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The Impact of Firm Digital Transformation on Financing Constraints: Evidence from China

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Abstract

This study examines the impact of digital transformation (DT) on financing constraints (FC) in Chinese A-share listed companies on the Shanghai and Shenzhen Stock Exchanges from 2010 to 2023. It uses the SA index as a proxy for FC and the frequency of keyword indicators in annual reports, across five core technologies: artificial intelligence, blockchain, cloud computing, big data, and digital applications. Using fixed-effects regression with Driscoll-Kraay standard errors, the results show that DT has a strong negative relationship with FC, with a coefficient significant at the 1% level. Additionally, being a state-owned enterprise (SOE) and owning shares in other financial institutions each has a significant negative impact at the 1% level. CEO duality and profit volatility (PV) have positive impacts, significant at 5% and 1%, respectively. A clean audit opinion negatively affects FC at the 10% level. Inflation rate positively influences FC, while GDP growth rate negatively influences FC, each at the 1% significance level. Furthermore, the findings indicate that DT moderates the link between PV and FC. The findings are robust to the use of the Whited-Wu index as an alternative measure of FC and apply a one-period lag to check for the causality effect. Further analysis reveals that artificial intelligence, cloud computing, big data, and digital applications significantly reduce FC, whereas blockchain's effect is insignificant. The study concludes that strategic investment in digital technology is an effective approach for enhancing access to external capital and mitigating the positive influence of PV on FC. Future studies could examine the different impacts across industries and explore the long-term impact of DT on financial stability and sustainable growth.

Keywords: Financing constraints, Digital transformation, holding shares of other financial institutions, SOE, Auditor opinion, CEO duality, profit volatility, inflation rate, GDP growth rate, information asymmetry

Introduction

Digital transformation (DT) has become a key stage for China and the global economy (Fang et al., 2023). According to the Digital China Development Report, China's digital economy in 2022 grew to 50.2 trillion RMB, making up 41.5% of GDP, which is a 10.3% increase from the previous year (Wei & Li, 2024; Xu, 2024). Enterprises play a vital role in driving the digital economy forward. As a leading force in DT, Chinese companies have made significant progress. In particular, 81.6% of Chinese firms are undergoing DT (Liao et al., 2023). Additionally, the government actively invests in developing infrastructure and encourages a coordinated effort to promote DT across all sectors, which is the main driver behind the increasing digitalization of the economy (Chen et al., 2024).

The adoption of advanced digital technologies, which this study focuses on the integration of artificial intelligence, big data, cloud computing, blockchain, and digital applications into business operations, has become a new driver for business growth and competitiveness. In China, especially among A-share listed companies, there is increasing interest in understanding how digital transformation (DT) impacts business financing, given the strategic need to strengthen competitive advantages amid global economic uncertainties and technological advancements (Bo et al., 2025).

A financing constraint (FC) refers to a situation where a company struggles to raise capital from external sources, such as the issuance of equity and debt securities. This issue is especially critical in emerging markets like China, where financial markets are still developing. The World Bank's Global Business Environment Report 2019 ranked China 80th out of 190 countries for enterprise access to credit, with 75% of Chinese non-financial companies facing FC, which significantly hampers their growth (Wang et al., 2021). Therefore, studying factors that can ease FC is essential.

Several studies have attempted to explore the impact of DT on FC. However, there are three main shortcomings: (1) Some of them, like the study conducted by Guo et al. (2024) failed to examine the impact of individual advanced technologies separately, which would have provided more insights. (2) In other studies, such as Gao et al. (2024) and Guo et al. (2024), the control variables are often chosen without proper caution; for example, the use of firm size and age as controls when the same size and age factors are included in constructing the size-age (SA) index used to measure FC. This causes severe overfitting of the model and diminishes the analysis's meaningfulness. (3) Others demonstrate methodological rigor, such as the study by Bo et al. (2025), which addresses the previous issues; however, it does not perform essential data diagnostic tests like heteroscedasticity, serial correlation, cross-sectional dependence, and normality. Ignoring these crucial tests undermines the assurance of the regression's validity.

This study aims to address the limitations identified in previous research on this topic. It employs a two-step approach: first, it assesses the overall impact of digitalization; second, it breaks down this influence to highlight the specific roles of five key technologies—artificial intelligence, blockchain, cloud computing, big data analysis, and digital applications. The study systematically incorporates exogenous variables into the model and conducts thorough data diagnostic tests. The results could benefit managers and policymakers by providing insights showing that strategic investments in digital technology can lower barriers to external capital access. Additionally, it offers empirical evidence of the relationship between information management and corporate finance and can serve as a foundation for future studies.

