

Empowering SMEs: mechanisms and impacts of digital inclusive finance

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Abstract

Purpose – This paper examines whether digital inclusive finance alleviates SMEs’ financing constraints and identifies the underlying mechanisms. It further explores whether these effects vary by ownership structure, industry type, and regulatory environment, and whether easing financing constraints improves firm performance.

Design/methodology/approach – This study develops a four-sector theoretical model to analyse how digital inclusive finance influences SME financing constraints through cost and information channels. A composite financing-constraint index is constructed using liquidity, profitability, and robustness indicators. Using panel data on Chinese GEM-listed SMEs from 2015–2022, the analysis employs year- and city-level fixed effects, instrumental-variables estimation, mechanism tests, and heterogeneity analyses.

Findings – Digital inclusive finance significantly reduces SMEs’ financing constraints, with the effects persisting over time. Cost reduction and improved information transparency are the main transmission channels. Easing financing constraints enhances firm performance. The effects are stronger for non-state-owned firms, high-tech enterprises, and firms located in regions with lower regulatory intensity.

Originality/value – This study integrates theoretical modelling, mechanism analysis, and economic consequences into a unified framework. It proposes a novel composite measure of financing constraints and distinguishes SME risk types within a four-sector model. The findings provide new evidence on the heterogeneous and performance-enhancing effects of digital inclusive finance on SMEs.

Keywords Digital inclusive finance, Financing constraints, SMEs, Dynamic effects, Economic consequences

Paper type Research article

1. Introduction

In the wave of 21st-century economic development, small and medium-sized enterprises (SMEs) have become a key driving force for global economic growth. Statistics show that SMEs account for 90% of all businesses worldwide, provide 70% of global employment, and contribute 50% of the global GDP [1]. However, SMEs face varying degrees of financing difficulties in both developed and developing countries (Roux and Savignac, 2024; Chen *et al.*, 2024; Lou *et al.*, 2024). Traditional financial services struggle to meet SMEs’ financing needs, and the issues of “difficult and expensive financing” have long constrained their development (Brown *et al.*, 2012; Liu *et al.*, 2017). This problem has been further exacerbated by the long-term impacts of the COVID-19 pandemic, as SMEs face weakened demand, reduced consumption willingness, and significant financial pressure caused by declining profitability (Khan, 2022; Xie and Tian, 2023). Therefore, exploring new financing channels and financial innovations is crucial to support the sustainable development of SMEs.



In China, SMEs are a vital part of the national economy, playing a key role in driving innovation, promoting employment, and improving livelihoods. From an economic contribution perspective, China's SMEs have exceeded 57 million in number [2], owning 56.2% of registered trademarks and 63.7% of authorised invention patents nationwide. SMEs contribute 60% of the GDP, more than 50% of tax revenue, over 70% of technological innovation, and more than 80% of employment opportunities [3]. However, Chinese SMEs are also often overlooked by traditional financial institutions (Song *et al.*, 2018; He *et al.*, 2024). Regarding financial support, only 29.9% of SMEs receive loans from financial institutions, with loan demand satisfaction at just 48.5%, leaving a financing gap of 53.7 trillion RMB [4]. Daily operational funding is already difficult to secure, let alone the long-term capital required for sustained development.

To address SMEs' financing challenges, China has proposed the development of *digital finance* and *inclusive finance*, encouraging financial product innovation and optimising the structure of capital supply to allocate more financial resources to SMEs. Digital inclusive finance has revolutionised the traditional operational model of financial institutions (Gomber *et al.*, 2017). Through the application of internet technology in finance, it facilitates information sharing, lowers transaction costs, and reduces financial service barriers for SMEs (Abbasi *et al.*, 2021; Feng *et al.*, 2023). However, some studies suggest that digital inclusive finance can act as a "disruptive innovation" for financial services. The application of fintech increases the interconnectedness of financial institutions and the complexity of financial systems, which poses challenges to the financing stability and long-term sustainability of real sector enterprises (Goldstein *et al.*, 2019; Xie *et al.*, 2021). Thus, an urgent research question arises: How can digital inclusive finance effectively empower SMEs and address their financing constraints? This question requires in-depth investigation to explore viable solutions and offer policy guidance for alleviating SMEs' financing difficulties.

The financing challenges faced by SMEs have long been a focus of academic attention, with their financing constraints influenced by both external environments and internal factors. From an external environment perspective, there have long been problems of adverse selection and moral hazard induced by information asymmetry between banks and enterprises (Stiglitz and Weiss, 1981; Sun *et al.*, 2024). Imperfect policies and institutional frameworks, as well as defects in financial markets, are important factors causing financing constraints for enterprises (Love, 2003; Chen and Guariglia, 2013). Uncertainty in monetary policy exacerbates the information asymmetry between borrowers and lenders, prompting banks to raise credit thresholds and increasing the cost of external financing for enterprises (Tran, 2019; Xiang and Li, 2022). Bank-dominated financial systems, plagued by inefficiency and financial repression, result in "ownership discrimination" and "size discrimination" (Brandt and Li, 2003; Huang and Qiu, 2021). In regions with high banking concentration, SMEs face more severe financing constraints (Ryan *et al.*, 2014; Li and Zhu, 2023).

From an internal perspective, the financing constraints faced by SMEs are closely related to their information and financial quality (Berger *et al.*, 2005; Wang *et al.*, 2020). On the one hand, SMEs are often "credit newcomers" with short survival periods and poor management norms, which are inherent weaknesses that lead to a lack of continuous and stable high-quality credit information. This makes it difficult for financial institutions to grant them precise credit or provide continuous follow-up (Fazzari *et al.*, 1988; Chit, 2019). On the other hand, compared with large enterprises, SMEs often lack effective guarantees and collateral as well as sound financial systems, and their limited capital and scale result in weaker risk resistance, placing them at a disadvantage in the financing process (Duarte *et al.*, 2018; Ma *et al.*, 2019). Additionally, factors such as the robustness of accounting information (Zhang *et al.*, 2017), corporate ESG performance (Shi *et al.*, 2024; Tang *et al.*, 2024), and the characteristics of the executive team (Jia and Zhang, 2024) are also important influencing factors.

As a product of the deep integration of inclusive finance and digital technology, digital inclusive finance is gradually penetrating and influencing multiple levels of the real economy. At the macro level, digital inclusive finance effectively narrows the digital divide, helps

optimise the allocation of financial resources (Gomber *et al.*, 2018), stimulates innovation and entrepreneurship (Chen *et al.*, 2019), and promotes inclusive economic growth (Zhang *et al.*, 2019; Guo *et al.*, 2024). At the micro level, digital inclusive finance effectively alleviates the phenomenon of credit mismatch in financial markets (Buchak *et al.*, 2018; Bu *et al.*, 2024), and plays an important role in promoting corporate innovation (Li *et al.*, 2023a, b; Wang *et al.*, 2024a, b), improving investment efficiency (Ye *et al.*, 2024), and enhancing corporate financial performance (Wu and Huang, 2022).

