ISSN 2409-2665
Journal of Logistics, Informatics and Service Science
Vol. 13 (2026) No. 7, pp. 240-259
DOI:10.33168/JLISS.2026.0715

Application and Risk Analysis of Blockchain-based Digital Financial Platform in Supply Chain Financial Services

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Abstract. With the development of the digital economy, supply chain finance has become a key path to solve the financing problems of small, medium and micro enterprises and enhance the overall resilience of the supply chain. However, the traditional supply chain finance model is facing development bottlenecks due to inherent flaws such as information asymmetry, difficulty in credit transmission, and high operational risks. This study proposes a theoretical conceptual model that encompasses technical features (transparency, security, traceability), platform service capabilities (financing efficiency, credit enhancement), perceived risks (technical risk, operational risk, compliance risk), and platform performance (operational efficiency improvement, financing cost reduction). A questionnaire was designed and 358 valid sample data from core enterprises in the supply chain, small and medium-sized enterprises in the upstream and downstream, financial institutions and fintech companies were collected. The structural equation model was used to conduct an empirical analysis of the data. The research results show that: (1) The technical characteristics of blockchain have a significant positive impact on the service capabilities of the platform; (2) The improvement of the platform's service capabilities has significantly promoted the enhancement of platform performance, that is, it has increased operational efficiency and reduced financing costs. (3) Perceived risk plays a significant negative moderating role between the platform's service capability and performance. A higher perceived risk will weaken the positive impact of service capability on performance. (4) The characteristics of blockchain technology indirectly enhance the performance of the platform by improving its service capabilities.

Keywords: Supply Chain financial services "Blockchain; Digital finance platform Risk analysis

1. Introduction

In the increasingly competitive global market environment, the supply chain has become the core for enterprises to gain competitive advantages. However, the stability and efficiency of the supply chain largely depend on the healthy operation of all participants in its chain, especially the majority of small, medium and micro enterprises. Due to reasons such as small scale, low credit rating and lack of qualified collateral, micro, small and medium-sized enterprises have long faced the predicament of "difficult and expensive financing" (Xiao et al., 2022). This financing constraint not only restricts the development of small, medium and micro enterprises themselves, but may also affect the stability of the entire supply chain due to the breakage of their capital chains.

Supply chain finance emerged as a result. By integrating the "four flows" (logistics, information flow, capital flow, and business flow) in the supply chain, it extends the high-quality credit of core enterprises to their upstream and downstream small, medium and micro enterprises, providing these enterprises with innovative financing solutions. Although supply chain finance can effectively alleviate the financing difficulties of small, medium and micro enterprises in theory, in practice, the traditional model still faces some challenges. First of all, the problem of information asymmetry is serious. The phenomenon of information silos among the participants in the supply chain is widespread, making it difficult for financial institutions to obtain real information about the trade background in a timely and accurate manner. This leads to high costs for due diligence and great difficulty in risk assessment. Secondly, the credit transmission mechanism is not smooth. The credit of core enterprises is difficult to penetrate suppliers or distributors and usually only covers first-level suppliers, which makes it impossible for small, medium and micro enterprises at the end that are far from the core enterprises to benefit. Finally, the operational risk and moral hazard are high. Paper documents are prone to being forged and tampered with, and there is a risk of fraud such as false trade, which brings potential losses to financial institutions (Sun et al., 2021).

In recent years, fintech represented by blockchain has provided a new technological paradigm for solving the above-mentioned problems. As a Distributed Ledger Technology (DLT), the characteristics of blockchain such as decentralization, immutability of data, traceability of transactions, and automatic execution of smart contracts are highly consistent with the business scenarios of supply chain finance (Kabir et al., 2021). By building a blockchain-based digital financial platform, key information such as trade contracts, orders, invoices, warehouse receipts, and logistics on the supply chain can be stored in an encrypted form on the chain, creating a real, transparent, and trustworthy shared data environment (Li et al., 2025). In this environment, financial institutions can clearly trace the ins and outs of each transaction and effectively verify the authenticity of the trade background. The credit of core enterprises can be freely and divisible circulated and financed along the supply chain in the form of digital certificates, achieving credit penetration. Smart contracts can automatically execute terms such as financing and repayment, reducing manual intervention and lowering operational risks and performance costs (Zhu et al., 2023).