Literature Review

DT is a process where organizations adopt and integrate digital technologies to increase productivity, create value, and improve social welfare. Worldwide, DT initiatives are expanding quickly. For example, in the USA and the UK, 94% of large companies have a DT strategy, and spending on DT is projected to reach $3.9 trillion by 2027, up from $2.5 trillion in 2024. The regional statistics for global DT spending in 2023 indicate that the USA, Western Europe, and China account for 35.8%, 22.7%, and 16.8%, respectively (BacklincoTeam, n.d.). This growth is driven by progress in cloud infrastructure, IoT, and 5G connectivity. Other significant trends in digitalization include robotic process automation, a move toward cloud and edge computing, and advancements toward upcoming connectivity (6G and 7G). Besides adopting digital technology, it is vital to focus on empowering employees, enhancing customer satisfaction through hyper-customization, and building collaborative ecosystems to leverage its benefits fully (Wei & Li, 2024).

The benefits of DT are wide-ranging, including increased efficiency and profits, reduced costs through streamlining and automation, better customer experience via virtual interactions, and personalized support based on data insights. This is vital for maintaining and gaining a competitive advantage, encouraging innovation, and developing new business

models. It also improves labor productivity through automation and boosts security with advanced safeguards (Yan et al., 2025).
While offering many benefits, the DT also brings challenges like significant infrastructure costs, ethical issues about data privacy, and complicate regulatory system (Ahomed, 2020).

Financing constraints (FC) refer to the difficulties an enterprise faces in obtaining capital from capital markets due to market imperfections, including information asymmetry, agency problems, and high transaction costs. These issues make external capital expensive or even inaccessible. FC hinders firms' ability to invest in high-return projects and their growth (Rajan et al., 2000). Especially Small and medium-sized businesses (SMEs) and younger companies face more constraints because they often have less tangible collateral, a shorter track record, or a higher risk profile (Szabo, 2016). During economic crises, these restrictions become even more severe (Fazzari et al., 1996).

To measure FC, researchers use various methods, including the sensitivity of investment to cash flow used by Fazzari et al. (1987), the KZ index used by Kaplan and Zingales (2000), the Whited-Wu index developed by Whited and Wu (2006), and the SA (Size-Age) index developed by (Hadlock & Pierce, 2010). These indices measure the FC from different perspectives.

Information asymmetry exists when one party in an exchange has more or better information than the other (Afzal, 2015). This idea has been important in economics since the 1970s because of key works by Akerlof, Spence, and Stiglitz, which show how unequal information distribution can distort markets (Lofgren et al., 2002; Rosser, 2003). Akerlof's famous "The Market for Lemons" paper demonstrates this by showing how a lack of information about a product's quality can affect market performance (Akerlof, 1970). Information asymmetry affects several decisions (Tilles et al., 2011). It appears as adverse selection, where hidden information before a deal leads to poor choice, and moral hazard, a situation that provides an incentive to take more risk by one party knowing that the other party bears the full cost (Afzal, 2015). Monopolies on knowledge also amplify these problems, as sole control of information by one party creates an imbalance (Hanks, 2005; Spence, 2002).

The methods to reduce information asymmetry include signaling, where informed parties convey signals, and screening, where less informed parties create methods to gather private information. (Connelly et al., 2011). Setting mandatory disclosures, offering guarantees, and providing incentives are also used to minimize the gap.

Digitalization improves the quality and timeliness of companies' financial reporting systems. This narrows the information gap between company managers and capital providers, such as investors and creditors. As a result, it lowers perceived risk (or boosts investor confidence), which makes raising external capital easier. Therefore, this study hypothesizes:

H1: A firm's DT significantly reduces FC by lowering the information asymmetry between managers and external capital providers, and
H2: DT moderates the impact of profit volatility on FC.

The study uses historical data from Chinese A-share listed companies on the Shanghai and Shenzhen Stock Exchanges. Data is collected from the China Stock Market and Accounting Research (CSMAR) database, which is a comprehensive and reliable dataset commonly used in research on Chinese firms.

Methodology

Sample selections are based on strict criteria to ensure quality. First, securities that have been in special treatment (ST), suspended from trade (ST*), or placed under particular transfer (PT) status are excluded because they indicate financial distress or unusual business conditions that could bias the results. Second, to reduce the influence of extreme outliers that could skew outcomes, all continuous variables are winsorized at the 1st and 99th percentiles.

The study period spans from 2010 to 2023, offering a snapshot of China's significant progress in digital transformation. 2010 marked the year when major industrial nations began implementing digitalization programs—such as the Advanced Manufacturing Partnership in the USA, Industry 4.0 in Germany, and the Industrial Value Chain strategy in Japan. During this time, China transitioned from a "world factory" to an industrial manufacturing powerhouse, driving strong demand for Digital Transformation (DT) across various industries (Guo & Xu, 2021). The initial efforts to promote the integration of informatization and industrialization began around 2010, and in 2015, the Made in China 2025 strategy was introduced, emphasizing smart manufacturing. The study period is limited to 2023 because data on digital transformation for 2024 had not yet been released during the study.

The resulting final sample is an unbalanced panel data set, which captures variations in firm entry and exit over the study period. This strategy aims to utilize available information as fully as possible while maintaining high-quality data standards. The statistical software used for analysis is Stata 17.