Digital inclusive finance, as a new form and model of financial development in the digital economy era, provides SMEs with broader financing opportunities. First, the inclusive nature of digital inclusive finance enables diversified financial services for disadvantaged groups, partially addressing the size and ownership discrimination inherent in traditional finance (Li *et al.*, 2023a, b; Mu *et al.*, 2023). Second, through online financing platforms, digital inclusive finance not only broadens SMEs' financing channels but also reduces transaction costs between parties and improves the accessibility of financing services for SMEs (Tang and Geng, 2024; Lin and Dong, 2024). Moreover, digital inclusive finance effectively overcomes the temporal and spatial limitations of traditional finance, expands the coverage of financial services, and diminishes the "elitist" nature of financial services (Ding *et al.*, 2022; Gao *et al.*, 2024a, b).

With its informational advantages, digital inclusive finance further optimises SMEs' financing environment and the efficiency of resource allocation. Corporate financing is a typical information game between borrowers and lenders (Bessler *et al.*, 2011; Liberti and Petersen, 2019). Digital finance, relying on digital technology platforms, tracks the "digital footprints" of borrowers, surpassing traditional methods in data acquisition, processing, and prediction, thereby accelerating the credit approval process (Berg *et al.*, 2020; Murinde *et al.*, 2022). The application of big data and artificial intelligence technologies has enhanced the accuracy of financial institutions' credit assessments for SMEs (Lin and Dong, 2024; Ding *et al.*, 2024). Blockchain technology, through consensus mechanisms and smart contracts, ensures data tamper resistance and traceability, further improving information transparency (Du *et al.*, 2023; Han *et al.*, 2023).

Current research on digital inclusive finance and SME financing constraints has made important progress, yet several limitations remain.

First, the theoretical analysis of transmission mechanisms is still relatively underdeveloped. Existing studies mainly examine the directional relationship between digital inclusive finance and financing constraints. However, in empirical analyses, digital inclusive finance is often treated as a linear extension of traditional finance, with insufficient attention paid to the distinctive risk-screening capabilities of digital financial institutions. Consequently, the fundamental logic of why and how digital inclusive finance can overcome traditional credit rationing remains, to some extent, a theoretical "black box".

Second, the measurement of financing constraints remains limited. The existing literature relies primarily on cash-flow sensitivity methods and established indices such as the KZ, WW, and SA indices. However, these approaches are either difficult to quantify precisely or depend heavily on capital market data and strong parametric assumptions. For SMEs, which often do not distribute dividends and are characterised by opaque information, these methods may generate considerable endogeneity problems and measurement bias. This, in turn, restricts deeper analysis of the dynamic evolution of financing constraints and their broader economic consequences.

Third, the existing analytical framework is not sufficiently comprehensive. Most studies continue to follow a unidirectional logic of "digital inclusive finance → financing constraints". Few have integrated transmission mechanisms and economic consequences into a unified analytical framework for systematic investigation. Moreover, limited attention has been given to the heterogeneous effects of contextual factors, such as ownership structure, industry characteristics, and the regulatory environment. As a result, the existing research system lacks both completeness and systematic coherence.

To address the above limitations, this paper makes the following potential marginal contributions.

First, in response to the insufficient theoretical analysis of transmission mechanisms, this paper develops a four-sector theoretical model that incorporates both high-quality and low-quality SMEs. By introducing parameters that capture digital financial institutions' risk-screening probability and risk-control capabilities, the model uses comparative static analysis to reveal the dual channels through which digital inclusive finance improves SMEs' financing environment: the cost effect and the information effect. In doing so, this paper deepens the theoretical understanding of how digital inclusive finance alleviates SME financing constraints.

Second, in response to the limitations of existing measurement methods for financing constraints, this paper selects seven representative indicators from three dimensions: liquidity, profitability, and financial robustness. It then constructs a financing constraint index using an assignment scoring model. Compared with traditional indices, this approach avoids excessive reliance on capital market data and strong parametric assumptions, reduces potential endogeneity bias, and provides a more reliable measurement basis for analysing the dynamic evolution of financing constraints and testing their economic consequences.

Third, in response to the fragmentation of existing analytical frameworks, this paper constructs an integrated research framework that incorporates both transmission pathways and economic consequences. Specifically, it examines the information effect and cost effect as key mechanisms, while further analysing the impact of financing constraint alleviation on firm performance. In addition, the paper systematically investigates heterogeneity in the effects of digital inclusive finance from three dimensions: ownership structure, industry characteristics, and the regulatory environment. This helps establish a more complete logical chain from "mechanism identification" to "financing improvement" and finally to "performance enhancement."

The remainder of this paper is organised as follows: The second section outlines the theoretical mechanism and research hypotheses; the third section details the research design; the fourth section presents the empirical results and analysis; and the fifth section concludes with key findings and implications.

2. Theoretical mechanism and research hypotheses

Building on the theories of information asymmetry, credit rationing, and collateral by [Stiglitz and Weiss \(1981\)](#) and adopting the framework proposed by [Zhou and Wang \(2023\)](#), this study constructs a four-sector theoretical model including traditional financial institutions, digital financial institutions, high-quality SMEs, and non-high-quality SMEs. By analysing credit scenarios under different conditions, it explores the potential of digital inclusive finance in optimising the financing environment for SMEs.

2.1 Theoretical model of SME financing

2.1.1 SMEs. Assume the SME market consists of two types of enterprises $i \in \{g, b\}$: high-quality enterprises g and non-high-quality enterprises b . SMEs have an initial capital input, and their production function is $f(k_i) = z_i k_i^{\alpha_i}$, where k is the initial capital input, α_i is the output elasticity coefficient representing the contribution of capital input to output, and z_i is production efficiency. Moreover, $\alpha_g > \alpha_b$, $z_g > z_b$. The profit function of SMEs is:

$$E_i(k_i) = f(k_i) - (1 + r_i)q_i = z_i k_i^{\alpha_i} - (1 + r_i)q_i \quad (1)$$

where r_i is the loan interest rate, and q_i is the loan size. SMEs obtain capital through bank loans, which inevitably incur capital losses (such as preparation costs and service fees) $c_i = c_i(\lambda)$, where λ represents the development level of digital inclusive finance, $\lambda \geq 0$, $0 \leq c_i(\lambda) < 1$, $c_i'(\lambda) < 0$. Therefore, the actual capital size of loans for SMEs is $k_i = (1 - c_i)q_i$.

The profit maximisation problem for enterprises becomes:

$$\frac{\partial E_i}{\partial q_i} = z_i \alpha_i k_i^{\alpha_i - 1} \frac{\partial k_i}{\partial q_i} - (1 + r_i) = (1 - c_i) z_i \alpha_i k_i^{\alpha_i - 1} - (1 + r_i) = 0 \quad (2)$$

The constraint condition is derived as:

$$1 + r_i = (1 - c_i) z_i \alpha_i k_i^{\alpha_i - 1} \quad (3)$$

The compliance probability of SMEs is denoted as θ_i , where $\theta_g > \theta_b$. If SMEs default, financial institutions are expected to recover the collateral assets of the enterprise, with the value of the collateral denoted as M_i .