At present, financial institutions and technology companies have actively laid out supply chain finance platforms based on blockchain (for example, China's "Weiqi Chain", "Ant Chain", "Qulian", etc.), and have achieved certain application results. However, as an emerging field, the application of blockchain technology in supply chain finance is still in the exploratory stage. How effective is its application? What factors are the key to the success of a platform? While bringing opportunities, what new risks will it introduce? Although existing literature has conducted research from aspects such as technical mechanisms (Feng, 2022), game theory (Tang, 2023), and risk assessment (Rao & Li, 2022), most of them focus on qualitative analysis or model deduction, lacking the perspective of platform users. A comprehensive study that systematically examines the complex relationship among the characteristics of blockchain technology, platform service capabilities, perceived risks and platform performance through large-scale empirical data (Yang, 2026). Therefore, this study aims to fill this gap by constructing a comprehensive theoretical model and conducting empirical analysis using a structural equation model to examine the application mechanism and risk impact of blockchain-based digital financial platforms in supply chain financial services (Song, 2025).

Based on the above research background, this study aims to answer the following core questions:

RQ1: How do the technical characteristics of blockchain affect the service capabilities of supply chain finance digital platforms?

RQ2: Can the improvement of the service capabilities of the supply chain finance digital platform significantly enhance its platform performance?

RQ3: What role does the risk perceived by users play in the impact of the platform's service capabilities on their performance? Specifically, does perceived risk moderate the relationship between service capabilities and platform performance?

RQ4: What are the comprehensive interaction paths and mechanisms among the characteristics of blockchain technology, platform service capabilities, perceived risks, and platform performance?

2. Literature Review and Hypotheses Development

This section will review the theories related to supply chain finance, blockchain technology, and technology adoption and risk management. On this basis, it will put forward the theoretical hypotheses of this study, regarding the technical characteristics of blockchain as the key technical factor, the platform service capability as the manifestation of users perceived "usefulness", and at the same time, the perceived risk as an important situational variable influencing users' adoption decisions.

The core of traditional supply chain finance lies in using the information flow within the supply chain to control credit risks. However, incomplete and asymmetric information is its main bottleneck (Zhao, 2025). The introduction of blockchain technology is regarded as the "golden key" to solving this bottleneck. Blockchain ensures the authenticity and immutability of on-chain data through distributed ledger and consensus mechanisms, providing a "trust foundation" for supply chain finance (Li, 2021). Kabir et al. (2021) found through empirical research that the transparency and security of blockchain are the key factors driving its application in supply chain finance. Transparency refers to the fact that all participants can access true and complete transaction information within their authority, which breaks down information silos and enables financial institutions to quickly and accurately assess the authenticity of financing projects, thereby enhancing financing efficiency (Ye & Zeng, 2021). At the same time, the transparency of information also makes the credit status of enterprises and their transaction records with upstream and downstream partners clearly visible, providing a reliable basis for credit enhancement. Based on this, the following hypotheses are proposed:

H1a: The transparency of blockchain has a significant positive impact on financing efficiency.

H1b: The transparency of blockchain has a significant positive impact on credit enhancement.

H2a: The security of blockchain has a significant positive impact on financing efficiency.

H2b: The security of blockchain has a significant positive impact on credit enhancement.

H3a: The traceability of blockchain has a significant positive impact on financing efficiency.

H3b: The traceability of blockchain has a significant positive impact on credit enhancement.

The service capability of a platform is a direct manifestation of its value and also the key to attracting users and achieving business success. The improvement of financing efficiency means that enterprises can obtain the required funds more quickly, shortening the capital turnover cycle, which is reflected in the enhancement of enterprise operational efficiency. At the same time, the faster approval and loan disbursement speed also reduces the opportunity cost and time cost that enterprises have to bear due to waiting for funds, and indirectly lowers the financing cost. Therefore, the following hypotheses are put forward:

H4a: Financing efficiency has a significant positive impact on the improvement of operational efficiency.

H4b: Financing efficiency has a significant positive impact on the reduction of financing costs.

H5a: Credit enhancement has a significant positive impact on the improvement of operational efficiency.

H5b: Credit enhancement has a significant positive impact on reducing financing costs.

