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Determinants of Performance in Technology-Finance Enterprises: A QCA-Based Analysis

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Abstract:

Using panel data from Chinese technology-finance enterprises between 2010 and 2020, this study applies Qualitative Comparative Analysis (QCA) to examine how six antecedent conditions-fintech investment, process-optimization construction, technological readiness, debt level, operational capability, and managerial capability-combine in different configurations to influence enterprise performance. The analysis identifies five distinct pathways that lead to high performance, which can be broadly categorized into debt-driven and fintech-investment-driven mechanisms. A comparative investigation of banking and non-banking technology-finance enterprises further highlights substantial heterogeneity in performance-enhancing pathways. Banking enterprises typically achieve superior outcomes through configurations featuring high debt levels coupled with strong managerial capabilities, whereas non-banking enterprises rely more heavily on pathways characterized by intensive fintech investment, enhanced process-optimization construction, and elevated technological readiness.

Keywords:

technology finance; enterprise performance; qualitative comparative analysis; configurational pathways

1. Introduction

In the transition to the global post-pandemic era, the integration of finance, technology, and the real economy has attracted increasing attention. The technology-finance industry ecosystem is primarily composed of technology enterprises, financial institutions, regulatory bodies, research organizations, and industry associations. Technology enterprises mainly provide high-end technical services for financial institutions and regulators in areas such as risk control, marketing, customer service, investment advisory, and credit assessment, thereby demonstrating substantial financing demand. Financial enterprises, dominated by commercial banks, serve as the core financial service providers within the entire ecosystem. Technology-finance enterprises formed through the collaboration of financial enterprises and technology enterprises have become the key carriers driving the development of China's technology-finance industry. Currently, China's technology-finance industry holds a leading global position, achieving notable outcomes in market expansion, application scenarios, and industry influence. As a result, the development of technology finance has become an essential factor in promoting China's high-tech innovation and economic advancement [1]. Improving the operational efficiency and competitiveness of technology-finance enterprises is therefore crucial for enhancing enterprise performance and fostering the sustainable development of the national technology-finance system.

From the perspective of existing research, scholars have examined the contribution of technology finance to economic growth and its role in reducing financing constraints and improving financing efficiency [2]. However, few studies treat technology-finance enterprises as an independent research domain and systematically explore their growth patterns and performance-influencing mechanisms. Research on this topic is particularly valuable for identifying the unique performance-enhancement pathways of modern technology-finance enterprises and understanding the differences among various categories of such enterprises.

Based on current studies related to the development of technology-finance enterprises, it has been found that large-scale capital investment and strong managerial incentives can significantly shape enterprise growth. Research adopting a dual fixed-effects model suggests that technology investment contributes positively to improving the performance of technology-finance enterprises [3]. Other studies indicate that both public and market-oriented technology-finance investments exert significant positive effects on the technological innovation performance of enterprises [4]. Research has also shown that R&D investment and managerial incentives can jointly enhance enterprise outcomes, while innovation investment and compensation incentives exhibit a similar positive synergy with performance [5]. Although these findings offer useful insights into the performance mechanisms of technology-finance enterprises, limitations remain. Many existing studies focus on single-factor influences, whereas enterprise performance is typically the result of the joint effect of multiple factors that are correlated and inseparable. Moreover, the influence of these factors may vary across different contexts, potentially leading to inconsistent conclusions. In addition, policies designed to enhance enterprise performance may yield divergent outcomes when applied to enterprises operating in different environments, creating performance gaps that may result from the overlooked combinations of interacting factors.

Within the context of technology-finance enterprises, a key challenge lies in understanding the nonlinear and complex mechanisms through which multiple factors collectively influence high performance. Consequently, identifying the configurational pathways that lead to superior performance requires not only examining individual factors but also uncovering how different combinations of conditions jointly and effectively shape performance outcomes.

2. Related Work

To better understand performance dynamics in technology-finance enterprises, recent studies have adopted a combination of qualitative comparative methods and computational modeling. Structured text analysis with dynamic temporal windows has shown significant promise for asset return forecasting, supporting more responsive models of financial behavior [6].

