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Research on the Impact Mechanism of Digital Inclusive Finance on Enterprise Value

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Abstract:

The steady enhancement of enterprise value during the development process is of critical importance to firms themselves and also serves as a micro-level foundation for achieving high-quality economic development at the national level. Using A-share listed companies in Shanghai and Shenzhen from 2018 to 2023 as the research sample, this study systematically investigates the impact of digital inclusive finance on enterprise value and its underlying mechanisms. The empirical results indicate that digital inclusive finance significantly promotes enterprise value. Specifically, digital inclusive finance not only enhances enterprise value through two parallel and independent mediating channels-namely increasing R&D investment and promoting substantive innovation-but also improves enterprise value through a chain mediation mechanism in which R&D investment facilitates substantive innovation. The conclusions remain robust after endogeneity treatment and robustness tests. Further heterogeneity analysis reveals that the above impact mechanisms vary across different ownership structures and regional levels of economic development.

Keywords:

digital inclusive finance; enterprise value; R&D investment; substantive innovation

1. Introduction

At present, China is in a critical stage of economic structural transformation. The optimization and upgrading of the industrial structure, as well as the conversion between old and new growth drivers [1], are inseparable from the healthy and sustainable development of real-sector enterprises. Finance serves as the “bloodstream” of the real economy. Existing studies have shown that financial development can promote economic growth by improving capital allocation efficiency, facilitating technological progress, and enhancing total factor productivity. As micro-level entities within the macroeconomic environment, enterprises constitute the foundation of high-quality economic development. Therefore, examining the impact of financial development on enterprise growth contributes to a deeper understanding of the micro-level mechanisms through which finance drives economic expansion. The report of the 20th National Congress emphasized the central role of innovation in China's modernization strategy and further highlighted the implementation of the innovation-driven development strategy [2]-[3].

However, technological innovation is typically characterized by high investment intensity, long return cycles, and elevated risk, requiring firms to possess a solid innovation foundation and sustained financial support. With the rapid advancement of the digital economy and digital technologies, digital inclusive finance has emerged as a transformative financial model. It has reshaped the traditional financial ecosystem, improved the accessibility of financial services, and provided liquidity support to a broader range of “long-tail” customers. By alleviating financing constraints and reducing financing costs, digital inclusive finance offers

essential capital support for enterprises' innovation activities and thus plays a significant role in promoting corporate innovation.

Based on this background, this study constructs a composite multiple mediation model to incorporate digital inclusive finance and enterprise value into a unified analytical framework. It systematically investigates the impact of digital inclusive finance on enterprise value and its underlying mechanisms, with particular attention to whether the development dividend of digital inclusive finance can be leveraged to enhance R&D investment and, subsequently, increase substantive innovation output, thereby improving enterprise value. Furthermore, this study examines whether the effect of digital inclusive finance on enterprise value varies across different ownership structures and regional levels of economic development.

This research contributes to the literature in several aspects. First, it enriches existing studies on the microeconomic effects of digital inclusive finance at the enterprise level. Second, it provides new micro-level evidence on the relationship between digital finance and high-quality development of the real economy. Finally, the findings offer meaningful policy implications for government decision-making and valuable managerial insights for enterprise practice.

2. Related work

The methodological foundation of the proposed framework builds upon recent advances in causal modeling, representation learning, graph-based reasoning, adaptive learning paradigms, and uncertainty-aware machine learning. These developments provide complementary methodological principles that collectively guide the design of robust data-driven analytical frameworks for complex financial systems.

A fundamental methodological component derives from causal modeling and structural reasoning frameworks that enable interpretable inference in complex data environments. Recent studies have demonstrated that causal representation learning can effectively capture latent causal dependencies among high-dimensional variables, thereby improving both model robustness and interpretability [4]. Related work further extends causal reasoning to structured knowledge representations, enabling analytical models to support intervention-aware reasoning and decision-oriented analysis [5]. In addition, dynamic spatiotemporal causal graph frameworks have been proposed to model complex relational dependencies across interconnected entities while simultaneously capturing temporal evolution patterns [6]. Hybrid reasoning frameworks integrating causal structures with large language models have also shown the potential to automate complex diagnostic reasoning processes by combining symbolic reasoning with data-driven inference mechanisms [7]. These causal modeling paradigms collectively provide methodological guidance for constructing interpretable analytical frameworks capable of capturing latent structural dependencies and causal pathways.

Beyond causal reasoning, graph-based deep learning architectures provide important capabilities for modeling complex relational structures embedded in high-dimensional systems. Graph-structured representation learning methods enable models to capture interactions among heterogeneous entities and identify latent structural patterns across interconnected components [8]. Related research further demonstrates that graph neural networks can effectively model structural dependencies within distributed systems, enabling scalable representation learning across large-scale relational environments [9]. Multi-scale feature fusion strategies have also been incorporated into graph-based architectures to enhance representation quality by integrating heterogeneous features across multiple semantic levels [10]. These approaches collectively highlight the effectiveness of graph-based learning mechanisms in extracting structured knowledge from complex relational datasets.