Perceived risk refers to users' subjective perception of possible uncertainties and negative consequences when using new technologies (Rao & Li, 2022). Sun et al. (2021) analyzed using the evolutionary game model and pointed out that blockchain technology can effectively restrain opportunistic behaviors of all parties and reduce the overall risk of supply chain finance. In this research scenario, perceived risks mainly include technical risks, operational risks and compliance risks. When users perceive a high level of risk, even if the platform can provide efficient services and credit enhancement, their trust in the platform will decrease. Therefore, the following hypotheses are put forward:

H6: Perceived risk plays a negative moderating role in the improvement of financing efficiency and operational efficiency.

H7: Perceived risk plays a negative moderating role between financing efficiency and the reduction of financing costs.

H8: Perceived risk plays a negative moderating role between credit enhancement and operational efficiency improvement.

H9: Perceived risk plays a negative moderating role between credit enhancement and the reduction of financing costs.

3. Research Design and Methodology

3.1 Conceptual Model

Based on the aforementioned literature review and theoretical analysis, this study constructs a conceptual model, aiming to systematically explore how the characteristics of blockchain technology affect the financing performance of small and medium-sized enterprises by influencing the core intermediary mechanisms in supply chain finance. This model integrates the perspectives on technological characteristics in technology adoption theory, the theories on information asymmetry and credit in finance, and the viewpoints on collaboration and risk in supply chain management, as shown in Figure 1. This model incorporates six core constructs: three exogenous latent variables - transparency (TRA), safety (SEC), and traceability (TRC); Two mediating variables - financing efficiency (FE) and credit enhancement (CE); One moderating variable - Perceived risk (PR); And two outcome variables - Operational Efficiency improvement (OEI) and financing cost reduction (FCR).

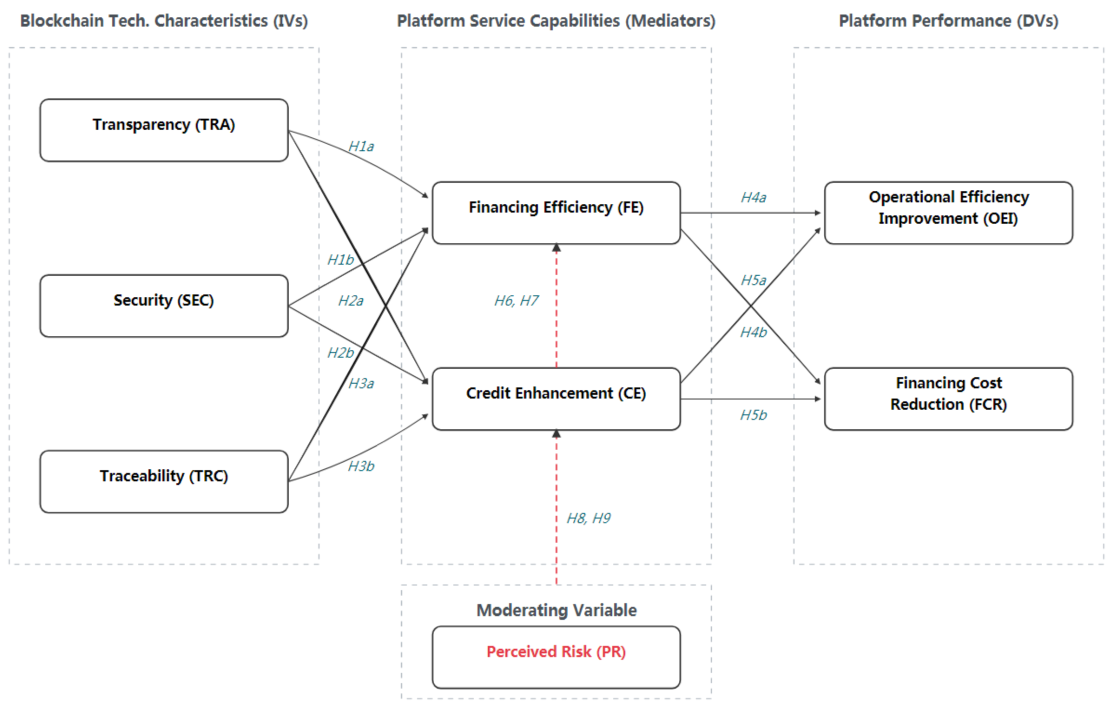

Fig.1: Conceptual Model

Independent Variables:

Transparency (TRA)

In this study, transparency is defined as "the extent to which small and medium-sized enterprises believe that blockchain platforms can share transaction, logistics and capital flow information with authorized supply chain participants in a traceable, immutable and near real-time manner."