The SA (Size-Age) index is the dependent variable of the analysis, which serves as a proxy for FC. The index was developed by Hadlock and Pierce (2010). Compared to other indices, such as the KZ index, the SA index is preferred as it avoids issues of endogeneity inherent in the other indices that use multiple financial metrics for computation (Bo et al., 2025). The SA index exclusively uses a firm's size and age—two exogenous factors that are less susceptible to inverse causation—rendering it a more robust proxy for financing constraints. It is computed as follows:

$$SA_{i,t} = -0.737 * size_{i,t} + 0.043 * size^2{}_{i,t} - 0.04 * age_{i,t} \quad (1)$$

Where:
size : Natural logarithm of total assets
age : Years in business, which is computed by subtracting the company incorporation date (year) from the observation year (current accounting period)
High value indicates high constraints.

To measure the level of digital transformation (DT) of firms, this study uses the frequency of keywords DT indicators in annual reports, a methodology initially applied by (Wu et al., 2021).

In the database, a company's DT level is categorized into artificial intelligence technology, blockchain technology, cloud computing technology, big data technology, and digital technology applications. With reference to the studies of Bo et al. (2025) and Chen et al. (2024), the natural logarithm of the sum of the keyword frequencies of the five categories is used as a measure of the overall firm's DT level in baseline analysis. The impact of each digital technology is further examined.

To isolate the impact of DT on FC from other confounding factors, the study controls for several firm-specific and macroeconomic factors that could affect the relationship. The firm-specific factors included are shareholdings in different financial institutions, state-owned enterprises or not, type of audit opinion, CEO or general manager duality, and profit volatility. Annual interest and the GDP growth rates are included as macroeconomic factors. The explanations of the variables are presented in Table 1.

Table 1 Variable Explanations

Variable type	Variable name	Variable abbreviation	Explanation
Dependent variable	Size-Age index	SA	An index used as a proxy for the financing constraint.
Independent variable	Digital transformation	lnDT	Natural logarithm of the frequency of the keywords of DT indicators in annual reports.
Control variables	Holding shares of other financial institutions	HSI	A dummy variable equals 1 if the firm holds shares of other financial institutions, and 0 if not.
	State-owned-enterprise	SOE	A dummy variable equals 1 if the controlling shareholder is the state and 0 otherwise.
	Auditor opinion	Opinion	A dummy variable equals for the standard unqualified opinion and 0 otherwise.
	Chairman or General Manager Duality	Duality	A dummy variable with a value of 1 if the chairman or general manager is the same person and 0 if not.
	Profit volatility	PV	3-year volatility of EBIT/ total assets.
	Inflation rate	Inf	Annual inflation rate computed based on CPI.
	Gross domestic product	GDP	Annual GDP growth rate

To test the hypothesis, the study uses the following econometric model:

$$Y_{i,t} = \beta_0 + \beta_1 X_{i,t} + \gamma Z_{i,t} + \alpha_i + \eta_t + \epsilon_{i,t} \quad (2)$$

The econometric model includes, $Y_{i,t}$, which denotes the dependent (outcome) variable for entity i at time t. The outcome is a function of a constant intercept (β_0), an independent variable ($X_{i,t}$) multiplied by its coefficient (β_1), a set of control variables ($Z_{i,t}$), where the relationships between the control variables and the dependent variable are captured through their respective coefficients, collectively represented by the vector γ, an industry dummy (α_i), year dummy (η_t) and the error term ($\epsilon_{i,t}$), which accounts for all unobserved factors that impact $Y_{i,t}$, but are not included in the model.

Panel data, also known as longitudinal data, is a type of data of multiple entities observed over several periods. The analysis using the data can be static or dynamic, and this study relies on the former type, which consists of pooled ordinary least squares, random effects, and fixed effects. The Pooled OLS treats panel data as a single cross-section, disregarding entity-specific effects. Though it has the advantage of simplicity, this model can lead to biased outcomes if unobserved factors are present and vary between entities.

The Fixed Effects model considers time-invariant, unobserved individual traits by allocating a unique intercept to each entity. It controls the impact of these factors, confirming that just within-entity variations influence the outcomes, which makes the estimates more efficient. This model assumes that these unobserved qualities are correlated with the independent variables.

The Random Effects model assumes that unobserved entity-specific effects are random variables and are uncorrelated with the explanatory variables. These assumptions are strong and rarely hold in reality; therefore, they limit the model's application.

The model selection process follows a logical sequence of steps to determine the most appropriate regression approach. Firstly, the Breusch-Pagan Lagrange multiplier ascertains whether a simple pooled OLS estimate is suitable or if unobserved individual traits necessitate a panel structure. If the test result indicates the existence of panel effects, the choice between fixed and random effects depends on the Hausman test result.

In addition to model selection tests, several data diagnostic tests, such as multicollinearity, heteroskedasticity, and serial correlation (or autocorrelation), are necessary to ensure the validity of the estimates.

Results and Discussions

Table 2 shows the descriptive statistics of the variables, including the number of observations, mean, standard deviation, minimum, and maximum values for the period from 2010 to 2023.