Another important methodological component involves anomaly detection and risk modeling mechanisms designed to identify latent irregularities in complex systems. Recent research has proposed reconstruction-consistency-based anomaly ranking frameworks that detect deviations between learned latent structures and observed behaviors, enabling effective identification of abnormal patterns within enterprise-level datasets [11]. Contrastive dependency modeling techniques further enhance anomaly detection by learning discriminative representations of normal system behaviors and identifying deviations from expected dependency structures [12]. Federated risk discrimination frameworks based on siamese learning architectures have also been developed to enable collaborative anomaly detection while preserving data privacy across distributed environments [13]. These approaches collectively provide robust modeling strategies for detecting structural irregularities and latent risk signals within complex data systems.

Adaptive learning strategies further contribute to improving model generalization and robustness in dynamic environments. Meta-learning frameworks have been introduced to enable adaptive anomaly detection across evolving system environments by learning transferable knowledge from multiple related tasks [14]. Unified meta-learning and domain adaptation mechanisms extend this capability by enabling models to adapt to distributional shifts across heterogeneous data domains [15]. These adaptive learning paradigms provide methodological support for building models capable of maintaining performance stability under dynamic and non-stationary data conditions.

Recent advances in generative modeling and uncertainty-aware learning also contribute important methodological insights for robust decision-making systems. Wasserstein-based generative modeling approaches enable robust optimization under distributional uncertainty by learning probabilistic representations of complex data distributions [16]. Diffusion-based generative frameworks further extend generative modeling capabilities by enabling controllable data generation through conditional stochastic processes [17]. In addition, uncertainty-aware reasoning mechanisms have been proposed to quantify model confidence and incorporate risk-aware decision strategies within large language model-based summarization and reasoning processes [18]. These approaches collectively highlight the importance of incorporating uncertainty quantification and probabilistic modeling into modern machine learning systems.

Multi-agent learning and collaborative intelligence frameworks also provide methodological inspiration for modeling complex interactive environments. Game-theoretic multi-agent modeling frameworks enable the analysis of systemic interactions among heterogeneous decision agents and capture the propagation dynamics of complex system-level risks [19]. Trust-aware orchestration mechanisms have been proposed to enhance robustness in multi-agent collaboration by dynamically managing trust relationships among participating agents [20]. Lightweight coordination protocols further enable efficient detection and repair of role inconsistencies within collaborative agent systems, thereby improving the stability of distributed learning environments [21]. These multi-agent modeling paradigms provide important methodological insights for capturing distributed decision-making dynamics and collaborative interactions in complex systems.

Large language model-based reasoning and representation learning techniques also contribute methodological innovations for complex analytical tasks. Semantic calibration mechanisms have been introduced to improve adversarial robustness in text-based classification tasks by aligning semantic representations with calibrated reasoning processes [22]. Parameter-efficient adaptation strategies such as multi-scale low-rank adaptation further enable efficient fine-tuning of large models across diverse tasks while maintaining computational efficiency [23]. Autonomous knowledge structuring mechanisms have also been explored to support self-driven exploration and knowledge organization in open-world intelligent agents [24]. These techniques demonstrate how large-scale representation learning frameworks can enhance reasoning capabilities in complex analytical environments.

Finally, broader theoretical studies on digital finance, financial systems, and innovation-driven economic structures provide contextual foundations for modeling complex financial ecosystems. Research on digital finance and fintech ecosystems highlights the structural transformation of financial intermediation systems driven by digital technologies [25-27]. Related work on financial economics and innovation financing emphasizes the role of financial systems in supporting technological innovation and enterprise growth through improved capital allocation and risk-sharing mechanisms [28-31]. These studies provide systemic insights that motivate the integration of advanced data-driven analytical methods into financial system modeling.

3. Theoretical Analysis and Research Hypotheses

3.1 Digital Inclusive Finance and Enterprise Value

The direct impact of digital inclusive finance on enterprise value is primarily reflected in several aspects. First, by leveraging technologies such as big data and cloud computing, digital inclusive finance reduces information screening costs for financial institutions, thereby enabling small and medium-sized enterprises and asset-light firms-which are often underserved by traditional financial services-to obtain credit support. Adequate funding can be directly applied to production expansion, equipment upgrading, or short-term liquidity turnover, preventing operational interruptions caused by capital chain disruptions and thereby enhancing enterprise value through stable operations and profit growth.

Second, compared with traditional financial services, digital inclusive finance reduces financing fees, time costs, and management expenses. Direct cost savings contribute to increased profitability, which in turn enhances enterprise value based on earnings performance.