Fuzzy-set Qualitative Comparative Analysis (fsQCA) is increasingly applied in entrepreneurship and innovation research. It enables researchers to examine complex causal configurations and identify multiple sufficient pathways for performance outcomes [7]. This method has also been used to investigate small firm strategies and business model themes [8], as well as innovation performance linked to R&D partnerships [9].

Cross-national fintech studies further contribute insights into regional influences on firm performance. For instance, research in Russia highlights how digital infrastructure and strategic priorities shape fintech efficiency [10], while studies in Saudi Arabia emphasize the evolving regulatory environment and capital dynamics [11]. Analyses in OECD countries identify financial structure and innovation as key factors for performance [12].

In emerging markets, the impact of ICT infrastructure on fintech growth is particularly pronounced, with evidence from BRICS economies demonstrating its pivotal role in enterprise competitiveness [13]. On the modeling front, causal inference combined with graph attention mechanisms has enabled researchers to uncover structural dependencies among enterprise variables, enhancing the interpretability of complex financial systems [14].

Within the traditional banking sector, empirical evidence suggests that technology investment contributes positively to both performance and market valuation, particularly through efficiency enhancements [15]. Graph neural networks have also been applied to enterprise credit networks to identify default risk, offering an effective framework for evaluating structural financial vulnerabilities [16].

Comparative assessments between fintech firms and banks reveal the disruptive impact of innovation-driven entrants, leading incumbents to adopt new operational and strategic approaches [17]. Methodologically, fsQCA has been further developed to address configuration complexity in business research, reinforcing its value in high-dimensional analysis [18]..

3. Research Method Selection and Model Construction

3.1 Research Method Selection

Existing quantitative methods such as linear regression models, factor analysis, and fixed-effects models can, in principle, incorporate additional interaction terms to examine how conditions jointly influence outcome variables. However, when the number of antecedent conditions becomes large, it becomes difficult to clearly interpret the interactions. Considering these methodological limitations, this study adopts the Qualitative Comparative Analysis (QCA) approach to examine how multiple configurations of conditions influence enterprise performance, thereby identifying the pathways through which technology-finance enterprises achieve performance improvement from a holistic perspective.

QCA is a set-theoretic analytical method based on Boolean algebra, designed to investigate how combinations of multiple antecedent conditions lead to specific outcomes. Its purpose is to reveal the configuration patterns produced by the interdependence of conditions in real-world settings, providing a comprehensive framework for interpreting causal complexity and exploring causal mechanisms with multiple conjunctural effects [19]. The method relies on prior theoretical and empirical identification of relevant conditions. Therefore, based on existing quantitative studies on enterprise performance, this research extracts key conditions affecting the performance of technology-finance enterprises and utilizes QCA to explore their complex configurational effects.

QCA includes three main variants: csQCA (crisp-set QCA), mvQCA (multi-value QCA), and fsQCA (fuzzy-set QCA). These methods differ in how variables are calibrated. csQCA divides variables into binary values “0-1”, where 0 indicates full non-membership and 1 indicates full membership. mvQCA divides variables into three or more discrete categories. fsQCA is designed for continuous variables and calibrates them into three qualitative anchors, assigning values across the “0-0.5-1” scale, where 0 represents full non-membership, 0.5 represents the crossover point, and 1 represents full membership. Among these, fsQCA is more robust, more sensitive to abnormal values, and avoids issues of representativeness in small samples without assuming specific data distributions [19]. Since the variables in this study are continuous, fsQCA is selected to model how multiple conditions jointly influence the performance of technology-finance enterprises.

3.2 Model Construction

Based on extensive prior research on enterprise performance, this study extracts relevant condition variables and identifies six key factors influencing the performance of technology-finance enterprises: financial technology investment, process-optimization construction investment, technological preparedness, debt level, operational capability, and managerial capability[20-26]. Each factor has been shown to significantly affect enterprise performance across various studies, and these indicators are also essential for evaluating enterprise growth and development. By integrating these conditions, the study constructs a performance-improvement mechanism model for technology-finance enterprises (as illustrated in Figure 1) to explore the pathways through which enterprises can rapidly enhance performance.