2.1.2 Financial institutions. Financial institutions engage exclusively in deposit and loan services, absorbing household deposits at an interest rate ρ . They are not subject to funding constraints when providing financing to SMEs. The loan management cost is expressed as $\frac{s\eta(\lambda)}{1+\eta(\lambda)} q_i^{1+\frac{1}{\eta(\lambda)}}$, where $\eta(\lambda)$ represents capital cost elasticity, $\eta(\lambda) > 1$, and $\eta'(\lambda) > 0$. For traditional financial institutions, $\eta(\lambda) = 1$. The collateral value required per unit of loan is denoted as $\Gamma_i = \frac{M_i}{q_i} \in [0, 1]$, where a higher value indicates lower tolerance for SME default by banks.

Traditional lending technologies depend on the quality of entrepreneurs' information. Financial institutions passively accept information from entrepreneurs and cannot distinguish between SME risk types. Therefore, financial institutions design loan contracts based on a hypothetical entrepreneur m , whose risk and profitability levels lie between those of high-quality and non-high-quality enterprises, to balance loan conditions. The profit function of a traditional financial institution is:

$$E_{B_t} = \theta_m(1 + r_m)q_m + (1 - \theta_m)M_m - \rho q_m - \frac{s}{2}q_m^2 \quad (4)$$

When maximising profit:

$$\frac{\partial E_{B_t}}{\partial q_m} = \theta_m(1 + r_m) + (1 - \theta_m)\Gamma_m - \rho - sq_m = 0 \quad (5)$$

The optimal loan size is derived as:

$$q_m = \frac{\theta_m(1 + r_m) + (1 - \theta_m)\Gamma_m - \rho}{s} \quad (6)$$

Compared to traditional financial institutions, digital financial institutions have the following advantages: first, digital financial institutions can identify the risk type of loan applicants with a probability of $v(\lambda) = \frac{\lambda}{1+\lambda} \in [0, 1]$. For identified high-quality enterprises, they offer innovative loans, treating the enterprise's credit cost as quasi-collateral to provide pure credit loans. For unidentified applicants, traditional loan arrangements are applied. Second, digital financial institutions rely on big data technology for risk control. Higher risk control capabilities increase the probability of loan repayment. Risk control capabilities are denoted as $w(\lambda) \in [0, 1]$, where $w'(\lambda) > 0$. The profit function of a digital financial institution is:

$$\begin{aligned} E_{B_f} = & [1 - v(\lambda)] [\theta_f(1 + r_f)q_f + (1 - \theta_f)M_f - \rho q_f] \\ & + v(\lambda) [w(\lambda)(1 + r_f)q_f - \rho q_f] - \frac{s\eta(\lambda)}{1 + \eta(\lambda)} q_f^{1+\frac{1}{\eta(\lambda)}} \end{aligned} \quad (7)$$

When maximising profit:

$$\frac{\partial E_{B_f}}{\partial q_f} = [1 - v(\lambda)][\theta_f(1 + r_f) + (1 - \theta_f)\Gamma_f - \rho] + v(\lambda)[w(\lambda)(1 + r_f) - \rho] - sq_f^{\frac{1}{\eta(\lambda)}} = 0 \quad (8)$$

The optimal loan size is derived as:

$$q_f = \left\{ \frac{\theta_f(1 + r_f) + (1 - \theta_f)\Gamma_f - \rho}{s(1 + \lambda)} + \frac{\lambda[w(\lambda)(1 + r_f) - \rho]}{s(1 + \lambda)} \right\}^{\eta(\lambda)} \quad (9)$$

2.1.3 Comparative static analysis. From [equation \(7\)](#), it can be seen that the loan size of digital financial institutions consists of two parts: the loan size under traditional technology and the loan size under new technology. The effect of applying new loan technology must exceed that of traditional loan technology; otherwise, digital financial institutions would not adopt new technology. Therefore, the following constraint condition holds:

$$\theta_m(1 + r_f)q_f + (1 - \theta_f)M_f - \rho q_f \leq w(\lambda)(1 + r_f)q_f - \rho q_f \quad (10)$$

$$\theta_f(1 + r_f) + (1 - \theta_f)\Gamma_f - \rho \leq w(\lambda)(1 + r_f) - \rho \quad (11)$$

In the traditional loan technology, the following parameter conditions must hold:

$$\theta_f = \theta_m, \quad r_f = r_m, \quad M_f = M_m \quad (12)$$

If the loan conditions of digital financial institutions were stricter, SMEs would opt for traditional financial institutions, pushing digital financial institutions out of the market. Therefore, we have:

$$\theta_m(1 + r_m) + (1 - \theta_m)\Gamma_m - \rho \leq w(\lambda)(1 + r_f) - \rho \quad (13)$$

Substituting [equations \(12\) and \(13\)](#) into [equation \(9\)](#) yields:

$$q_f \geq \left\{ \frac{\theta_m(1 + r_m) + (1 - \theta_m)\Gamma_m - \rho}{s(1 + \lambda)} + \frac{\lambda[\theta_m(1 + r_m) + (1 - \theta_m)\Gamma_m - \rho]}{s(1 + \lambda)} \right\}^{\eta(\lambda)} \\ = \left\{ \frac{\theta_m(1 + r_m) + (1 - \theta_m)\Gamma_m - \rho}{s} \right\}^{\eta(\lambda)} \quad (14)$$

Thus, $q_f \geq q_m^{\eta(\lambda)}$, and since $\eta(\lambda) > 1$, it follows that $q_f \geq q_m$. Compared with traditional financial institutions, the loan size of digital financial institutions is increased, better meeting the financing needs of SMEs. Under the context of digital inclusive finance, digital financial institutions can more accurately identify the risk types of SMEs applying for loans and provide larger loan sizes to SMEs with development potential, thereby improving the credit accessibility of SMEs and better satisfying their financing needs. Accordingly, the following hypothesis is proposed:

H1. The development of digital inclusive finance can alleviate SMEs' financing constraints.

2.2 Cost effect analysis

From the comparative static analysis, it is evident that for traditional loans provided by digital financial institutions, $r_f = r_m$, whereas for innovative loans, the interest rate must satisfy

$r_f < r_m$. SMEs would prefer traditional loans due to their lower financing costs if $r_f > r_m$, leading to the conclusion that the loan interest rate of digital financial institutions satisfies $r_f \leq r_m$.