Third, broader coverage of digital inclusive finance implies more standardized financial service support. Improved operational transparency and credit information recognition strengthen market confidence, reduce investors' risk premium expectations, attract additional capital inflows, and elevate stock prices or firm valuation-directly reflecting enhanced enterprise value at the market level.

In summary, digital inclusive finance exerts a positive effect on enterprise value through improved capital acquisition, cost control, and market recognition. Empirical evidence from related studies also supports this conclusion [32-34]. Based on the above analysis, the following hypothesis is proposed:

H1: Digital inclusive finance significantly promotes enterprise value.

3.2 The Mediating Effect of R&D Investment

R&D activities are characterized by high risk, substantial investment, and long return cycles. Enterprises often face insufficient R&D funding due to constraints in traditional financing channels. Digital inclusive finance alleviates information asymmetry through big data-based risk control mechanisms, expands financing channels, and provides stable funding sources for R&D activities-thereby directly promoting increased R&D investment.

Sufficient R&D investment facilitates technological breakthroughs, product upgrading, and process improvement, thereby forming differentiated competitive advantages. According to innovation theory, technological innovation enhances production efficiency, product value-added, and pricing power, which further strengthens profitability and long-term growth potential, ultimately improving enterprise value. Based on the above reasoning, the following hypothesis is proposed:

H2: R&D investment plays a mediating role in the relationship between digital inclusive finance and enterprise value-that is, digital inclusive finance indirectly enhances enterprise value by increasing R&D investment.

3.3 The Mediating Effect of Substantive Innovation

Substantive innovation refers to high-quality innovation activities aimed at promoting technological advancement and acquiring competitive advantages [35-36]. Such innovation is characterized by high risk, significant sunk costs, and long development cycles. Owing to information asymmetry and risk aversion, traditional financial systems often provide insufficient support for such activities.

Digital inclusive finance, through big data mining of innovation potential, blockchain-based tracing of R&D achievements, and intelligent risk assessment of innovation projects, can precisely match the funding demands of substantive innovation, reduce financing constraints, and encourage firms to allocate more resources toward high-quality innovation.

Substantive innovation generates difficult-to-imitate technological barriers and competitive advantages, such as unique product lines or service models, expanded market share, improved production efficiency, reduced unit costs, enhanced profitability, and accumulation of high-value intangible assets, thereby improving firm valuation. This mediating pathway emphasizes that only innovation activities transformed into core technological breakthroughs can serve as the key link connecting financial support and enterprise value growth. Empirical findings from related research also indicate that technological innovation partially mediates the value-enhancing effect of digital inclusive finance [37-39]. Accordingly, the following hypothesis is proposed:

H3: Substantive innovation plays a mediating role in the relationship between digital inclusive finance and enterprise value-that is, digital inclusive finance indirectly enhances enterprise value by encouraging substantive innovation.

3.4 The Chain Mediating Effect of R&D Investment and Substantive Innovation

Digital inclusive finance expands financing channels, reduces financing costs, and mitigates information asymmetry, thereby providing financial support for corporate R&D activities [40]. This effect is particularly significant for small and medium-sized enterprises facing traditional financing constraints, leading to increased R&D investment.

Adequate R&D investment lays the foundation for substantive innovation. R&D funds can be allocated to frontier technology exploration, recruitment of high-end talent, or acquisition of experimental equipment. Sustained R&D investment supports long-term and high-risk original research, which is more likely to generate substantive innovation outcomes.

Substantive innovation-in the form of technological barriers, distinctive products, or advanced processes-enhances product value-added and pricing power, increases profitability, accumulates high-value intangible assets, improves investor expectations regarding long-term growth, reduces dependence on external technologies, and lowers operational risk. These effects are ultimately reflected in improved enterprise value.

This chain mediation pathway reveals a complete transmission mechanism through which financial support is transformed into enterprise value-namely, “capital-investment-innovation-value.” It highlights that R&D investment serves as the foundation of substantive innovation, while substantive innovation represents the critical link through which R&D investment translates into enhanced enterprise value. Together, they

constitute the indirect transmission channel through which digital inclusive finance influences enterprise value. Based on the above analysis, the following hypothesis is proposed:

H4: R&D investment and substantive innovation jointly constitute a chain mediating effect in the relationship between digital inclusive finance and enterprise value-that is, digital inclusive finance increases R&D investment, which promotes substantive innovation, ultimately leading to enhanced enterprise value.

The theoretical framework of this study is illustrated in Figure 1.

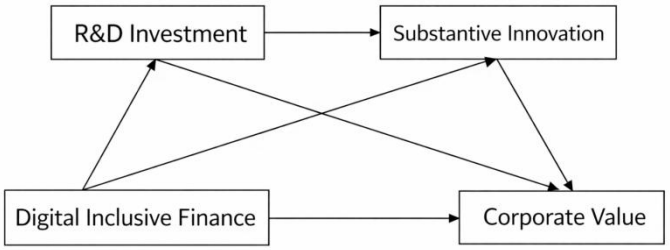

Figure 1. Theoretical Framework of the Study

4. Research Design

4.1 Sample and Data Sources

This study selects A-share listed companies in Shanghai and Shenzhen from 2018 to 2023 as the initial research sample. Financial firms, ST and *ST companies, as well as observations with significant financial anomalies or missing data, are excluded.