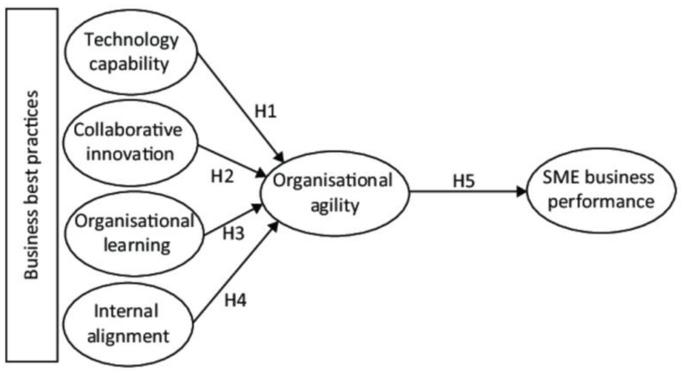

Figure 1. Mechanism Model of Performance Generation in Technology-Finance Enterprises

3.3 Variable Description

The sample consists of listed technology-finance enterprises, covering the period from 2010 to 2020. The data were obtained from the Guotai Junan database. After excluding observations with missing data items, a final sample of 114 enterprises was retained. The descriptions of the condition variables and the outcome variable used in this study are presented in Table 1.

Table 1: Descriptions of Condition Variables and Outcome Variable

Variable Type	Variable Name	Variable Description
Outcome Variable	Enterprise Performance Level	Net profit of the enterprise
Condition Variables	Fintech Investment	Investment in financial technology construction
	Process-Optimization Construction Investment	Investment in process-optimization construction
	Technological Preparedness	Investment in technological preparedness
	Debt Level	Asset-liability ratio of the enterprise
	Operational Capability	Asset turnover ratio

	Managerial Capability	Total compensation of the top three executives

4. QCA Analysis

4.1 Descriptive Statistical Analysis of Variables

Fintech investment, process-optimization construction investment, and technological preparedness are measured based on the corresponding investment values, obtained from the Guotai Junan database. Debt level is represented by the enterprise's asset-liability ratio, operational capability is measured by the asset turnover ratio, and managerial capability is measured by the total compensation of the top three executives. The descriptive statistics of all condition variables and the outcome variable are presented in Table 2.

Table 2: Descriptive Statistics of the Sample

Item	Enterprise Performance Level	Fintech Investment	Process-Optimization Construction Investment	Technological Preparedness	Debt Level	Operational Capability	Managerial Capability
Mean	0.103 5	27.305 9	12.934 9	12.3427	0.796 4	0.070 7	6.777 1
Median	0.097 5	18	6	6	0.861 3	0.032 3	6.79
Standard Deviation	0.054 2	28.0175	19.723 5	16.9425	0.171 3	0.112 6	0.334 1
Maximum Value	0.45	166	156	110	0.948 6	0.779 9	7.73
Minimum Value	0.002 3	1	1	1	0.040 9	0.000 7	5.6

According to Table 2, the standard deviations of enterprise performance level, debt level, operational capability, and managerial capability are relatively small, indicating relatively stable distributions. In contrast, fintech investment, process-optimization construction investment, and technological preparedness show more dispersed distributions, with some enterprises exhibiting extremely high values of fintech investment and process-optimization construction investment, which significantly affect overall variation.

4.2 Data Calibration

The QCA method requires recalibrating the measured variables into set membership scores. After calibration, the membership values range from 0 to 1, and three thresholds must be established to represent full membership, the crossover point, and full non-membership. The selection of thresholds may draw upon established theoretical guidelines or empirical quantiles but must remain reasonable and transparent. Therefore, following prior research[27,28], this study adopts the commonly used approach of setting thresholds at the 95th percentile (full membership), 50th percentile (crossover point), and 5th percentile (full non-membership). The calibration thresholds are shown in Table 3.

Table 3: Calibration Thresholds of Variables

Variable	Full Membership	Crossover Point	Full Non-Membership
Enterprise Performance Level	0.187 7	0.097 5	0.029 4
Fintech Investment	84.45	18	3
Process-Optimization Construction Investment	54.1	6	1
Technological Preparedness	43	6	1
Debt Level	0.940 3	0.858 4	0.398 9
Operational Capability	0.319 6	0.032 3	0.015 3
Managerial Capability	7.257 7	6.786 9	6.255 3

4.3 Necessity Analysis

Before conducting the standard QCA analysis, it is essential to determine whether any single condition is necessary for the outcome[29]. A necessity condition refers to a condition that must be present whenever the outcome occurs, meaning that the outcome cannot emerge in its absence. In practice, a condition is typically considered necessary if its consistency score reaches 0.9 and if it demonstrates sufficient coverage.