From equation (3), the capital scale of SMEs when profits are maximised is: $k_i = \left[\frac{1+r_i}{(1-c_i)z_i\alpha_i} \right]^{\frac{1}{\alpha_i-1}}$. Thus, it follows:

$$\frac{\partial k_i}{\partial r_i} = \frac{1}{(\alpha_i - 1)(1 - c_i)z_i\alpha_i} \left[\frac{1 + r_i}{(1 - c_i)z_i\alpha_i} \right]^{\frac{2-\alpha_i}{\alpha_i-1}} < 0 \quad (15)$$

$$\frac{\partial k_i}{\partial c_i} = -\frac{z_i\alpha_i}{(1 - \alpha_i)(1 + r_i)} \left[\frac{(1 - c_i)z_i\alpha_i}{1 + r_i} \right]^{\frac{\alpha_i}{1-\alpha_i}} < 0 \quad (16)$$

This indicates that increases in loan interest rates or capital losses reduce the actual capital input of SMEs. Since $c_i'(\lambda) < 0, f'(k_i) > 0$, the development of digital inclusive finance reduces the financing costs and capital losses in SMEs' financing processes, thereby increasing SMEs' actual capital input and promoting output growth.

The application of big data and information technology enables financial institutions to respond quickly to enterprises' financing needs, reducing loan costs and debt mismatch losses (Tang and Geng, 2024; Lin and Dong, 2024). Simultaneously, digital finance reduces redundant costs in financing through real-time credit data mining. New loan models, such as those offered by online banks, and government support policies have also effectively alleviated the financing burden on SMEs (Zhang *et al.*, 2023; Wang *et al.*, 2024a, b). Accordingly, the following hypothesis is proposed:

H2. Digital inclusive finance alleviates SMEs' financing constraints through cost effects.

2.3 Information effect analysis

Enterprise information can be divided into "hard" information C , which is objective and easily accessible, and "soft" information φ , which accumulates over long-term cooperation between banks and enterprises. Suppose there are two types of credit screening technologies $j \in \{t, f\}$, where I_j represents the set of SME information that financial institutions can access, and X is the set of true information. Then:

$$X = I_j + \mu_j \quad (17)$$

Here, μ_j represents the information error, and $\frac{\mu_j}{X}$ reflects the degree of information asymmetry between financial institutions and SMEs. $\delta_j = \frac{\varphi_j}{C_j + \varphi_j}$ denotes the proportion of soft information captured under a specific loan technology. Hard information about enterprises is easily obtained through financial statements and collateral assets, so:

$$C_t = C_f = C \quad (18)$$

Under traditional loan technology, financial institutions can only access hard information C , thus $I_t = C, \mu_t = \frac{\varphi}{X}$. New loan technology can track the "digital footprint" of borrowers and extract $\vartheta(\lambda)$ as soft information, where $\vartheta'(\lambda) > 0$. Therefore:

$$I_f = C + \vartheta(\lambda)\varphi \quad (19)$$

$$\mu_f = \frac{\varphi - \vartheta(\lambda)\varphi}{X} < \mu_t \quad (20)$$

$$\frac{\partial \mu_f}{\partial \lambda} = -\frac{\varphi}{X} \vartheta'(\lambda) < 0 \quad (21)$$

Compared to traditional loan technology, new loan technology uses digital tools to extract more soft information, alleviating information asymmetry between banks and enterprises. Since $\delta_t = 0$, and:

$$\delta_f = \frac{\vartheta(\lambda)\varphi}{C + \vartheta(\lambda)\varphi} \quad (22)$$

$$\frac{\partial \delta_f}{\partial \lambda} = \frac{C\varphi\vartheta'(\lambda)}{[C + \vartheta(\lambda)\varphi]^2} > 0 \quad (23)$$

As digital inclusive finance develops, digital financial institutions use big data technology to transform soft information into hard information, converting previously unobservable behaviours, such as enterprise and individual transactions, browsing, and search activities, into standardised hard information. This mitigates information asymmetry between banks and enterprises, promotes information transparency, and identifies SMEs with growth potential. Accordingly, the following hypothesis is proposed:

H3. Digital inclusive finance alleviates SMEs' financing constraints through information effects.

3. Research design

3.1 Data source

This study focuses on listed companies on China's Growth Enterprise Market (GEM) from 2015 to 2022. Enterprise data are sourced from the CSMAR (China Stock Market and Accounting Research) database, while other macroeconomic data are obtained from the National Bureau of Statistics of China website and regional statistical yearbooks. The GEM is primarily established to support high-growth SMEs, which are smaller in size, with limited capital strength and market influence compared to large enterprises on the main board market. To ensure the representativeness of the sample data, the following procedures are applied: Exclude financial enterprises. Exclude *ST, ST, and PT enterprises. Exclude insolvent enterprises. Exclude enterprises with significant data missing. Winsorise continuous variables at the 1% level on both tails.

3.2 Variable definitions

3.2.1 Dependent variable. The dependent variable is SMEs' financing constraints (FC). Existing studies mainly measure financing constraints using the cash-flow sensitivity approach and established index-based methods. The cash-flow sensitivity approach identifies financing constraints by examining changes in corporate cash flow (Fazzari *et al.*, 1988; Almeida *et al.*, 2004). Index-based methods measure the degree of financing constraints using established indices, such as the KZ index (Kaplan and Zingales, 1997), the WW index (Whited and Wu, 2006), and the SA index (Hadlock and Pierce, 2010). However, the former is difficult to quantify accurately, while the latter often involves strong endogeneity concerns, which may

limit a deeper analysis of the dynamic evolution of financing constraints and their economic consequences.

Financing constraints essentially reflect a firm’s limited access to funds due to internal and external frictions. They are mainly manifested in three core dimensions: short-term liquidity pressure, long-term profitability support, and operational robustness. Specifically, liquidity determines a firm’s short-term solvency and capital turnover capacity; profitability reflects its potential for internal financing; and robustness captures long-term operational risk and serves as an important basis for external credit assessment. Accordingly, this paper selects seven core indicators from these three dimensions, as shown in [Table 1](#). These indicators comprehensively capture the conceptual scope of financing constraints and avoid the narrowness associated with relying on a single indicator.

The core empirical analysis of this paper consists of two parts. The first examines the contemporaneous and dynamic effects of digital inclusive finance on SMEs’ financing constraints. The second tests whether financing constraints mediate the relationship between digital inclusive finance and firm performance. In this context, the traditional indices have certain limitations. The SA index relies mainly on firm size and age, both of which change only slightly over a three-to five-year period, making it seriously biased when used as a mediating variable. Although the KZ and WW indices can capture year-to-year variation, they are subject to endogeneity problems that may interfere with the causal identification of the mediating mechanism.

By contrast, the FC index constructed in this paper can more effectively capture changes in the financing environment brought about by the development of digital inclusive finance. Therefore, it is more suitable for use as a mediating variable in the analysis of economic consequences.

Based on the above considerations, this paper employs an assignment scoring method to construct the FC index [\[5\]](#). To further verify the robustness of the results, [Section 4.2](#) reports regression results using the SA, WW, and KZ indices as alternative measures of financing constraints.

3.2.2 Explanatory variable. The primary explanatory variable is the regional digital inclusive finance development level (DF). Digital inclusive finance combines fintech and inclusive finance principles, utilising digital technology to enhance the accessibility of financial services. The density of fintech companies in a region reflects the level of digital finance penetration and maturity. Following the method of [Song et al. \(2021\)](#), company names and business scopes containing keywords such as “big data” “cloud computing” “blockchain” and “Internet of Things” were searched on the “Tianyancha” platform, excluding companies explicitly prohibited from engaging in financial services. The annual count of fintech companies in each region was calculated, incremented by one, and then log-transformed to measure the region’s digital inclusive finance level.