Table 2 Descriptive Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
SA	43561	-3.837	.269	-4.557	-3.141
lnDT	48677	1.332	1.389	0	6.301
HFI	43572	.044	.205	0	1
SOE	42575	.339	.473	0	1
Opinion	44204	.962	.191	0	1
Duality	42458	.304	.46	0	1
PV	43547	.039	.054	.001	.346
Inf	44230	2.028	1.11	.235	5.411
GDP	60592	6.409	2.133	2.35	10.64

The summary statistics for the SA index indicate that the sample firms are predominantly large and mature companies, as evidenced by the significantly negative average of -3.837. However, there is considerable variation within the sample (Std. Dev. = 0.269), with values ranging from -4.557 to -3.141. This broad spread allows for a meaningful classification of the companies, where those with scores closer to -3.141 (near the maximum) may be seen as facing more financial constraints. In contrast, those with more negative scores (approaching -4.557) are likely experiencing fewer obstacles in obtaining external financing.

Similarly, the summary statistics for firms' digital transformation levels (lnDT), show a moderately high average of adoption among sample companies (Mean = 1.332). However, the substantial standard deviation of 1.389 and a wide-ranging minimum of 0 to a maximum of 6.301 indicates significant diversity in how deeply firms have embraced digital technologies. This notable heterogeneity confirms that our sample encompasses both those who have yet to undergo transformation and organizations far along in their digital journeys, offering a suitable basis for analysis.

As shown in Figure 1, a consistent upward trend in the DT levels of firms in the sample. It is measured by the annual average of the natural logarithm of the frequencies of indicator keywords in annual reports. The excursion started at a relatively low level (mean of lnDT = 0.33 in 2010), indicating that digitalization was in its early stages. From 2010 to 2015, there was a steady increase, with the average surpassing 1.0 by 2015. This stage likely reflects initial adoption and experimentation with digital technologies, possibly influenced by broader national policy initiatives like "Internet Plus" launched in 2015. The most significant and sudden growth occurred in the second half of the decade, from 2016 to 2020. The average of the lnDT value increased from 1.25 to 1.68, indicating a period of deep integration and maturation of digital strategies within company operations. During these years, the upward trend is notably sharp and direct, suggesting a sector-wide race to digitize. A brief pause is seen in 2021, where the value stayed almost the same as in 2020. This stagnation reflects the initial operational halt caused by the COVID-19 pandemic. However, this break was short-lived. The trend picked up again in 2022 and reached its peak in 2023 (average of lnDT = 1.80), showing a strong rebound and a renewed focus on digital transformation as a key part of long-term resilience and competitive edge.

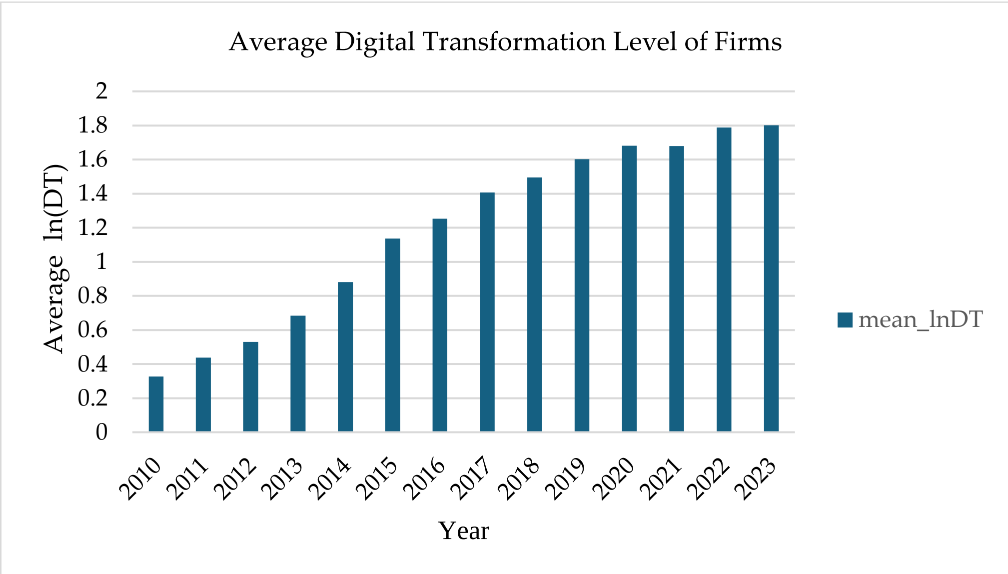

Fig. 1 Average digital transformation level of firms in the sample

Figure 2 presents the annual average financing constraints in the sample, measured by the Size-Age (SA) index. A higher (less negative) SA index value signifies greater financing constraints. The figure clearly shows a consistent decline in financing constraints over the 14 years, although there are also noticeable fluctuations from year to year. While the mean SA index generally moved toward more negative values, indicating a decline in average financing difficulties faced by firms, the change was not entirely smooth. Closer analysis reveals the decline slowed slightly from 2015 to 2017 before picking up pace afterward. This suggests the financial environment and firms' access to funding followed a more complex pattern than a simple steady improvement. Looking more closely at the timeframe, the years from 2010 to 2015 saw early signs of looser constraints. This may be related to China's financial markets and funding options gradually expanding. The period from 2016 to 2019 maintained downward momentum, possibly reflecting maturing companies with improved access to capital. Most notably, the downward momentum was barely disrupted when COVID-19 shook the world in 2020. The existing easing trend continued smoothly, showing that the financial system and listed companies had resilience, possibly supported by stimulus policies. By 2023, constraints hit their lowest point in the sample period, with the SA index averaging -3.97, indicating a long-term shift toward easier financing access.