The digital inclusive finance index is obtained from the Peking University Digital Inclusive Finance Index. Data on R&D investment and patent information are sourced from the China Research Data Services Platform (CNRDS). Other financial and firm-level data are collected from the China Stock Market and Accounting Research Database (CSMAR). Data processing and preliminary analysis are conducted using Excel and SPSS.

4.2 Variable Definitions

1) Explanatory Variable-Digital Inclusive Finance

The Peking University Digital Inclusive Finance Index comprehensively reflects the level of digital financial development across regions and has been widely adopted in prior research due to its reliability and representativeness. Given the relatively large magnitude of the index, and following the approach of prior studies [41], the index value is divided by 100 for empirical analysis.

2) Dependent Variable-Enterprise Value

Various indicators can be used to measure enterprise value, including economic value added, earnings per share, return on net assets, and Tobin's Q. Tobin's Q not only reflects historical firm performance but also incorporates market expectations regarding future value, thereby providing a comprehensive assessment of both book value and market value. Accordingly, Tobin's Q is employed to measure enterprise value in this study.

3) Mediating Variables-R&D Investment and Substantive Innovation

R&D investment is denoted by RD and measured as the natural logarithm of R&D expenditure plus one.

Substantive innovation is denoted by INNO. Among the three types of patents, invention patents are considered to exhibit the highest level of innovativeness. Therefore, the number of granted invention patents is used to proxy substantive innovation, and the natural logarithm of the number of invention patents plus one is applied in the regression analysis.

4) Control Variables

Based on relevant domestic and international literature, this study controls for firm size, firm age, cash holdings, the proportion of fixed assets, institutional ownership, CEO duality, the proportion of independent directors, and ownership concentration. Detailed variable definitions are presented in Table 1.

Table 1: Variable Definitions

Variable Type	Symbol	Variable Name	Measurement Method
Dependent Variable	Tobin's Q	Enterprise Value	Market value of the firm / Total assets at year-end
Explanatory Variable	DIFI	Digital Inclusive Finance	Digital inclusive finance index divided by 100
Mediating Variable	RD	R&D Investment	Natural logarithm of R&D expenditure plus 1
Mediating Variable	INNO	Substantive Innovation	Natural logarithm of granted invention patents plus 1
Control Variable	Size	Firm Size	Natural logarithm of total assets
Control Variable	Age	Firm Age	Ln (Current year − Year of establishment + 1)
Control Variable	Cash	Cash Holdings	Net cash flow from operating activities / Total assets
Control Variable	FIXED	Fixed Asset Ratio	Net fixed assets / Total assets
Control Variable	INST	Institutional Ownership	Sum of institutional investors' shareholding ratios
Control Variable	Dual	CEO Duality	Dummy variable-equals 1 if the chairman concurrently serves as CEO, otherwise 0
Control Variable	Indep	Independent Director Ratio	Number of independent directors / Total number of directors × 100%
Control Variable	Top10	Ownership Concentration	Sum of shareholding ratios of the top ten shareholders

4.3 Model Specification

To test Hypothesis H1, the following baseline model is constructed:

Model (1):

$$\text{Tobin's Q} = \alpha_0 + \alpha_1 \text{DIFI} + \alpha_i \sum \text{Control} + \varepsilon$$

If the coefficient α_1 of DIFI in Model (1) is significantly positive, it indicates a positive association between digital inclusive finance and enterprise value-suggesting that the development of digital inclusive finance contributes to the enhancement of enterprise value.

To test Hypotheses H2, H3, and H4, and following the methodological framework of prior mediation analysis studies [42], a chain multiple mediation model is constructed as Models (2)-(4).

Model (2):

$$\text{RD} = \beta_0 + \beta_1 \text{DIFI} + \beta_i \sum \text{Control} + \varepsilon$$

Model (3):

$$\text{INNO} = \gamma_0 + \gamma_1 \text{DIFI} + \gamma_2 \text{RD} + \gamma_i \sum \text{Control} + \varepsilon$$

Model (4):

$$\text{Tobin's Q} = \delta_0 + \delta_1 \text{DIFI} + \delta_2 \text{RD} + \delta_3 \text{INNO} + \delta_i \sum \text{Control} + \varepsilon$$

Model (2) examines the impact of digital inclusive finance on R&D investment. Model (3), controlling for digital inclusive finance, tests the effect of R&D investment on substantive innovation. Model (4), controlling for digital inclusive finance and R&D investment, tests the effect of substantive innovation on enterprise value.