Table 1. Composition of the financing constraint indicators

Dimension	Indicator name	Indicator description
Liquidity	Cash Ratio	Reflects the enterprise’s ability to repay short-term debt
	Solvency Ratio	
Profitability	Return on Assets (ROA)	Reflects the efficiency of the enterprise in generating profit from its assets
Robustness	Enterprise Size	Reflects the enterprise’s long-term stability and growth potential
	Years Since Establishment	
	Net Fixed Asset Ratio	
	Accounts Receivable Ratio	

3.2.3 Control variables. Referring to the research by [Li et al. \(2020\)](#), firm-level control variables include enterprise size (Size), enterprise age (ListAge), leverage ratio (Lev), enterprise growth (Growth), cash flow (Cashflow), board independence (Indep), board size (Board), and ownership separation (Seperate). Additionally, city-level controls include GDP and population, as regions with higher GDP tend to have more developed economies and greater demand for financial services, while larger populations indicate bigger market sizes and customer bases.

3.3 Model construction

The following regression model is constructed for analysis:

$$FC_{i,t} = \alpha + \beta DF_{m,t} + \gamma Controls + \delta_i + \theta_j + \varepsilon_{i,t} \quad (24)$$

Where: $FC_{i,t}$: Degree of financing constraints faced by enterprise i in year t . $DF_{m,t}$: Digital inclusive finance level in the city where enterprise i located in year t . *Controls*: Control variables. δ_i : Time fixed effects. θ_j : City fixed effects. α : Constant term. γ : Coefficients of control variables. $\varepsilon_{i,t}$: Random error term. β : Effect of the core explanatory variable on SME financing constraints, expected to be significantly negative. The standard errors are adjusted for firm-level clustering effects.

3.4 Descriptive statistics

[Table 2](#) presents the descriptive statistics. Before log transformation, the median fintech company count (DFR) is 360, while the mean is 1111.2773, indicating a certain level of development in digital inclusive finance at the city level. The mean significantly exceeds the median, suggesting that the distribution of fintech company counts is heavily right-skewed. Therefore, using a log transformation ($DF = \ln(1+DFR)$) provides a more accurate measure of regional digital inclusive finance development. Additionally, the statistics of other control variables are generally consistent with findings from prior research.

4. Empirical results and analysis

4.1 Baseline regression

Column (1) of [Table 3](#) reports the baseline regression results. The coefficient of DF is significantly negative at the 5% level (coefficient = -0.0105 , t-value = -1.9833), providing support for [H1](#).

Table 2. Summary statistics

Var	N	Mean	SD	Min	Med	Max
FC	3,732	0.6179	0.1069	0.2812	0.6250	0.8750
DFR	3,732	1111.2773	1192.9516	0.0000	360.0000	3196.0000
DF	3,732	5.8360	1.9251	0.0000	5.8889	8.0700
Size	3,732	21.5672	0.8408	19.6537	21.4907	24.3610
Cashflow	3,732	0.0462	0.0624	-0.1587	0.0450	0.2523
Lev	3,732	0.3333	0.1753	0.0515	0.3093	0.9017
Dual	3,732	0.4204	0.4937	0.0000	0.0000	1.0000
Growth	3,732	0.2125	0.3858	-0.6234	0.1547	2.6093
Indep	3,732	38.5332	5.4021	33.3300	37.5000	57.1400
Board	3,732	2.0453	0.1907	1.6094	2.0794	2.5649
Seperate	3,732	2.9613	5.5687	0.0000	0.0000	28.3182
ListAge	3,732	5.1369	3.1289	0.0000	5.0000	13.0000
GDP	3,732	3.4157	5.5780	0.3049	1.7752	43.2148
Pop	3,732	0.3998	0.3151	0.0265	0.3719	1.2382

Table 3. Baseline regression

	(1) FC	(2) FC	(3) FC	(4) FC
DF	−0.0105** (−1.9833)			
L.DF		−0.0091* (−1.8238)		
L2.DF			−0.0111* (−1.9409)	
L3.DF				−0.0040 (−0.4616)
Size	−0.0297*** (−6.5728)	−0.0300*** (−5.3664)	−0.0290*** (−4.2989)	−0.0286*** (−3.4984)
Cashflow	−0.1151*** (−5.9331)	−0.1261*** (−5.9769)	−0.1249*** (−5.2078)	−0.1365*** (−4.8673)
Lev	0.3814*** (23.5414)	0.3608*** (19.3883)	0.3560*** (16.7337)	0.3325*** (12.9727)
Growth	−0.0210*** (−6.8720)	−0.0241*** (−7.9444)	−0.0270*** (−7.2857)	−0.0254*** (−5.2125)
Indep	−0.0012*** (−2.6029)	−0.0012** (−2.2617)	−0.0015** (−2.5472)	−0.0010 (−1.4760)
Board	−0.0350** (−2.2153)	−0.0213 (−1.2473)	−0.0344* (−1.7437)	−0.0351 (−1.5793)
Seperate	0.0007 (1.6013)	0.0006 (1.2792)	0.0004 (0.7877)	−0.0000 (−0.0458)
ListAge	−0.0025* (−1.6872)	−0.0020 (−1.1658)	−0.0016 (−0.7567)	−0.0035 (−1.3977)
GDP	0.0018 (1.3392)	0.0018 (0.9483)	0.0021 (1.0099)	0.0005 (0.1334)
Pop	0.0247 (0.7780)	0.0301 (0.9690)	0.0414 (1.3859)	0.0420 (1.3892)
_cons	1.2969*** (11.4470)	1.2689*** (9.3335)	1.2913*** (7.9429)	1.2545*** (6.6173)
Year/city fixed effects	Yes	Yes	Yes	Yes
N	3,732	2,925	2,275	1703
Within R ²	0.3744	0.3561	0.3560	0.3192

Note(s): *, **, and *** indicate significance levels at 10%, 5%, and 1%, respectively. The model employs robust standard errors clustered at the firm level, and t-values are reported in parentheses. The same notation applies to subsequent tables

Digital inclusive finance leverages big data technology to provide more financial information and data, thereby increasing transparency in financial markets. Financial institutions can accurately identify SMEs that lack collateral but have growth potential, making loan and credit services more cost-effective. This reduces the financing difficulties faced by SMEs, alleviating their financing constraints.

The advancement of digital inclusive finance has effectively alleviated SMEs' financing difficulties in the short term, but does it have the potential to sustainably reduce SMEs' financing pressure? To address this question, the long-term effects of digital inclusive finance (DF) were analysed. Specifically, lagged terms of digital inclusive finance (from 1 to 3 periods) were introduced into the baseline regression model to observe its dynamic impact on SMEs' financing constraints. The results are presented in Columns (2) to (4) of Table 3.