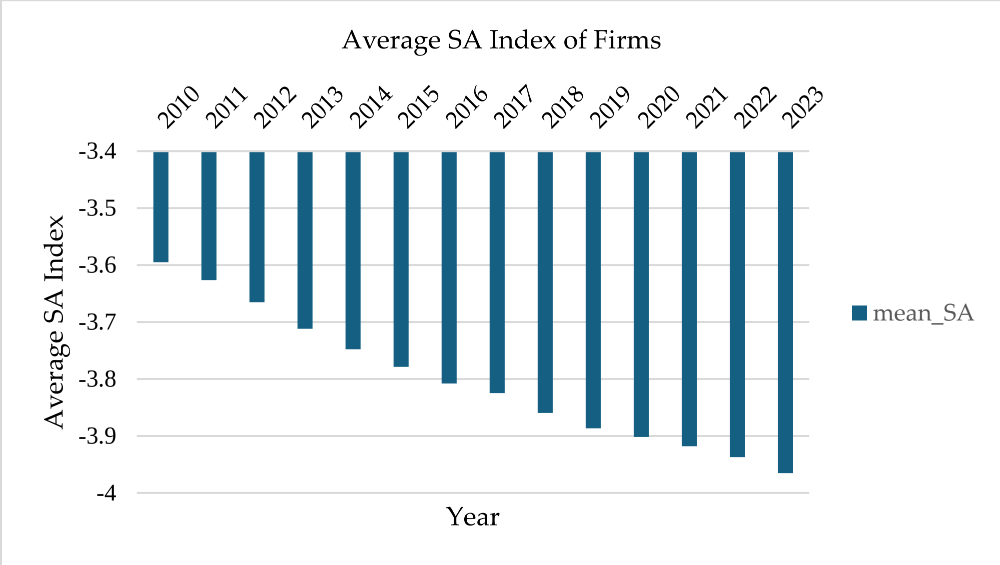

Fig. 2 Average SA index of firms in the sample

The pairwise correlation matrix presented in Table 3 indicates among other things that there is a negative correlation between financing constraints (SA) and digital transformation (lnDT), and a positive correlation between profit volatility and the SA index, both statistically significant at the 1% level. These preliminary findings support the hypotheses of this study. Additionally, the correlations between the independent variables are generally modest, suggesting the absence of serious multicollinearity concern, which is essential for regression analysis (Meng et al., 2023).

Table 3 Pairwise Correlations

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
(1) SA	1.000								
(2) lnDT	-0.087*	1.000							
	(0.000)								
(3) HFI	0.062*	-0.109*	1.000						
	(0.000)	(0.000)							
(4) SOE	-0.101*	-0.146*	0.185*	1.000					
	(0.000)	(0.000)	(0.000)						
(5) Opinion	0.025*	0.015*	0.017*	0.032*	1.000				
	(0.000)	(0.002)	(0.001)	(0.000)					
(6) Duality	0.087*	0.110*	-0.088*	-0.318*	0.014*	1.000			
	(0.000)	(0.000)	(0.000)	(0.000)	(0.005)				
(7) PV	0.024*	0.026*	-0.061*	-0.135*	-0.344*	0.059*	1.000		
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)			
(8) Inf	0.271*	-0.226*	0.161*	0.094*	-0.033*	-0.064*	0.015*	1.000	
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.002)		
(9) GDP	0.281*	-0.250*	0.176*	0.100*	-0.006	-0.068*	-0.034*	0.290*	1.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.219)	(0.000)	(0.000)	(0.000)	

** Shows significance at p<0.01*

To further assess the potential for multicollinearity among the independent variables, the Variance Inflation Factor (VIF) is utilized. As shown in Table 4, all VIF values are notably low, with a mean VIF of only 1.135. The highest individual VIF score is 1.176, and the smallest tolerance value (1/VIF) is 0.85. Since all VIF values are well below the conservative threshold of 5 proposed by Kennedy (2008) and the strict threshold of 10 suggested by Neter et al. (1996), it is concluded that severe multicollinearity does not present a problem in the regression model.

Table 4 Variance Inflation Factor

Variable	VIF	1/VIF

SOE	1.176	.850
GDP	1.168	.856
Inf	1.148	.871
PV	1.144	.874
Opinion	1.123	.891
lnDT	1.121	.892
Duality	1.120	.893
HFI	1.079	.927
Mean VIF	1.135	.