The necessity test is performed separately for high enterprise performance and non-high enterprise performance. Two indicators are used: consistency and coverage. Consistency is used to assess whether a condition is necessary for the outcome, whereas coverage evaluates the explanatory relevance of the condition. The formula for consistency is:

$$\text{consistency}(x_i < y_i) = \frac{\sum[\min(x_i, y_i)]}{\sum y_i} \tag{1}$$

The formula for coverage is:

$$\text{coverage}(x_i < y_i) = \frac{\sum[\min(x_i, y_i)]}{\sum x_i} \tag{2}$$

In these equations, x_i represents the observed value of condition i, and y_i represents the observed value of the outcome variable.

According to Table 4, among all conditions, the asset-liability ratio shows the highest consistency value of 0.859 941. However, this value does not meet the commonly accepted threshold of 0.9, indicating that none of the single conditions can be regarded as necessary conditions. Therefore, for technology-finance enterprises, individual conditions do not sufficiently explain either high enterprise performance or non-high enterprise performance. As a result, this study proceeds with subsequent configurational analysis.

Table 4: Results of Necessity Analysis

Condition Variable	High Enterprise Performance Consistency	High Enterprise Performance Coverage	Non-High Enterprise Performance Consistency	Non-High Enterprise Performance Coverage
High Fintech Investment	0.644 675	0.689 183	0.564 804	0.649 752
Non-High Fintech Investment	0.672 371	0.589 443	0.729 818	0.688 499
High Process-Optimization Construction Investment	0.581 131	0.680 556	0.535 426	0.674 753
Non-High Process-Optimization Construction Investment	0.722 270	0.590 958	0.746 516	0.657 283
High Technological Preparedness	0.635 938	0.700 968	0.545 135	0.646 611
Non-High Technological Preparedness	0.679 396	0.581 237	0.747 897	0.688 538
High Debt Level	0.859 941	0.710 990	0.572 044	0.508 955
Non-High Debt Level	0.406 079	0.468 584	0.675 164	0.838 381
High Operational Capability	0.567 531	0.631 649	0.574 723	0.688 337
Non-High Operational Capability	0.719 974	0.611 382	0.692 446	0.632 758
High Managerial Capability	0.648 953	0.619 625	0.664 825	0.683 092
Non-High Managerial Capability	0.668 093	0.649 405	0.629 796	0.658 772

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4.4 Configurational Analysis and Interpretation of Results

1) Configurational Analysis

Drawing on the viewpoint of a leading scholar in comparative configurational analysis, this study adopts a relatively strict consistency threshold of 0.80 and sets the minimum acceptable number of cases to 1. Using fsQCA 3.0 software, standard analysis is conducted separately for high enterprise performance and non-high enterprise performance. The resulting configurational solutions for high enterprise performance are presented in Table 5, and the configurational solutions for non-high enterprise performance are shown in Table 6.

Table 5: Configurational Analysis of High Enterprise Performance

Condition Variable	H1	H2	H3	H4	H5	H6	H7
Consistency	0.846 9	0.814 2	0.855 7	0.815 5	0.849 4	0.853 1	0.865 5
Coverage	0.449 0	0.534 2	0.413 6	0.392 2	0.274 8	0.378 0	0.309 2
Unique Coverage	0.007 6	0.030 3	0.008 6	0.000 4	0.001 9	0.069 0	0.027 4
Solution Consistency	-	-	-	0.812 7	-	-	-
Solution Coverage	-	-	-	0.736 1	-	-	-

Notes: ● indicates the presence of a core condition; ⊗ indicates the absence of a core condition; ● indicates the presence of a peripheral condition; ⊗ indicates the absence of a peripheral condition; a blank cell indicates that the condition is irrelevant to the outcome.