Within the chain multiple mediation framework, the two parallel independent mediation paths are "digital inclusive finance-R&D investment-enterprise value" and "digital inclusive finance-substantive innovation-enterprise value," with effect sizes represented by $\beta_1\delta_2$ and $\gamma_1\delta_3$, respectively. The chain mediation path is "digital inclusive finance-R&D investment-substantive innovation-enterprise value," with effect size $\beta_1\gamma_2\delta_3$. The total mediation effect equals the sum of the two independent mediation effects and the chain mediation effect.

5. Empirical Results

5.1 Descriptive Statistics

The descriptive statistics reported in Table 2 indicate that the minimum and maximum values of digital inclusive finance (DIFI) are 2.63 and 4.74, respectively, with a mean of 3.8795, a median of 3.8749, and a standard deviation of 0.47434. The mean slightly exceeds the median, suggesting that the overall level of digital inclusive finance in recent years has improved, thereby raising the average value.

Table 2: Descriptive Statistics

Variable	N	Min	Max	Mean	Std. Dev.	Median
DIFI	24,260	2.63	4.74	3.8795	0.47434	3.8749
Tobin's Q	24,260	0.61	41.97	1.9367	1.45579	1.5225

RD	24,260	0	24.63	16.8801	4.91479	18.0148
INNO	24,260	0	8.1	1.4439	1.35566	1.0986
Size	24,260	17.95	28.7	22.3229	1.32834	22.0928
Age	24,260	1.39	4.19	3.0387	0.29844	3.091
Cash	24,260	-0.74	0.84	0.0499	0.07356	0.0487
FIXED	24,260	0	0.95	0.1922	0.14943	0.1603
INST	24,260	0	0.99	0.4184	0.2497	0.4196
Dual	24,260	0	1	0.3311	0.47063	0
Indep	24,260	14.29	80	38.0061	5.57738	36.36
Top10	24,260	0.09	0.99	0.5848	0.15543	0.5925

For enterprise value (Tobin's Q), the minimum is 0.61 and the maximum is 41.97, with a mean of 1.9367, a median of 1.5225, and a standard deviation of 1.45579. The mean being greater than the median indicates a right-skewed distribution, implying substantial variation in enterprise value across firms, with some firms exhibiting relatively high valuation in certain years.

R&D investment (RD) ranges from 0.00 to 24.63, with a mean of 16.8801, a median of 18.0148, and a standard deviation of 4.91479. The mean is lower than the median, indicating a left-skewed distribution and substantial disparities in R&D investment among firms.

Substantive innovation (INNO) ranges from 0.00 to 8.10, with a mean of 1.4439, a median of 1.0986, and a standard deviation of 1.35566. The right-skewed distribution suggests significant heterogeneity in substantive innovation levels, with a small number of firms achieving relatively high innovation output.

5.2 Correlation Analysis

The Pearson correlation results presented in Table 3 show that digital inclusive finance (DIFI) is significantly positively correlated with enterprise value (Tobin's Q) ($\beta = 0.058$, $p < 0.01$). DIFI is also significantly positively correlated with R&D investment (RD) and substantive innovation (INNO) ($\beta = 0.115$ and 0.119, respectively, $p < 0.01$). Furthermore, RD is significantly positively correlated with Tobin's Q ($\beta = 0.019$, $p < 0.01$). These findings provide preliminary support for the hypothesized relationships among the main variables.

Table 3: Pearson Correlation Matrix

Variable	DIFI	Tobin's Q	RD	INNO
DIFI	1	1	1	1
Tobin's Q	0.058***			
RD	0.115***	0.019***		
INNO	0.119***	-0.029***	0.417***	

*Note: *p < 0.10; **p < 0.05; **p < 0.01 (two-tailed).

However, INNO is significantly negatively correlated with Tobin's Q (β = -0.029, p < 0.01), which is inconsistent with prior expectations. Therefore, further regression analysis is required to verify the nature of this relationship.

5.3 Regression Analysis

The multiple regression results are reported in Table 4. Column (1), with enterprise value as the dependent variable, shows that the coefficient of DIFI is 0.047 (p < 0.01), indicating that digital inclusive finance has a significant positive effect on enterprise value. Thus, H1 is supported.