The Breusch and Pagan Lagrangian multiplier test is performed to choose between pooled OLS and panel effects models. The null hypothesis of this test states that there is no significant difference across the panels. As shown in Table 5, the test results produced a significant p-value, indicating the presence of panel effects. The second test is the Hausman test, which helps determine whether to use a random effects or fixed effects model. In this test, the null hypothesis assumes that the unobservable, time-invariant factors are randomly distributed and uncorrelated with the independent variables; in other words, the random effects model is the efficient and consistent estimator. The test also yielded a significant p-value, providing evidence to reject the null hypothesis. Consequently, the fixed effects model is identified as the most suitable for the regression analysis.

Table 5 Breusch and Pagan LM, and Hausman Tests

Test	T statistic	p-value
Breusch and Pagan LM	chibar2 (01) = 1.3e+05	0.0000
Hausman	chi2 (8) =594.61	0.0000

To identify the type of variance of the errors (residuals), this study employs the Modified Wald test for groupwise heteroskedasticity in a fixed effects regression model. The null hypothesis is that the variance of the error is the same for each entity (i) (homoskedastic). The test result, shown in Table 6, has a significant p-value, providing strong evidence that the errors are not constant (heteroskedasticity). To address this issue, this study uses robust standard errors.

Table 6 Modified Wald Test

Test	T statistic	p-value
Modified Wald	chi2 (5055) = 4.4e+35	0.0000

This study uses the Wooldridge test for autocorrelation in panel data (Wooldridge, 2010). The null hypothesis for this test is that there is no first-order autocorrelation. As shown in Table 7, the test produced a statistically significant p-value ($p < 0.05$), leading to the rejection of the null hypothesis. This confirms the presence of serial correlation in the standard errors. Although the Modified Wald test also indicated heteroskedasticity, the serial correlation poses a significant threat to the reliability of the standard errors (Baum, 2001). Therefore, the regression analysis employs Driscoll-Kraay standard errors, which are robust to heteroskedasticity, serial correlation, cross-sectional dependence, non-stationarity, and normality—issues that could otherwise affect the regression results (Driscoll & Kraay, 1998; Hoechle, 2007).

Table 7 Wooldridge Test

Test	T statistic	p-value
Wooldridge	F (1,4328) = 2497.804	0.0000

Finally, based on the test results from previous sections, a panel data fixed-effects regression with Driscoll-Kraay standard errors is used to examine the relationships in the econometric model shown in equation 2. The results are provided in Table 8. The analysis includes three models: Model 1, without control variables (univariate analysis); Model 2, with control variables to test hypothesis 1 (H1); and Model 3, with an interaction term to test hypothesis 2 (H2). Standard errors are in parentheses, and ***, **, and * indicate statistical significance at 1%, 5%, and 10%, respectively.

Table 8 Baseline Regression

VARIABLES	(1) SA	(2) SA	(3) SA
lnDT	-0.00435***	-0.00394***	-0.000737
	(0.000930)	(0.000976)	(0.00144)
HFI		-0.0549***	-0.0542***
		(0.0110)	(0.0110)
SOE		-0.0147***	-0.0137**
		(0.00464)	(0.00457)
Opinion		-0.0251*	-0.0256*
		(0.0124)	(0.0125)
Duality		0.00459**	0.00450**
		(0.00164)	(0.00159)
PV		0.105***	0.224***
		(0.0336)	(0.0506)
lnDTxPV			-0.0801***
			(0.0236)
Inf		0.259***	0.260***
		(0.000647)	(0.000586)
GDP		-0.521***	-0.522***
		(0.00131)	(0.00158)
Constant	-3.637***		
	(0.0315)		
Observations	43,520	41,425	41,425
Number of Firms	5,130	5,052	5,052
Within R-squared	0.8454	0.8588	0.8600
Firm FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes

As shown in Table 8, model 1 of the analysis reveals a strong negative relationship between a firm's DT and FC (measured by the SA index). It indicates that a 1% increase in DT results in a 0.00394 decrease in the SA index. This coefficient is statistically significant at the 1% level.

Similarly, in model 2, we observe that after including the control variables, the nature of the relationship and its statistical significance remain the same, which strengthens the idea that DT reduces FC. Therefore, hypothesis 1 (H1), suggesting that firm DT significantly lowers FC, is accepted. The control variables show that among company-specific attributes, shares held in other financial institutions are significantly negatively related to FC at the 1% level. Additionally, SOE has a negative and significant coefficient at 1%, suggesting that state-owned enterprises encounter notably less FC than private companies, in line with research on implicit government guarantees. The audit opinion has a negative and marginally significant relationship at the 10% level, implying that a standard unqualified opinion is weakly associated with lower FC. When the chairman and general manager are the same person—used as a proxy for governance quality—has a positive and significant relationship with FC at 5%, indicating that holding both roles increases the constraints. Profit volatility shows a strong, significant positive association with constraints at the 1% level, reflecting that riskier companies face greater financing challenges. This finding is essential for testing hypothesis 2 (H2).