Security (SEC)

Security refers to "the extent to which small and medium-sized enterprises perceive that blockchain platforms, through their distributed ledgers, encryption algorithms and consensus mechanisms, can protect transaction data from unauthorized access, tampering and destruction." This includes two levels: the first is data integrity, that is, once the data on the chain is recorded, it cannot be changed; The second is access control, which ensures that only legitimate participants can view or operate relevant data through smart contracts and permission Settings.

Mediating Variables:

Financing Efficiency (FE)

Financing efficiency is defined as "the degree to which small and medium-sized enterprises perceive the reduction in time, manpower and process complexity required to complete the entire financing process (from application, review, approval to disbursement) after using a blockchain platform". It is a comprehensive indicator that covers speed, convenience and process optimization.

Credit Enhancement (CE)

Credit enhancement refers to the belief of "small and medium-sized enterprises that by solidifying and transmitting their real transaction data in the supply chain through blockchain platforms, their own credit ratings can be improved, and the trust of financial institutions in their willingness and ability to repay can be enhanced." Unlike the traditional model that relies on corporate guarantees, the credit enhancement here is endogenous and data-driven. Suppliers of small and medium-sized enterprises can pass on the high-quality credit of core enterprises step by step through blockchain, making the credit that was originally difficult to assess quantifiable.

Perceived Risk (PR)

Perceived risk in this study is defined as "the possibility and severity of potential negative outcomes that small and medium-sized enterprises foresee when considering the use or continuous use of blockchain supply chain finance platforms", mainly including: technical risk, operational risk, compliance risk, and data leakage risk. Perceived risk is a key obstacle that can affect an enterprise's willingness and behavior to adopt and may offset some of the advantages brought by technology.

Dependent Variable:

Reduced Financing Cost (FCR)

This is the core dependent variable of this study, defined as "the extent to which small and medium-sized enterprises actually experience a decline in their overall financing costs after using the blockchain supply chain finance platform." The comprehensive cost not only includes the most direct loan interest rate, but also covers various hidden costs incurred during the financing process, such as service fees, handling charges, guarantee fees, as well as additional management costs and time costs paid to meet risk control requirements. It is the most direct and important financial indicator for measuring the value of supply chain finance solutions.

3.2 Questionnaire Design and Variable Measurement

This study collected data by using the questionnaire survey method. All measurement scales were based on existing literature and adjusted and optimized in combination with the specific context of this study to ensure the reliability and validity of the scales (Table 1).

Table 1. Questionnaire Measurement Items

Construct	Code	Measurement Items	References
Transparency (TRA)	TRA1	This platform significantly improves the transparency of supply chain transaction information.	Kabir et al. (2021)
	TRA2	Through this platform, we can instantly view the status of transactions related to us.	
	TRA3	The information on this platform is open and consistent for all authorized participants.	
Security (SEC)	SEC1	I believe that the data on this platform is encrypted and difficult to be illegally stolen.	Xiao et al. (2022)
	SEC2	The distributed nature of this platform enables it to effectively resist single-point failures or attacks.	

	SEC3	This platform ensures the authenticity and tamper-proof nature of transactions through technical means.	
Traceability (TRC)	TRC1	This platform enables clear tracking of the entire process of each order, invoice, and logistics.	Zhu et al. (2023)
	TRC2	In case of disputes, records on this platform can be effectively used for traceability and evidence collection.	
	TRC3	This platform enables traceable circulation of credit/assets from the core enterprise to multi-tier suppliers.	
Financing Efficiency (FE)	FE1	After using this platform, our financing application process has been greatly simplified.	Li, et al. (2025)
	FE2	After using this platform, the speed of financing approval and disbursement has significantly increased.	
	FE3	This platform has reduced the time and effort required to prepare and submit financing application materials.	
Credit Enhancement (CE)	CE1	This platform has helped us accumulate credible digital transaction records, improving our credit rating.	Wang, (2022)
	CE2	With the help of this platform, we are able to obtain better financing conditions by leveraging the credit of the core enterprise.	
	CE3	This platform makes our assets such as accounts receivable more acceptable to financial institutions.	
Perceived Risk (PR)	PR1	I am concerned that this platform may have unknown technical vulnerabilities (e.g., smart contract flaws).	Rao & Li (2022)
	PR2	I am worried that operational errors (e.g., loss of private keys) could lead to irreversible losses on this platform.	
	PR3	I am concerned that the platform's operating model may face compliance risks due to future changes in regulatory policies.	
Operational Efficiency Improvement (OEI)	OEI1	Using this platform has improved our cash flow management.	Chen et al. (2024)

