:

Firstly, the higher the degree of digital transformation is, the smaller the corporate financial risks. This finding supports the conclusion of Wang *et al.* (2022) regarding the negative correlation between digital transformation and debt default risk. The regression results of control variables indicate that an increase in enterprise size, return on equity, interest coverage ratio, liquidity ratio, and ownership concentration can significantly reduce the financial risk ratio of corporates. These results align with the research conclusions of Zhao *et al.* (2024). Moreover, from the perspective of different digital transformation categories, the greater the application of artificial intelligence, blockchain, cloud computing, big data, and other digital technologies, the lower the corporate financial risks. These results both support the main hypothesis and complement gaps in previous studies, demonstrating that different types of digital technologies can provide positive feedback, ultimately reducing corporate financial risks.

Secondly, the inhibition effect of digital transformation on corporate financial risks can be realized in two ways: by increasing analyst following and improving information transparency. From the external oversight perspective, digital transformation significantly increases analyst following. As discussed by Roeder *et al.* (2022), a higher degree of analyst following leads to more comprehensive external supervision of the enterprise, signaling its good development to the outside world. This, in turn, enables the enterprise to gain more stakeholder trust, improve resource acquisition, and enhance performance, thereby reducing corporate financial risks. Additionally, from the perspective of internal disclosure, the continuous improvement of information technology through digital transformation significantly enhances the quality of information disclosure, reduces information asymmetry, facilitates better risk identification, and strengthens the financial risk resilience of corporations. This finding also supports the findings of Abiodun *et al.* (2023) on industrial digital transformation.

Lastly, from the perspective of enterprise heterogeneity, digital transformation in non-high-tech and non-labor-intensive enterprises effectively reduces corporate financial risks. This is because these enterprises have greater access to and reliance on capital and technology. Digital transformation helps improve their technical capabilities, while also gaining more policy and institutional support, yielding more significant benefits and fostering sustainable competitiveness. Consequently, enterprises that pursue technological renewal, resource acquisition, and competitiveness through digital transformation can reduce their financial risks and are more inclined to continue their transformation, thereby creating a virtuous cycle.

Conclusions and Implications

Main Findings

Based on data from China's A-share listed companies from 2011 to 2022, this study conducts an in-depth analysis from multiple dimensions, including the direct impact of digital transformation on corporate financial risks, the mechanisms underlying digital transformation, and heterogeneity analysis based on different corporate characteristics. The research findings indicate that: first, digital transformation significantly reduces corporate financial risks. This conclusion holds even after various robustness tests and endogeneity analyses, such as changes in variable measurement methods, the adoption of the PSM-DID method, and instrumental variable regression. Second, from a mechanism perspective, analyst following can enhance the efficiency of information interpretation and strengthen external supervision, while information transparency helps reduce the cascade effect of corporate information and prevents the accumulation of bad information. Both factors thus act as intermediaries between digital transformation and corporate financial risks. Finally, differences in corporate attributes lead to heterogeneity in the impact of digital transformation on corporate financial risks. Specifically, the inhibition effect of digital transformation on corporate financial risks is more pronounced in non-high-tech and non-labor-intensive enterprises.

Managerial Implications

First, enterprises should develop clear digital transformation strategies that align with their overall development goals. During the transformation process, it is crucial to strengthen data management and build robust information systems to ensure data accuracy, completeness, and timeliness. Additionally, enterprises should introduce advanced data analysis tools and technologies to enhance data processing and analysis capabilities. A sound information disclosure mechanism must be established to provide timely and accurate reports on financial status, operational results, and other major corporate matters. Enterprises should also provide convenient channels for information access, such as official websites and social media platforms, to facilitate analysts and investors in obtaining relevant enterprise information. This will help strengthen internal governance and risk management, ensuring the stability and sustainability of business operations. To continuously improve digital transformation efforts, enterprises should implement a feedback mechanism that collects and analyzes feedback from analysts, investors, employees, and other stakeholders, ensuring that the transformation results align with expectations.