The macroeconomic factors exert notably strong effects on FC. The inflation rate has a highly significant positive correlation with constraints, with a coefficient significant at the 1% level, indicating that companies face increased FC during periods of rising prices. Conversely, GDP growth shows a strong negative relationship with constraints, with a coefficient significant at the 1% level, suggesting that economic expansion improves firms' access to capital. The models' high explanatory power, as indicated by the within R-squares of about 0.86, demonstrates a good model fit. Specifically, the variables in each model explain around 86% of the variation in the SA index. Firm, industry, and year fixed effects indicate that the estimation controls for time-invariant firm and industry characteristics as well as temporal shocks.

In Model 3, we see that the interaction term for DT and profit volatility (lnDTxPV) has a strong negative association with SA. The coefficient is statistically significant at 1%. This result provides strong evidence to support the hypothesis (H2), which proposes that DT moderates the relationship between profit volatility and financing constraints.
The statistical software omits the constant term after including the control variables; however, this does not cause a problem in the analysis, as the goal is to examine the relationship between the variables of interest. This issue persists in the subsequent analyses.

To check the robustness of the baseline regression results, the Whited-Wu index is used as an alternative measure for FC. The index is computed using the following formula.

$$ww_{i,t} = -0.091cf_{i,t} - 0.062div_{i,t} + 0.021lev_{i,t} - 0.044size_{i,t} + 0.102isg_{i,t} - 0.035sg_{i,t} \quad (3)$$

The formula to calculate the index encompasses cf, representing the ratio of cash flows to total assets, calculated as net cash flows from operating activities divided by total assets. div is a dummy variable for cash dividend payment with a value of 1 if dividends are paid in the current period and zero if not. lev is the firm's leverage level, which is the ratio of long-term debt to total assets. size is the firm size computed as the natural logarithm of total assets. isg is the industry's average sales growth rate, where the sector is classified using 2-digit codes for manufacturing and 1-digit codes for all other domains as per the CAPCO Industry Categorization. Lastly, sg is the firm's sales growth rate. Similar to the SA index, a higher value indicates greater constraints.

The fixed effects regression results with Driscoll-Kraay standard errors, using the Whited-Wu index as a measure of a firm's level of FC, are presented in Table 9. ***, **, and * indicate significance at 1%, 5%, and 10%, respectively, and the standard errors are in parentheses.

Table 9 Robustness check: Using Alternative FC Measure

VARIABLES	(1) WW	(2) WW	(3) WW
lnDT	-0.00515***	-0.00476***	-0.00604***
	(0.000858)	(0.000737)	(0.000745)
HFI		-0.00307**	-0.00336**
		(0.00118)	(0.00113)
SOE		0.00814***	0.00773***
		(0.00151)	(0.00144)
Opinion		-0.0294***	-0.0291***
		(0.00347)	(0.00339)
Duality		-0.000770	-0.000699
		(0.000711)	(0.000699)
PV		0.181***	0.132***
		(0.0226)	(0.0256)
lnDTxPV			-0.0324***
			(0.00771)
Inf		0.0509***	0.0510***
		(0.000829)	(0.000814)
GDP		-0.129***	-0.129***
		(0.00236)	(0.00235)
Constant	-1.039***		
	(0.0146)		
Observations	37,682	35,866	35,866
Number of Firms	4,975	4,899	4,899
Within R-squared	0.2281	0.2824	0.2846

Firm FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes

The examination of the impact of DT on FC using the Whited-Wu index shows similar results to the baseline regression. That is, the coefficients for "lnDT" are negative, with all being statistically significant at 1% across all models. Additionally, the coefficients for control variables also closely match the baseline findings, and the interaction term, "lnDTxPV," remains negative with statistical significance at 1%. Therefore, both hypotheses of the study are supported in this analysis too.

The lower within R-squared values of all the models in this analysis compared to their counterparts in the baseline regression indicate that the baseline regression models are more fitting.

In general, the findings in the baseline analysis are robust to the change of measurement for the FC from the SA index to Whited-Wu index.

To test the cause-and-effect relationship between DT and FC, the impact of lag 1 of DT on FC is examined. The results are shown in Table 10, with standard errors in parentheses and ***, **, and * indicating statistical significance at the 1%, 5%, and 10% levels, respectively. The industry dummy is excluded because the software was unable to provide results due to multicollinearity. As shown in the table, $lnDT_{t-1}$ has a significant negative impact on both models 1 and 2, indicating that increases in DT lead to a statistically significant reduction in SA at the 1% level. Furthermore, the interaction term continues to show the moderating effect of DT on the relationship between profit volatility (PV) and FC.