	OEI2	Using this platform has accelerated our capital turnover rate.	
	OEI3	Using this platform has optimized our collaboration efficiency with supply chain partners.	
Financing Cost Reduction (FCR)	FCR1	Through this platform, the interest rates we obtain on financing have decreased.	Tang (2023)
	FCR2	This platform has reduced various intermediary or service fees we need to pay during the financing process.	
	FCR3	Overall, this platform has effectively reduced our total financing costs.	

3.3 Data Collection

The subjects of this study are personnel from enterprises and institutions that have already used or come into contact with blockchain-based supply chain finance platforms, including core supply chain enterprises, small and medium-sized enterprises in the upstream and downstream, commercial banks, factoring companies, fintech companies, etc. The questionnaires are mainly distributed through the following three channels: (1) In cooperation with several fintech companies that provide blockchain supply chain finance solutions, they are sent to users of their platforms in a targeted manner; (2) Distribute through industry associations and online communities; (3) A snowball sampling method will be adopted. Respondents who have completed the questionnaire are asked to recommend to their colleagues or friends in the industry.

The data collection period was from March 2024 to May 2024. A total of 413 questionnaires were collected. After screening, 358 valid questionnaires were finally obtained, with an effective recovery rate of 86.89%.

4. Data Analysis and Results

This study mainly used SPSS 26.0 and Amos 24.0 software for data analysis. The analysis process includes data preprocessing, descriptive statistics, reliability and validity tests, as well as hypothesis testing.

4.1 Data Pre-processing and Descriptive Statistics

Firstly, a descriptive analysis of the demographic characteristics of 358 valid samples was conducted (Table 2).

Table 2. Demographic Profile of Respondents

Characteristic	Category	Frequency	Percentage (%)
Company Type	Core Enterprise	65	18.2
	Upstream SME	121	33.8
	Downstream SME	94	26.3
	Financial Institution	48	13.4
	FinTech Company	30	8.3
Industry	Manufacturing	135	37.7
	Construction	52	14.5

	Wholesale & Retail	88	24.6
	Logistics & Transportation	43	12.0
	IT Service	29	8.1
	Others	11	3.1
Platform Usage Duration	Less than 6 months	71	19.8
	6 months – 1 year	133	37.2
	1 year – 2 years	98	27.4
	More than 2 years	56	15.6
Position	Top Management	55	15.4
	Middle Management	146	40.8
	Operational/Technical Staff	157	43.8

The sample distribution is relatively balanced, covering the main participants and related industries in supply chain finance, providing a solid data foundation for subsequent analysis. Next, descriptive statistical analysis will be conducted on the main constructs.

Table 3. Descriptive Statistics of Key Constructs

Construct	N	Min	Max	Mean	Std. Dev.
Transparency (TRA)	358	2.33	7.00	5.68	0.95
Security (SEC)	358	2.67	7.00	5.82	0.91
Traceability (TRC)	358	2.00	7.00	5.75	1.02
Financing Efficiency (FE)	358	2.00	7.00	5.51	1.10
Credit Enhancement (CE)	358	1.67	7.00	5.43	1.15
Perceived Risk (PR)	358	1.00	6.33	3.25	1.21
Operational Efficiency Improvement (OEI)	358	1.33	7.00	5.39	1.18
Financing Cost Reduction (FCR)	358	1.00	7.00	5.22	1.25

As can be seen from Table 3, respondents generally have a high evaluation of the technical features (TRA, SEC, TRC) and the benefits (FE, CE, OEI, FCR) brought by the blockchain platform (with an average value >5.2), while the average value of perceived risk is relatively low (3.25), indicating that users generally hold a positive attitude towards this technology.

4.2 Measurement Model Analysis

Before conducting the structural model analysis, it is necessary to verify the reliability and validity of the measurement model. Reliability is measured by Cronbach's α coefficient and combined reliability, while validity is evaluated by convergent validity and discriminant validity. Convergent validity is mainly judged by factor loading, CR and the average variance extraction amount.