Table 6: Configurational Analysis of Non-High Enterprise Performance

Condition Variable	H1	H2	H3	H4	H5	H6	H7	H8	H9
Fintech Investment	⊗	⊗	●	●	●	⊗	●	⊗	●
Process-Optimization Construction Investment	●	⊗	●	●	⊗	●	●	●	●
Technological Preparedness	⊗	●	⊗	●	⊗	●	⊗	⊗	⊗
Debt Level	⊗	⊗	⊗	●	●	⊗	⊗	⊗	●

Operational Capability	⊗	⊗	●	⊗	●	●	⊗	●	●
Managerial Capability	●	●	⊗	⊗	●	⊗	●	●	●
Consistency	0.917 8	0.953 0	0.933 8	0.964 9	0.942 2	0.971 2	0.970 2	0.962 6	0.957 9
Coverage	0.356 0	0.292 1	0.392 3	0.250 7	0.273 4	0.219 0	0.226 1	0.241 0	0.230 7
Unique Coverage	0.006 3	0.042 1	0.029 8	0.002 4	0.007 2	0.000 3	0	0	0.001 8
Solution Consistency	-	-	-	-	-	-	0.921 8	-	-
Solution Coverage	-	-	-	-	-	-	0.542 8	-	-

2) *Interpretation of Results*

a) *Configurational Results for High Enterprise Performance*

According to Table 5, seven configurations lead to high enterprise performance, each demonstrating consistency above 0.8. The overall solution consistency is 0.812 7, indicating that all seven configurations are sufficient conditions for producing high performance. The solution coverage is 0.736 1, suggesting that the model explains approximately 74% of the instances of high enterprise performance. These seven high-performance configurations can be summarized into five core combinations of conditions, representing five distinct pathways that lead to superior enterprise performance.

(1) Debt-level-driven pathway. Configurations H1 and H2 reflect a pathway in which high debt level appears as the core condition, while other conditions are either absent or peripheral. This indicates that a high debt level plays a significant role in enabling enterprises to achieve superior performance. In configuration H1, approximately 45% of the high-performance cases are explained, while configuration H2 accounts for about 53% of the cases. Although the debt level does not reach the threshold to be considered a necessary condition, it consistently appears as a sufficient condition in these configurations, revealing its substantial impact. Representative enterprises in this pathway include Jiangsu Bank, Bank of Ningbo, China Merchants Bank, and China Zheshang Bank. Most technology-finance enterprises in this pathway are commercial banks, whose abundant funding sources and strong financial leverage allow the high debt level to serve as a key driver of performance, enhancing revenue-generating capabilities and improving capital returns.

(2) Fintech-investment-driven under high debt level. Configuration H3 represents a pathway where non-high process-optimization construction investment and high debt level serve as core conditions, while fintech investment functions as a supplementary condition. This configuration explains 41% of the high-performance cases. Representative enterprises include Bank of Beijing, Bank of Shanghai, and Bank of Communications. These institutions have actively engaged in digital transformation and increased fintech investment as part of their development strategies. For example, Bank of Beijing has adopted blockchain technologies to build its online trading platform “Jingxin Chain”, enabling automated contract execution, enhancing data security, and reducing labor and operational costs. This pathway suggests that when firms possess strong leverage capacity, fintech investment can significantly amplify performance gains.

(3) Dual-driver pathway of high debt level and strong operational capability. Configurations H4 and H5 indicate pathways where high debt level is the core condition, complemented by strong operational capability. Configuration H4 explains 39% of high-performance cases, while H5 explains 27%. Representative enterprises include China Everbright Bank, China Guangfa Bank, China Construction Bank, and Bank of Wujiang. Within this pathway, enterprises leverage both high debt capacity and efficient asset utilization to quickly improve performance without relying heavily on other conditions.

(4) Combined effects of fintech investment, technological preparedness, and debt level. Configuration H6 consists of fintech investment, technological preparedness, high debt level, and non-high managerial capability as core conditions, explaining 38% of the high-performance cases. Representative enterprises include Nanjing Bank, Bank of Leshan, and Bank of Guiyang. In this pathway, enterprises rely on simultaneous investment in fintech, technology accumulation, and debt leverage to improve performance, while high managerial capability does not play a decisive role.