Table 4: Multiple Linear Regression Results

Variable	Column (1) Tobin's Q	Column (2) RD	Column (3) INNO	Column (4) Tobin's Q
DIFI	0.047*** (7.721)	0.117*** (18.517)	0.074*** (13.440)	0.035*** (5.808)
RD	0.368*** (65.661)			0.027*** (4.063)
INNO	0.070*** (9.892)			
Size	-0.377*** (-55.234)	0.188*** (26.435)	0.344*** (54.732)	-0.411*** (-56.183)
Age	0.000 (0.069)	-0.180*** (-27.461)	-0.028*** (-4.874)	0.012* (1.862)
Cash	0.129*** (21.162)	0.065*** (10.284)	-0.012** (-2.211)	0.127*** (20.765)
FIXED	-0.080*** (-12.970)	-0.008 (-1.229)	-0.056*** (-9.930)	-0.076*** (-12.291)
INST	0.239*** (30.855)	-0.090*** (-11.166)	0.019*** (2.734)	0.243*** (31.316)
Dual	0.043*** (6.862)	0.060*** (9.212)	0.014** (2.491)	0.039*** (6.209)
Indep	0.042*** (7.050)	-0.006 (-0.943)	0.006 (1.090)	0.042*** (7.057)
Top10	-0.166*** (-23.182)	-0.011 (-1.461)	-0.078*** (-11.945)	-0.160*** (-22.357)
Constant	10.490*** (52.085)	6.415*** (9.061)	-8.157*** (-47.816)	11.001*** (52.308)
N	24,260	24,260	24,260	24,260
R^2	0.144	0.072	0.294	0.15
F Value	455.320***	210.977***	1013.322***	390.674***

Column (2), using RD as the dependent variable, reports a DIFI coefficient of 0.117 (p < 0.01), suggesting that digital inclusive finance significantly promotes R&D investment.

Column (3), with INNO as the dependent variable, shows that the coefficient of DIFI is 0.074 ($p < 0.01$), and the coefficient of RD is 0.368 ($p < 0.01$), indicating that both digital inclusive finance and R&D investment positively affect substantive innovation.

Column (4), with enterprise value as the dependent variable, shows that the coefficients of DIFI, RD, and INNO are 0.035 ($p < 0.01$), 0.027 ($p < 0.01$), and 0.070 ($p < 0.01$), respectively. These results indicate that digital inclusive finance, R&D investment, and substantive innovation all have significant positive effects on enterprise value.

The results from Columns (1)-(4) demonstrate that digital inclusive finance enhances enterprise value not only by increasing R&D investment but also by promoting substantive innovation. The mediation effect proportions are calculated as follows: the independent mediation path "digital inclusive finance-R&D investment-enterprise value" accounts for 6.72%, and the independent mediation path "digital inclusive finance-substantive innovation-enterprise value" accounts for 11.02%.

In addition, the chain mediation path "digital inclusive finance-R&D investment-substantive innovation-enterprise value" is established, with an effect proportion of 6.41%. The total mediation effect proportion is 24.15%, confirming H2, H3, and H4.

To ensure robustness, the Bootstrap method proposed in prior research [43] is employed to further test the composite multiple mediation effects of digital inclusive finance on enterprise value, with the results reported in Table 5.

Table 5: Bootstrap Mediation Effect Test Results

Effect Type	Effect Value	95% Confidence Interval	Effect Proportion
Total Effect	0.1436	[0.1071, 0.1800]	100%
Direct Effect (DIFI-Tobin's Q)	0.1088	[0.0721, 0.1455]	75.77%
Total Indirect Effect	0.0348	[0.0293, 0.0407]	24.23%
DIFI-RD-Tobin's Q	0.0097	[0.0045, 0.0149]	6.75%
DIFI-INNO-Tobin's Q	0.0159	[0.0122, 0.0199]	11.07%
DIFI-RD-INNO-Tobin's Q	0.0092	[0.0072, 0.0113]	6.41%

The 95% confidence intervals for the total effect, direct effect, and all mediation effects do not include zero, indicating statistical significance. The direct effect of "digital inclusive finance-enterprise value" is 0.1088, accounting for 75.77% of the total effect. The total mediation effect is 0.0348, accounting for 24.23% of the total effect.

Specifically, the independent mediation effect of "digital inclusive finance-R&D investment-enterprise value" is 0.0097 (6.75%), supporting H2. The independent mediation effect of "digital inclusive finance-substantive innovation-enterprise value" is 0.0159 (11.07%), supporting H3. The chain mediation effect of

"digital inclusive finance-R&D investment-substantive innovation-enterprise value" is 0.0092 (6.41%), supporting H4.

5.4 Endogeneity Treatment

To address potential endogeneity arising from reverse causality among digital inclusive finance, R&D investment, substantive innovation, and enterprise value, a one-period lag of digital inclusive finance is introduced for re-estimation. The results, reported in Table 6, indicate that digital inclusive finance continues to significantly promote enterprise value after mitigating endogeneity concerns. Moreover, both the parallel independent mediation effects and the chain mediation effect remain statistically significant.

Table 6: Endogeneity Test Results

Effect Type	Effect Value	95% Confidence Interval	Effect Proportion
Total Effect	0.1203	[0.0874, 0.1532]	100%
Direct Effect (DIFI-Tobin's Q)	0.0882	[0.0550, 0.1214]	73.32%
Total Indirect Effect	0.0321	[0.0271, 0.0373]	26.68%
DIFI-RD-Tobin's Q	0.0089	[0.0042, 0.0138]	7.40%
DIFI-INNO-Tobin's Q	0.0148	[0.0115, 0.0185]	12.30%
DIFI-RD-INNO-Tobin's Q	0.0084	[0.0066, 0.0103]	6.98%

These findings suggest that the regression results are robust and reliable.