It is evident that while the coefficient of digital inclusive finance is no longer significant after a 3-period lag, it remains significant at least at the 10% level during the 1–2 period lags. This indicates that the alleviating effect of digital inclusive finance maintains strong momentum over a certain period, forming a cumulative overlay effect. Although its positive effect becomes statistically insignificant after the 3-period lag, this does not negate the long-term impact of digital

inclusive finance on SMEs' financing constraints. Instead, it suggests that the positive effects of digital inclusive finance are more pronounced in the early stages. Over time, these effects may gradually weaken or interact with other factors, leading to a reduction in statistical significance.

4.2 Robustness tests

4.2.1 Endogeneity issues. To address potential endogeneity in the model, this paper employs the instrumental variable (IV) approach and uses two types of instruments.

First, following [Gao et al. \(2024a, b\)](#), this paper uses the average of the one-period lagged city-level digital inclusive finance index and the corresponding provincial-level digital inclusive finance index as an instrumental variable, denoted as MeanIV. In terms of relevance, financial development generally exhibits strong time-series continuity. Therefore, the previous level of digital inclusive finance can effectively predict its current level, satisfying the correlation requirement for instrumental variables. In terms of exogeneity, the lagged city-level digital inclusive finance index is predetermined relative to firms' current financing constraints, which helps mitigate reverse causality arising from firms' financing behaviour. Moreover, the provincial-level digital inclusive finance index is determined by the overall development of all cities within a province and has strong macro-level characteristics. It is therefore unlikely to be influenced by the financing decisions of any individual SME. Taking the average of the city-level and provincial-level indicators further reduces potential disturbances caused by firm-level micro behaviours. In addition, the inclusion of city-level GDP and population controls for regional endowment differences, thereby alleviating potential confounding effects caused by the correlation between provincial lagged financial indicators and local financial environments.

Second, following [Goldsmith-Pinkham et al. \(2020\)](#), this paper constructs a city-level Bartik instrumental variable. Specifically, the one-period lagged number of fintech firms in each prefecture-level city is used as the local share and is multiplied by the national growth rate of fintech firms. The final Bartik instrumental variable, denoted as BartikIV, is obtained by adding one to the original value and taking the logarithm. In terms of relevance, the local stock of fintech firms provides an important industrial foundation for the development of urban digital inclusive finance and is therefore highly correlated with the core explanatory variable. In terms of exogeneity, national fintech industry growth reflects broader industry-level trends that are independent of local economic conditions, regional financial ecosystems, and individual firm characteristics. Such exogenous national trends should not directly affect SME financing constraints, but rather influence them indirectly by shaping the development level of local digital inclusive finance. This design helps reduce omitted-variable bias and other endogeneity concerns, thereby improving the reliability of the identification strategy.

Table 4 reports the regression results based on the two types of instrumental variables. Columns (1) and (2) present the two-stage regression results using MeanIV, while Columns (3) and (4) report the results using BartikIV. The first-stage results show that the coefficient of MeanIV on digital inclusive finance (DF) is 0.8722, with a t-value of 21.16, while the coefficient of BartikIV is 0.1674, with a t-value of 11.80. Both coefficients are significant at the 1% level, indicating that the two instrumental variables are strongly correlated with the endogenous explanatory variable.

The second-stage results show that, after correcting for potential endogeneity, digital inclusive finance continues to have a significantly negative effect on SME financing constraints. Specifically, the estimated coefficients are -0.0144 and -0.0428 , significant at the 5 and 1% levels, respectively. These results are consistent with the baseline regression findings, further supporting the conclusion that digital inclusive finance alleviates SME financing constraints.

The validity tests also indicate that the selected instruments are appropriate. The Kleibergen-Paap rk LM statistics for both instruments are significant at the 1% level, rejecting the null hypothesis of under-identification. In addition, both the Cragg-Donald Wald F statistic and the Kleibergen-Paap rk Wald F statistic exceed the Stock-Yogo critical value of 16.380 for the 10% maximal IV size, suggesting that weak identification is not a serious concern. Overall,

Table 4. Two-stage regression

	(1) DF	(2) FC	(3) DF	(4) FC
DF		−0.0144** (−2.0243)		−0.0428*** (−3.0638)
MeanIV	0.8722*** (21.1551)			
BartikIV			0.1674*** (11.8032)	
Kleibergen-Paap rk LM statistic	107.203***		127.650***	
Cragg-Donald Wald F statistic	8510.557 {16.380}		493.730 {16.380}	
Kleibergen-Paap rk Wald F statistic	447.698 {16.380}		139.366 {16.380}	
Controls	Yes	Yes	Yes	Yes
Year/city fixed	Yes	Yes	Yes	Yes
N	2,843	2,843	2,843	2,843

Note(s): { } indicates the Stock-Yogo weak ID test critical value at the 10% significance level. ** Significant at 5% confidence level, *** significant at the 1% confidence level

these results confirm the validity and appropriateness of the instrumental variables used in this paper.

4.2.2 Replacing the core explanatory variable. The Peking University Digital Inclusive Finance Index (DFindex) and its sub-indicator coverage breadth (DFcover), developed by [Guo et al. \(2020\)](#), were introduced as alternative variables for DF. Both indicators were log-transformed. In Columns (1) and (2) of [Table 5](#), the negative impacts of DFindex and DFcover on FC are significant at the 5% level, aligning with the conclusions of the baseline regression.

4.2.3 Replacing the dependent variable. First, following [Hadlock and Pierce \(2010\)](#), the SA index is calculated as follows:

$SA = -0.737 \times Size + 0.043 \times Size^2 - 0.040 \times Age$ The absolute value of the calculated result is used as the dependent variable. As shown in Column (3) of [Table 5](#), the coefficient of regional digital inclusive finance development (DF) on the SA index is significantly negative at the 10% level, which is consistent with the baseline regression results.

Second, the WW index ([Whited and Wu, 2006](#)) and the KZ index ([Kaplan and Zingales, 1997](#)) are used as alternative proxies for financing constraints. The results reported in Columns (4) and (5) show that the coefficients of DF are −0.0067 ($t = -2.9785$) and −0.1657 ($t = -1.7129$), respectively, both of which are statistically significant.

Table 5. Robustness tests with replacements of explanatory and dependent variables

	(1) FC	(2) FC	(3) SA	(4) WW	(5) KZ
DFindex	−0.2074** (−2.4091)				
DFcover		−0.1237** (−2.4070)			
DF			−0.0082* (−1.9489)	−0.0067*** (−2.9785)	−0.1657* (−1.7129)
Controls	Yes	Yes	Yes	Yes	Yes
Year/city fixed effects	Yes	Yes	Yes	Yes	Yes
N	3,732	3,732	3,732	3,732	3,635

Note(s): * Significant at the 10% level, ** significant at the 5% confidence level, *** significant at the 1% confidence level

Overall, the results remain robust when the SA, WW, and KZ indices are used as alternative measures of financing constraints. This indicates that the alleviating effect of digital inclusive finance on SME financing constraints does not depend on a specific measurement method, thereby further supporting the robustness of the main conclusions.