Table 10 Robustness Check for Casual-Effect Relationship

VARIABLES	(1) SA	(2) SA	(3) SA
$lnDT_{t-1}$	-0.00270***	-0.00262***	0.000707
	(0.000607)	(0.000765)	(0.00125)
HFI		-0.0533***	-0.0525***
		(0.00966)	(0.00955)
SOE		-0.0150***	-0.0141***
		(0.00458)	(0.00438)
Opinion		-0.0200*	-0.0213*
		(0.0108)	(0.0110)
Duality		0.00468**	0.00463**
		(0.00188)	(0.00181)
PV		0.0824**	0.200***
		(0.0302)	(0.0531)
$lnDT_{t-1}xPV$			-0.0782**
			(0.0272)
Inf		0.258***	0.258***
		(0.000774)	(0.000748)
GDP		-0.518***	-0.518***
		(0.00143)	(0.00134)
Constant	-3.704***		
	(0.0118)		
Observations	39,027	37,060	37,060
Number of Firms	4,878	4,811	4,811
Within R-squared	0.2281	0.2824	0.2846
Firm FE	Yes	Yes	Yes
Industry FE	Yes	No	No

Year FE	Yes	Yes	Yes

To offer more profound insights into how each digital technology affects FC, this section analyzes the separate impacts of artificial intelligence technology (AIT), blockchain technology (BCT), cloud computing technology (CCT), big data technology (BDT), and digital technology applications (DTA), along with their roles as moderators in the relationship between profit volatility and FC. The regression results are presented in Table 11.

Table 11 Further Analysis: Examination of the Impact of Each Digital Technology

	(1)	(2)	(3)	(4)	(5)
VARIABLES	SA	SA	SA	SA	SA
AIT	-0.000251***				
	(7.68e-05)				
AITxPV	-0.00522***				
	(0.00146)				
BCT		-0.00161			
		(0.00129)			
BCTxPV		-0.0484*			
		(0.0242)			
CCT			-0.000389***		
			(8.69e-05)		
CCTxPV			-0.00317**		
			(0.00130)		
BDT				-0.000464***	
				(0.000102)	
BDTxPV				-0.00508**	
				(0.00192)	
DTA					-0.000132**
					(4.85e-05)
DTAxPV					-0.00388***
					(0.00126)
HFI	-0.0549***	-0.0551***	-0.0548***	-0.0544***	-0.0547***
	(0.0109)	(0.0110)	(0.0110)	(0.0111)	(0.0111)
SOE	-0.0143***	-0.0146***	-0.0143***	-0.0137***	-0.0142**
	(0.00464)	(0.00474)	(0.00464)	(0.00447)	(0.00476)
Opinion	-0.0253*	-0.0250*	-0.0254*	-0.0257*	-0.0256*
	(0.0125)	(0.0123)	(0.0125)	(0.0125)	(0.0124)
Duality	0.00467**	0.00464**	0.00459**	0.00453**	0.00470**
	(0.00169)	(0.00169)	(0.00163)	(0.00166)	(0.00164)
PV	0.116***	0.110***	0.116***	0.118***	0.129***
	(0.0338)	(0.0336)	(0.0344)	(0.0338)	(0.0378)
Inf	0.261***	0.261***	0.261***	0.260***	0.261***
	(0.000964)	(0.000974)	(0.000909)	(0.000904)	(0.000895)
GDP	-0.522***	-0.522***	-0.521***	-0.522***	-0.522***
	(0.00154)	(0.00153)	(0.00137)	(0.00152)	(0.00153)
Observations	41,425	41,425	41,425	41,425	41,425
Number of Firms	5,052	5,052	5,052	5,052	5,052
Within R-squared	0.8589	0.8587	0.8590	0.8593	0.8590
Firm FE	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes

The findings show that AIT, CCT, and BDT each have a strong negative relationship with FC, with coefficients statistically significant at the 1% level, and the DTA at 5%, indicating they significantly decrease FC. However, BCT has an insignificant negative impact on FC.

The analysis of their moderation effects shows that AIT, CCT, BDT, and DTA moderate the positive relationship between PV and FC. While BCT exhibits a negative moderating impact, it is only statistically significant at the 10% level, indicating a comparatively weaker moderating role. The findings of the other control variables are the same as those in previous analyses.

Conclusion

This study provides strong empirical evidence that digital transformation (DT) reduces financing constraints (FC), as measured by the SA index, for listed companies in China's A-share market. The findings indicate that adopting digital technologies—especially artificial intelligence, blockchain, cloud computing, big data, and digital applications—greatly improves organizations' ability to access external capital. Additionally, the results show that DT moderates the positive impact of profit volatility on FC. The findings are consistent when the Whited-Wu is used as a measure for FC. The causal effect is confirmed using a one-period lag of DT, which produced similar results. Further analysis reveals that the moderating effect is particularly significant for AI, cloud computing, big data, and digital technology applications.

The findings offer insights for corporate managers to see that investments in digitization are more than just operational expenses; they are key strategic financial decisions that reduce the cost of capital and ease funding restrictions. For investors, they highlight how a company's commitment to digitalization can serve as a positive signal of investment value and growth potential, helping them make smarter portfolio choices. Moreover, policymakers, especially in emerging markets, emphasize the importance of fostering digital infrastructure and regulatory frameworks that support corporate digitalization.

Future studies could examine the different effects across industries and explore the long-term influence of digital transformation on financial stability and sustainable growth.

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