5.5 Robustness Tests

5) Alternative Measurement of Variables

To further verify the robustness of the empirical findings, the measurement of the mediating variable R&D investment is adjusted. Specifically, R&D intensity-measured as the ratio of R&D expenditure to operating revenue-is adopted as an alternative proxy. The regression results, reported in Table 7, remain consistent with the main conclusions, indicating that the previous findings are robust to alternative variable specifications.

Table 7: Robustness Test Results-Alternative Measurement of Variables

Effect Type	Effect Value	95% Confidence Interval	Effect Proportion
Total Effect	0.152	[0.1226, 0.1813]	100%
Direct Effect (DIFI-Tobin's Q)	0.117	[0.0874, 0.1465]	76.97%

Total Indirect Effect	0.035	[0.0299, 0.0402]	23.03%
DIFI-RD-Tobin's Q	0.0112	[0.0072, 0.0154]	7.37%
DIFI-INNO-Tobin's Q	0.0152	[0.0118, 0.0188]	10.00%
DIFI-RD-INNO-Tobin's Q	0.0086	[0.0069, 0.0105]	5.66%

6) Winsorization Treatment

To mitigate the potential influence of extreme values on the estimation results and avoid biased conclusions, all continuous variables are winsorized at the upper and lower 1% levels. This procedure effectively reduces the impact of outliers and enhances the reliability of the empirical analysis. The results, presented in Table 8, are consistent with the baseline findings, further confirming the robustness of the main conclusions.

Table 8: Robustness Test Results-Winsorization Treatment

Effect Type	Effect Value	95% Confidence Interval	Effect Proportion
Total Effect	0.152	[0.1226, 0.1813]	100%
Direct Effect (DIFI-Tobin's Q)	0.117	[0.0874, 0.1465]	76.97%
Total Indirect Effect	0.035	[0.0299, 0.0402]	23.03%
DIFI-RD-Tobin's Q	0.0112	[0.0072, 0.0154]	7.37%
DIFI-INNO-Tobin's Q	0.0152	[0.0118, 0.0188]	10.00%
DIFI-RD-INNO-Tobin's Q	0.0086	[0.0069, 0.0105]	5.66%

6. Heterogeneity Analysis

6.1 Heterogeneity by Ownership Structure

Within the institutional context and traditional financial system, state-owned enterprises (SOEs), due to their ownership characteristics, are more likely to obtain governmental fiscal support and bank credit, thereby facing relatively weaker financing constraints and operating within a more favorable financial environment. In contrast, non-state-owned enterprises (non-SOEs) often exhibit stronger financing demand while encountering more severe financing constraints [44].

Accordingly, the impact of digital inclusive finance on enterprise value may differ across ownership types. For SOEs, the marginal effect of digital inclusive finance may be limited because of their relatively sufficient access to capital. For non-SOEs, however, digital inclusive finance may significantly improve resource allocation efficiency through external financing channels, thereby enhancing enterprise value.

The subgroup regression results (Table 9) indicate that the total effect is statistically significant for both SOEs and non-SOEs, suggesting that digital inclusive finance promotes enterprise value across ownership types. However, in the SOE sample, the 95% confidence interval of the direct effect includes zero after introducing mediating variables, indicating that the direct effect is statistically insignificant. In contrast, both parallel independent mediation effects and the chain mediation effect remain significant, with substantive innovation representing the more important mediating channel.

Table 9: Heterogeneity Test Results by Ownership Structure

Sample	Total Effect	Direct Effect	Total Indirect Effect	Key Mediation Path (Largest Share)
State-Owned Enterprises	0.0751***	0.0532 (n.s.)	0.0219*** (29.16%)	DIFI-INNO-Tobin's Q (16.38%)
Non-State-Owned Enterprises	0.1403***	0.1058*** (75.41%)	0.0345*** (20.53%)	DIFI-INNO-Tobin's Q (12.90%)

In the non-SOE sample, the direct effect and the mediation paths related to substantive innovation and the chain effect remain statistically significant. Overall, for SOEs, the direct effect of digital inclusive finance is weaker and the mediation proportion is higher; for non-SOEs, the direct effect is stronger and the mediation proportion is relatively lower. In both subsamples, the key mediation pathway is "digital inclusive finance-substantive innovation-enterprise value."