Second, high-tech and non-labor-intensive enterprises should leverage the resources and information advantages offered by digital transformation to optimize their financial management processes, ensuring long-term sustainability and efficiency. On the other hand, non-high-tech and labor-intensive enterprises should clarify their strategic positioning in digital transformation and select transformation paths that align with their specific characteristics. These enterprises can mitigate the negative impact of the early stages of digital transformation by innovating traditional production models, enhancing information infrastructure, and optimizing human resource allocation.

Finally, from a policy perspective, the government should provide more targeted guidance to help enterprises implement digital strategies effectively and stimulate innovation. Given the challenges faced by some enterprises in digital transformation, such as high financial pressure and limited professional support, the government should offer tailored measures based on local industrial characteristics and enterprises' needs. These measures could include financial subsidies, tax incentives, and technical support, which would promote the successful implementation of digital transformation strategies, enhance business performance, reduce corporate financial risks, and help enterprises achieve high-quality development.

Limitations and Future Directions

Despite the contributions of this study, several limitations remain, and further expansion and improvement are needed. First, from a management and regulatory perspective, this study examines how digital transformation impacts corporate financial risks through internal and external supervision. Future research can expand this analysis by exploring the mechanisms of risk avoidance from a value creation perspective, such as investigating the effects of digital transformation on innovation capabilities and supply chain efficiency. Second, this study employs text analysis to measure digital transformation indicators; however, this method may be influenced by factors such as corporate characteristics and the policy environment. Therefore, future research could explore more objective and robust measures of digital transformation, such as statistical data on asset size or enterprise surveys. Third, the sample data selection in this study has certain limitations, and may not fully reflect the impact of digital transformation on corporate financial risks outside of China. Future studies could incorporate listed companies from other countries or regions with advanced digital transformation to enhance the generalizability and robustness of the findings.

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AR SKAITMENINĖ TRANSFORMACIJA MAŽINA ĮMONIŲ FINANSINĘ RIZIKĄ? DVEJOPA VIDAUS INFORMACIJOS ATSKLEIDIMO IR IŠORĖS PRIEŽIŪROS PERSPEKTYVA

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Santrauka. Skaitmeninės technologijos sukelia naują technologinių inovacijų ir transformacijos bangą. Tačiau esamoje literatūroje nepateikta sisteminių teorinių įžvalgų apie tai, ar skaitmeninė transformacija gali sumažinti įmonių finansinę riziką. Siekiant ištirti ryšį tarp skaitmeninės transformacijos ir įmonių finansinės rizikos, remiantis ištekliais pagrįsta teorija ir signalizacijos teorija, skaitmeninės transformacijos poveikis įmonių finansinei rizikai buvo analizuojamas pasitelkus A akcijų biržoje kotiruojamų įmonių Kinijoje imtį 2011–2022 m. Rezultatai atskleidė, kad vidaus informacijos atverties ir išorės priežiūros požiūriu skaitmeninė transformacija mažina finansinę riziką visų pirma didindama analitikų sekimą ir informacijos skaidrumą. Tolesnė analizė atskleidžia, kad slopinantis skaitmeninės transformacijos poveikis finansinei rizikai yra ryškesnis ne aukštųjų technologijų ir ne darbo jėgos reikalaujančiose įmonėse. Šio tyrimo išvadose pateikiami nauji empiriniai įrodymai apie tai, kaip skaitmeninė transformacija gali sumažinti įmonių finansinę riziką. Siūlomos teorinės gairės ir strateginė parama suinteresuotiems subjektams, kad jie galėtų priimti konkrečioms vietovėms skirtas skaitmeninės transformacijos strategijas, pagrįstas jų ištekliais ir rinkos aplinka.

Reikšminiai žodžiai: skaitmeninė transformacija; finansinė rizika; analitikų susirūpinimas; informacijos skaidrumas.