4.2.4 Exclusion of special samples. To address potential biases caused by the significant changes in economic activity after the COVID-19 pandemic in 2020, samples from these years were excluded. The results are presented in Column (1) of Table 6. Additionally, considering the unique economic policies of China's four directly governed municipalities, data from these municipalities were removed, with regression results shown in Column (2) of Table 6. In Column (1), after excluding samples from the post-2020 period, the coefficient remains significantly negative at the 10% level (t -value = -1.6601). In Column (2), after removing the four municipalities, the coefficient is also significantly negative at the 10% level (t -value = -1.7687). These results are consistent with the baseline regression, confirming the robustness of the findings even after excluding special samples.

4.3 Economic consequence analysis

To further clarify the practical value of digital inclusive finance in alleviating financing constraints, this paper uses return on total assets (ROA) and return on equity (ROE) as measures of firm performance. It then examines the relationships among digital inclusive finance, financing constraints, and corporate performance. ROA reflects the overall profitability of a firm's asset utilisation, while ROE captures the efficiency of returns on shareholders' equity. Together, these two indicators provide a relatively comprehensive measure of SMEs' operating performance.

Table 7 reports the corresponding regression results. Column (1) shows that the coefficient of digital inclusive finance (DF) is positive and significant at the 5% level, with a coefficient of

Table 6. Robustness tests excluding special years and municipality samples

	(1) FC	(2) FC
DF	-0.0093^* (-1.6601)	-0.0160^* (-1.7687)
Controls	Yes	Yes
Year/city fixed effects	Yes	Yes
N	2,901	3,189

Note(s): * Significant at the 10% confidence level

Table 7. Economic consequence analysis

	(1) ROA	(2) ROA	(3) ROE	(4) ROE
DF	0.0115^{**} (2.0024)	0.0078 (1.4334)	0.0234^{**} (2.1135)	0.0186^* (1.7329)
FC		-0.3509^{***} (-12.7586)		-0.4568^{***} (-8.9859)
Controls	Yes	Yes	Yes	Yes
Year/city fixed effects	Yes	Yes	Yes	Yes
N	3,732	3,732	3,732	3,732
Within R^2	0.2914	0.3419	0.2967	0.3238

Note(s): * Significant at the 10% level, ** significant at the 5% confidence level, *** significant at the 1% confidence level

0.0115. This indicates that the development of digital inclusive finance is positively associated with improvements in firms’ asset profitability. In Column (2), after financing constraints (FC) are introduced as a control variable, the positive effect of DF on ROA is no longer statistically significant. This preliminarily suggests that financing constraints may play a potential transmission role in the relationship between digital inclusive finance and corporate asset returns.

Column (3) shows that DF has a significantly positive effect on ROE, with a coefficient of 0.0234, significant at the 5% level. This indicates that the development of digital inclusive finance is positively associated with improved shareholder returns. In Column (4), after further controlling for FC, the significance of the coefficient on DF decreases to the 10% level, and the magnitude of the coefficient also declines. This pattern is consistent with the theoretical expectation that financing constraints serve as a transmission channel through which digital inclusive finance affects corporate performance.

From a theoretical perspective, financing constraints are a key factor restricting the operational development of SMEs (Qiao *et al.*, 2025; Li *et al.*, 2025a, b). Limited financing may lead to insufficient capital allocation and hinder firms’ operational expansion, thereby suppressing profitability. By leveraging technological advantages, digital inclusive finance can broaden firms’ financing channels and improve the efficiency of capital acquisition, thereby helping firms optimise their capital allocation conditions (Gu and Duan, 2026). As a result, SMEs are able to allocate more funds to production, business expansion, and other value-creating activities, which improves operational efficiency and profitability, strengthens market competitiveness, and supports sustainable growth.

Overall, the economic consequence analysis indicates that financing constraints may play a potential transmission role in the relationship between digital inclusive finance and SMEs’ financial performance. In other words, the alleviating effect of digital inclusive finance on financing constraints can be further translated into improvements in corporate performance, which is consistent with the theoretical logic discussed above.

4.4 Mechanism analysis

4.4.1 Cost effect. The ratio of interest expense to total liabilities is used to measure corporate financing costs (Cost) and to test the cost-effect pathway. As shown in Column (1) of Table 8, the coefficient of digital inclusive finance (DF) is -0.0044 and is significant at the 5% level, indicating that the development of digital inclusive finance is negatively associated with corporate financing costs.

Column (2) further shows that the coefficient of Cost is significantly positive, with a coefficient of 0.4485 and a t-value of 1.9122. This suggests that higher financing costs are associated with more severe financing constraints. More importantly, after Cost is introduced

Table 8. Mechanism analysis based on cost and information effects

	(1) Cost	(2) FC	(3) Transparency	(4) FC
DF	-0.0044^{**} (-2.3369)	-0.0117 (-1.0168)	0.1377^{*} (1.6717)	-0.0038 (-0.6503)
Transparency				-0.0132^{***} (-6.5797)
Cost		0.4485^{*} (1.9122)		
Controls	Yes	Yes	Yes	Yes
Year/city fixed effects	Yes	Yes	Yes	Yes
N	2,343	2,343	2,578	2,578

Note(s): * Significant at the 10% level, ** significant at the 5% confidence level, *** significant at the 1% confidence level

into the model, the coefficient of DF becomes statistically insignificant. This change is consistent with the theoretical logic of the cost transmission pathway, providing suggestive evidence in support of H2.

4.4.2 Information effect. Following Yao *et al.* (2020), this paper uses the natural logarithm of one plus the number of analyst followers as a proxy for corporate information transparency (Transparency) to examine the information-effect pathway.

As shown in Column (3) of Table 8, the coefficient of digital inclusive finance (DF) is positive and significant at the 10% level, indicating that the development of digital inclusive finance is positively associated with corporate information transparency. Column (4) further shows that the coefficient of Transparency is significantly negative, suggesting that higher information transparency is associated with weaker financing constraints.

Moreover, compared with the baseline regression, both the magnitude and statistical significance of the coefficient on DF decline noticeably after Transparency is introduced into the model. This pattern suggests that information transparency may play a potential transmission role in the relationship between digital inclusive finance and financing constraints, thereby providing empirical support for H3.

4.5 Heterogeneity analysis

4.5.1 Heterogeneity based on ownership structure. The development of the financial system often lags behind market practice, making it difficult for financial institutions to accurately assess firms' default risks. Due to implicit government guarantees, state-owned enterprises (SOEs) usually maintain closer relationships with financial institutions and possess inherent advantages in credit markets. To examine whether ownership structure affects the role of digital inclusive finance, SMEs are divided into state-owned and non-state-owned enterprises for separate regressions.

The results reported in Columns (1) and (2) of Table 9 show that, for the subsample of non-state-owned SMEs, the coefficient of digital inclusive finance (DF) is -0.0111 and is significant at the 10% level. By contrast, for state-owned SMEs, the coefficient of DF is -0.0021 and does not pass the significance test. These findings indicate that digital inclusive finance has a more pronounced alleviating effect on financing constraints among non-state-owned SMEs.