(5) Comprehensive pathway driven by fintech investment, technological preparedness, debt level, and operational capability. Configuration H7 includes fintech investment, technological preparedness, high debt level, and strong operational capability as core conditions. This configuration explains 31% of the high-performance cases. Representative enterprises include Bank of Wuxi and Industrial and Commercial Bank of China, suggesting that when multiple favorable conditions coexist, enterprises are more likely to achieve superior performance. Overall, the five pathways leading to high enterprise performance can be categorized into two major types: those primarily driven by high debt level, and those primarily driven by fintech investment. Pathways 1, 2, and 3 rely on high debt level as the core condition, demonstrating that financial leverage is a key factor underlying superior performance in technology-finance enterprises. Pathways 4 and 5 highlight the role of fintech investment, technological preparedness, and innovation capability, emphasizing the importance of digital investment and technological advantages in enhancing enterprise performance.

b) Configurational Results for Non-High Enterprise Performance

According to Table 6, nine configurations lead to non-high enterprise performance. All nine configurations exhibit consistency above 0.8, with an overall solution consistency of 0.921 8. Among the nine configurations, non-high debt level consistently appears as a core condition, indicating that enterprises failing to achieve high performance typically share the characteristic of low leverage levels. This finding further verifies that debt leverage serves as a critical driving condition for high performance in technology-finance enterprises.

4.5 Comparative Configurational Analysis of Banking and Non-Banking Enterprises

3) Data Calibration and Necessity Analysis

Consistent with the data processing procedures used earlier, the sample is divided into banking enterprises and non-banking enterprises. The condition variables and the outcome variable are then calibrated separately for each group. Following the standards proposed by a leading scholar in QCA, the calibration thresholds are set at the 95th percentile for full membership, the 50th percentile for the crossover point, and the 5th percentile for full non-membership. After calibration, a necessity analysis is conducted, and the results are presented in Table 7.

Table 7: Necessity Analysis Results for Banking and Non-Banking Enterprises

Condition Variable	Banking Enterprises Consistency	Banking Enterprises Coverage	Non-Banking Enterprises Consistency	Non-Banking Enterprises Coverage
High Fintech Investment	0.543 958	0.586 400	0.671 242	0.620 363
Non-High Fintech Investment	0.745 349	0.727 209	0.605 411	0.761 373
High Process-Optimization Construction Investment	0.471 580	0.542 641	0.654 927	0.617 616
Non-High Process-Optimization Construction Investment	0.816 295	0.753 373	0.566 537	0.701 818
High Technological Preparedness	0.502 147	0.555 405	0.685 929	0.619 636
Non-High Technological Preparedness	0.786 444	0.750 097	0.590 418	0.754 828
High Debt Level	0.787 876	0.774 417	0.686 617	0.773 172
Non-High Debt Level	0.470 660	0.503 279	0.589 438	0.622 303
High Operational Capability	0.932 120	0.667 252	0.708 327	0.676 444
Non-High Operational Capability	0.351 973	0.633 486	0.566 592	0.676 444
High Managerial Capability	0.628 808	0.670 774	0.606 264	0.664 808
Non-High Managerial Capability	0.631 159	0.621 752	0.613 552	0.665 859

Note: "¬" represents the Boolean operator for negation, denoting "non-high".

For non-banking enterprises, all consistency values for the conditions fall below the 0.9 threshold, indicating that none of the conditions can be regarded as necessary. In contrast, for banking enterprises, operational capability reaches a consistency value of 0.932 120, exceeding the 0.9 threshold and therefore constituting a necessary condition. This suggests that whenever a banking enterprise achieves high performance, strong operational capability is always present, confirming that high operational capability is a core driver of superior performance in banking enterprises. Consequently, operational capability is removed as a condition variable for subsequent configurational analysis of high-performance outcomes in banking enterprises.

4) Configurational Analysis for Banking and Non-Banking Enterprises

Consistent with the earlier data processing procedures and following the recommendations of a leading scholar in QCA, the threshold for configurational analysis is set at a consistency level of 0.8. Separate configurational analyses are conducted for banking and non-banking enterprises, and the results are reported in Tables 8 and 9. The overall solution consistency for banking and non-banking enterprises is 0.843 9 and 0.806 0, respectively, both exceeding the required threshold of 0.8, indicating that the configurational solutions exhibit satisfactory consistency.