6.2 Heterogeneity by Regional Development Level

From a regional perspective, areas with higher levels of economic development generally possess more financial infrastructure and institutional environments, as well as broader coverage of digital inclusive finance. The value-enhancing effect of digital inclusive finance may therefore be more pronounced in economically developed regions. Moreover, digital inclusive finance relies heavily on digital technologies such as big data and the Internet, whose application levels are closely associated with regional economic development. Regions with stronger digital foundations are more likely to exhibit amplified economic effects from digital finance [45].

The subgroup results (Table 10) show that the total and direct effects are significant across eastern, central, and western regions, indicating that digital inclusive finance promotes enterprise value in all regions. However, in the eastern region, the total indirect effect, both parallel mediation effects, and the chain mediation effect are all statistically significant. The impact pattern is characterized by a dominant direct effect supplemented by mediation effects-forming a multi-path mechanism of "direct effect + parallel mediation + chain mediation."

Table 10: Heterogeneity Results by Region

Region	Total Effect	Direct Effect	Total Indirect Effect	Mediation Significance
Eastern Region	0.2093***	0.1684*** (80.50%)	0.0408*** (19.50%)	Parallel and chain mediation effects significant

Central Region	0.2584***	0.2410*** (93.27%)	0.0174 (n.s.)	Mediation effects not significant
Western Region	0.4163***	0.4115*** (98.85%)	0.0048 (n.s.)	Mediation effects not significant

In contrast, in the central and western regions, the 95% confidence intervals of the mediation effects include zero, and the direct effect accounts for approximately 95% of the total effect. This suggests that the value-enhancing role of digital inclusive finance in these regions is primarily driven by the direct effect, while the mediation mechanisms through R&D investment and substantive innovation are relatively weak and statistically insignificant. Possible explanations include insufficient digital financial infrastructure penetration, lower R&D intensity, weaker innovation transformation capacity, or limited effectiveness of digital finance in stimulating innovation activities in these regions.

7. Conclusions and Policy Implications

7.1 Research Conclusions

Using panel data of A-share listed companies from 2018 to 2023, this study systematically examines the impact of digital inclusive finance on enterprise value from the perspective of R&D investment and substantive innovation. The main conclusions are as follows.

First, digital inclusive finance significantly enhances enterprise value.

Second, the value-enhancing effect operates through three channels: (1) the independent mediation path "digital inclusive finance-R&D investment-enterprise value"; (2) the independent mediation path "digital inclusive finance-substantive innovation-enterprise value"; and (3) the chain mediation path "digital inclusive finance-R&D investment-substantive innovation-enterprise value."

Third, heterogeneity analysis indicates that the impact mechanism varies across ownership types and regional development levels. In SOEs, mediation effects dominate and the direct effect becomes statistically insignificant after controlling for mediators. In non-SOEs, the direct effect remains dominant, while substantive innovation and the chain mediation path play significant roles. In the eastern region, both direct and mediation effects coexist; in the central and western regions, the direct effect dominates and mediation effects are weak or insignificant.

7.2 Policy Implications

Based on the above findings, several policy implications are proposed.

First, differentiated policy guidance should be implemented according to ownership structure. For SOEs, financial institutions should further optimize digital inclusive financial services and guide capital toward R&D and innovation-oriented projects-for example, through special funds, interest subsidies, and long-term credit support-to enhance their technological competitiveness. For non-SOEs, policies should focus on reducing financing thresholds, improving credit accessibility, and strengthening the direct value-enhancing effect of digital inclusive finance. Meanwhile, collaboration platforms linking industry, academia, and research institutions should be established to promote the transformation of innovation outcomes into enterprise value.

Second, regional differences should be fully considered. In economically developed regions, efforts should concentrate on improving the digital inclusive finance ecosystem, encouraging financial institutions to design innovation-oriented financial products such as intellectual property pledge loans and investment-loan linkage models, and strengthening the synergy between direct and mediation effects. In less developed regions, priority should be given to improving digital infrastructure, enhancing credit information sharing systems, expanding credit supply, and reducing financing costs-thereby reinforcing the direct effect of digital inclusive finance while gradually cultivating effective mediation channels.

Third, financial institutions should enhance financial technology research and application, improve the precision and efficiency of digital inclusive financial services, and utilize big data and artificial intelligence technologies to assess firms' R&D capabilities and innovation potential. Tailored financial products aligned with firms' innovation cycles should be provided-offering long-term and low-cost funding during the R&D phase and supporting commercialization during the innovation transformation stage.

Fourth, enterprises themselves should actively embrace digital inclusive finance, improve their digital capabilities, strengthen communication and cooperation with financial institutions, increase R&D investment, and enhance substantive innovation capacity. By transforming financial resource advantages into innovation-driven growth, firms can ultimately achieve sustained improvement in enterprise value.

In summary, digital inclusive finance promotes enterprise development through the transmission chain of “financing-R&D-innovation-value.” Coordinated efforts among government, financial institutions, and enterprises are essential to optimize resource allocation, deepen the integration of digital finance and real-sector innovation demand, and foster high-quality economic development.

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