A possible explanation is that non-state-owned enterprises generally lack explicit or implicit government credit support and therefore face greater financing disadvantages in traditional credit markets. As a result, they have stronger incentives to use digital inclusive finance to improve their credit records, reduce information asymmetry, and expand access to financing opportunities (Lu *et al.*, 2024; Chen *et al.*, 2026; Zhang *et al.*, 2026).

4.5.2 Heterogeneity based on industry characteristics. High-tech industries are typically characterised by high risk and high investment, requiring substantial financial support for

Table 9. Subsample analysis based on ownership structure, industry characteristics, and regulatory environment

	(1) State- owned	(2) Non- state- owned	(3) High-tech industry	(4) Non-high- tech industry	(5) High- regulation intensity	(6) Low- regulation intensity
DF	-0.0021 (-0.1010)	-0.0111^* (-1.9611)	-0.0096^* (-1.6951)	-0.0111 (-0.7446)	-0.0069 (-0.8598)	-0.0143^* (-1.7203)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year/city fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
N	279	3,453	3,052	680	2085	1647
Within R^2	0.3267	0.3902	0.3731	0.4117	0.3829	0.3879

Note(s): * Significant at the 10% confidence level

R&D and innovation activities. As a result, firms in these industries often face more severe financing constraints. By contrast, non-high-tech industries, such as agriculture and forestry, usually have relatively stable business models and do not rely heavily on continuous innovation to sustain operations. To examine the heterogeneous effects of digital inclusive finance across industries, this paper divides SMEs into high-tech and non-high-tech enterprises [6].

The results reported in Columns (3) and (4) of Table 9 show that digital inclusive finance plays a more prominent role in alleviating financing constraints for SMEs in high-tech industries. In contrast, its effect is not statistically significant for SMEs in non-high-tech industries. One possible explanation is that high-tech enterprises are R&D-intensive and rely heavily on sustained and stable external financing. However, their asset-light and technology-intensive characteristics often lead to limited collateral and relatively unstable cash flows, thereby increasing the difficulty of obtaining traditional financing (Wan *et al.*, 2025).

Digital inclusive finance can help address this problem by using multi-dimensional information to assess firms' development potential and, to some extent, substituting data-based credit evaluation for traditional collateral requirements. Its flexibility and innovation-oriented features are therefore better aligned with the financing needs of high-tech enterprises (Pu and Cai, 2025), helping to ease their financing constraints. For non-high-tech enterprises, which generally operate more steadily and have relatively smoother access to traditional financing channels, the marginal improvement brought by digital inclusive finance is likely to be more limited.

4.5.3 Heterogeneity based on regulatory environment. As finance remains the core of digital inclusive finance, its profit-oriented nature continues to exist. If financial regulation fails to adapt promptly to changes in financial operations, financial risks may become more difficult to identify and assess. To examine whether financial regulation affects the effectiveness of digital inclusive finance in alleviating financing constraints, this paper divides the sample into high- and low-regulation groups based on the median value of financial regulatory intensity [7].

Columns (5) and (6) of Table 9 report the effects of digital inclusive finance on SME financing constraints under different levels of financial regulatory intensity. In the low-regulation group, the coefficient of digital inclusive finance (DF) is significantly negative, with a coefficient of -0.0143 and a t -value of -1.7203 . By contrast, in the high-regulation group, the absolute value of the DF coefficient is smaller and statistically insignificant, with a coefficient of -0.0069 and a t -value of -0.8598 . These results suggest that the effectiveness of digital inclusive finance in alleviating SME financing constraints may depend on a flexible and moderately regulated environment.

A possible explanation is that, in a low-regulation environment, fintech firms have greater space for innovation and can develop more flexible service models. This enables them to better match the diverse, small-scale, and high-frequency financing needs of SMEs. However, excessive regulatory stringency may restrict technological iteration and the expansion of application scenarios for digital inclusive finance, thereby weakening its practical effectiveness in easing financing constraints.

These findings do not negate the necessity of financial regulation. Rather, they suggest that a dynamically adaptive, inclusive, and prudent regulatory framework may be more conducive to maximising the enabling role of digital inclusive finance for SMEs while maintaining effective risk control. This conclusion is consistent with the flexible regulatory perspective advocated by Tang *et al.* (2020) and Wu *et al.* (2026), which emphasises the importance of achieving a dynamic balance between risk prevention and innovation incentives.

5. Conclusion and implications

This paper constructs a four-sector theoretical model between SMEs and financial institutions and uses a fixed-effects model to examine the impact of digital inclusive finance on alleviating SME financing constraints and its mechanisms.

The findings are as follows: First, the development of digital inclusive finance significantly alleviates SMEs' financing constraints, with this alleviation effect being sustained over a certain period. Second, digital inclusive finance improves corporate performance by alleviating financing constraints. Third, digital inclusive finance primarily functions through two channels: reducing financing costs and enhancing corporate information transparency. Fourth, the alleviation effect of financing constraints is more pronounced for non-state-owned enterprises, high-tech industries, and under lower regulatory intensity.

Based on the findings, we propose the following recommendations for governments, financial institutions, and SMEs, respectively:

- (1) For government, they should develop forward-looking policies to improve fintech infrastructure, offering tax incentives and subsidies to stimulate innovation in financial and tech firms. They should also implement balanced regulatory strategies to prevent financial risks without inhibiting innovation and direct resources to high-tech and non-state-owned enterprises.
- (2) For financial institutions, they should accelerate digital transformation and innovate financial products and services. By leveraging big data and cloud computing, they can streamline loan approvals for SMEs and lower transaction costs. Collaborating with fintech companies will help build an integrated online-offline financing system to reduce information asymmetry.
- (3) For SMEs, they should actively embrace digital finance and strengthen cooperation with financial institutions. Utilising digital tools like e-ledgers and automated supply chain management will improve transparency. By maintaining strong credit records and exploring innovative partnership models, they can maximise the advantages of digital financial services, particularly non-state-owned enterprises and those in high-tech sectors.

Notes

1. <https://www.un.org/zh/207309>
2. https://www.gov.cn/yaowen/liebiao/202411/content_6987555.htm
3. https://wap.miit.gov.cn/xwdt/gxdt/sjdt/art/2024/art_0284e944c2f543e4b6541970ebfbc2aa.html
4. <https://data.eastmoney.com>
5. The financing constraint indicator (FC) is constructed as follows: For each sub-indicator of the sample enterprises, scores are assigned based on quintiles, ranking from high to low. The scores are then summed across all selected indicators to obtain the financing constraint indicator *FC*. Finally, the *FC* values are standardised for consistency and comparability.
6. According to the 2012 classification guidelines for listed companies issued by the China Securities Regulatory Commission (CSRC): Companies with classification codes C25–C29, C31–C32, C34–C41, I63–I65, and M73 are defined as high-tech industry companies. Companies outside these classification codes are defined as non-high-tech industry companies.
7. The intensity of financial regulation is measured by the ratio of regional financial regulation expenditures to the value-added of the financial industry.

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