Table 8: Configurational Analysis of High Performance in Banking Enterprises

Condition Variable	H1	H2	H3
Fintech Investment	●	●	⊗
Process-Optimization Construction Investment	⊗	⊗	○
Technological Preparedness	○	○	○
Debt Level	●	●	●
Managerial Capability	○	○	●
Consistency	0.871 9	0.880 4	0.903 0
Coverage	0.706 9	0.443 0	0.430 0
Unique Coverage	0.291 4	0.027 5	0.014 5
Solution Consistency	-	0.843 9	-
Solution Coverage	-	0.748 9	-

Table 9: Configurational Analysis of High Performance in Non-Banking Firms

Condition Variable	H1	H2	H3	H4
FinTech Investment	●	●		●
Non-high FinTech Investment	⊗		⊗	

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Process Optimization Investment	⊗	●		●
Non-high Process Optimization Investment	●		⊗	
Technological Reserve Level		●	●	●
Non-high Technological Reserve Level	⊗	⊗		
Debt Ratio	●	●	●	●
Non-high Debt Ratio				
Operating Capability	●	●	●	
Non-high Operating Capability				●
Managerial Capability	●	●	●	⊗

Based on the configurational results for banking and non-banking enterprises, three pathways leading to high performance can be identified for banking enterprises: (1) a pathway driven by non-high process-optimization construction investment combined with high debt level; (2) a pathway driven by non-high fintech investment, non-high technological preparedness, and high debt level; and (3) a pathway led by non-high process-optimization construction investment, high technological preparedness, and strong managerial capability. In contrast, four pathways generate high performance in non-banking enterprises: (1) a pathway driven by non-high process-optimization construction investment, non-high technological preparedness, high debt level, strong operational capability, and strong managerial capability; (2) a pathway led by fintech investment, high debt level, operational capability, and managerial capability, supplemented by non-high technological preparedness; (3) a pathway driven by fintech investment, process-optimization construction investment, non-high technological preparedness, non-high debt level, operational capability, and strong managerial capability; and (4) a pathway driven by fintech investment, process-optimization construction investment, high technological preparedness, high debt level, operational capability, and strong managerial capability.

Overall, it is evident that banking and non-banking enterprises exhibit notable differences in their pathways to achieving high performance. Banking enterprises tend to rely primarily on high debt level and managerial capability to enhance performance. In contrast, non-banking enterprises require additional support through substantial fintech investment or higher levels of technological preparedness to compensate for their structural limitations. This highlights that improving technological capacity and strengthening innovation are particularly important for non-banking enterprises, as fintech innovation and technological advancement have not yet become the primary drivers of performance growth in banking enterprises.

5. Conclusion

This study investigates the performance-enhancing mechanisms of FinTech enterprises in China by applying fuzzy-set Qualitative Comparative Analysis (fsQCA) to a sample of 114 listed firms from 2010 to 2020. By examining the configurational relationships among FinTech investment, process optimization, technological reserves, debt ratio, operating capability, and managerial capability, the study uncovers multiple pathways through which both banking and non-banking FinTech firms achieve high performance.

The results demonstrate that no single condition is sufficient to independently generate high performance. Instead, enterprise performance arises from various combinations of conditions acting together, confirming the complexity and conjunctural causality embedded in FinTech development. Across all high-performance configurations, the debt ratio and FinTech investment emerge as the most influential driving factors, either as core conditions or as essential components in combination with capability-related variables.

For banking-type FinTech firms, high performance is primarily driven by configurations featuring high debt ratio combined with managerial or technological capabilities. Banks often rely on strong capital leverage and management efficiency to realize performance gains, and the role of technological innovation-while relevant-is not the dominant driver.

In contrast, non-banking FinTech firms exhibit more diverse and innovation-oriented pathways. Their high-performance configurations frequently integrate FinTech investment, technology reserves, and process optimization, indicating that technological upgrading and innovation are crucial sources of competitive advantage for these firms. Compared with banks, non-banking FinTech enterprises rely more heavily on technological advancement to strengthen operational efficiency and market responsiveness.

Overall, the findings highlight that improving FinTech enterprise performance requires not only capital support but also the coordinated enhancement of digital capability, technological reserves, and operational efficiency. For policymakers and managers, this study underscores the importance of adopting differentiated strategies tailored to enterprise type: banks should continue optimizing capital structure and management efficiency, whereas non-banking firms should prioritize technological innovation and capability development. These insights contribute to a more nuanced understanding of FinTech performance and offer practical guidance for accelerating high-quality development within the FinTech sector.

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