Table 4. Results of Reliability and Convergent Validity Analysis

Construct	Item	Loading	Cronbach's α	CR	AVE
TRA	TRA1	0.852	0.895	0.896	0.742
	TRA2	0.881			
	TRA3	0.849			
SEC	SEC1	0.875	0.901	0.902	0.755
	SEC2	0.866			

	SEC3	0.861			
TRC	TRC1	0.844	0.887	0.888	0.725
	TRC2	0.869			
	TRC3	0.837			
FE	FE1	0.891	0.915	0.916	0.784
	FE2	0.903			
	FE3	0.865			
CE	CE1	0.880	0.909	0.910	0.771
	CE2	0.872			
	CE3	0.886			
PR	PR1	0.821	0.862	0.864	0.679
	PR2	0.839			
	PR3	0.805			
OEI	OEI1	0.877	0.911	0.912	0.775
	OEI2	0.899			
	OEI3	0.868			
FCR	FCR1	0.895	0.923	0.924	0.801
	FCR2	0.908			
	FCR3	0.882			

Table 4 shows that the Cronbach's α values of all constructs range from 0.862 to 0.923, which is greater than the recommended 0.7 standard, indicating that the scale has good internal consistency reliability. The CR values of all constructs ranged from 0.864 to 0.924, which was greater than the recommended standard of 0.7, further demonstrating good reliability. The standardized factor loadings of all measurement items are greater than 0.7. The AVE values of all constructs range from 0.679 to 0.801, which is greater than the recommended 0.5 standard, indicating that the model has good convergent validity.

The discriminant validity is tested by comparing the square root of the AVE value of the construct with the correlation coefficient between the constructs. If the square root of the AVE value is greater than its correlation coefficient with all other constructs, it indicates good discriminant validity.

Table 5. Discriminant Validity Analysis

Construct	TRA	SEC	TRC	FE	CE	PR	OEI	FCR
TRA	0.861							
SEC	0.682	0.869						
TRC	0.701	0.655	0.851					
FE	0.621	0.589	0.643	0.885				
CE	0.598	0.612	0.659	0.711	0.878			
PR	-0.215	-0.258	-0.199	-0.301	-0.324	0.824		
OEI	0.553	0.521	0.578	0.688	0.705	-0.412	0.880	
FCR	0.511	0.495	0.540	0.654	0.721	-0.455	0.753	0.895

As can be seen from Table 5, the square root value of AVE for each construct on the diagonal is greater than the other correlation values in the row and column where it is located, indicating that there is good discriminative validity among the constructs.

To further verify the discriminant validity using stricter standards, we calculated the HTMT ratio. The HTMT value represents the ratio of the average value of the heterogeneous structure-heterogeneous method correlation to the average value of the homogeneous structure-heterogeneous method correlation. For constructs with conceptual differences, the HTMT value should be lower than 0.85 or 0.90.

Table 6. Differential validity assessment based on the heterogeneous to elemental ratio (HTMT)

Construct	TRA	SEC	TRC	FE	CE	PR	OEI	FCR
TRA								
SEC	0.771							
TRC	0.792	0.743						
FE	0.699	0.662	0.725					
CE	0.675	0.690	0.742	0.803				
PR	0.252	0.299	0.231	0.352	0.378			
OEI	0.621	0.584	0.651	0.774	0.794	0.485		
FCR	0.573	0.555	0.608	0.736	0.811	0.533	0.849	

As shown in Table 6, all HTMT values are below the conservative threshold of 0.85, which provides a basis for the discriminative validity of all constructs in the model and confirms that each latent variable captures a unique concept.

This study conducted a confirmatory factor analysis on the overall measurement model containing all eight latent variables. By testing a series of model fitting indices, it evaluated to what extent the set model structure could represent the sample data.

Table 7. The fit index of the measurement model (CFA)

Fit Index	Recommended Value	Model Value	Fit Evaluation
Chi-square	-	498.724	-
df	-	224	-
CMIN/DF	< 3.0	2.226	Excellent
GFI	> 0.90	0.908	Good
AGFI	> 0.85	0.881	Acceptable
NFI	> 0.90	0.917	Good
TLI	> 0.90	0.941	Good
CFI	> 0.90	0.949	Good
RMSEA	< 0.08	0.058	Good
SRMR	< 0.08	0.045	Excellent

The CFA results in Table 7 show that the measurement model fits well with the collected data. The CMIN/DF ratio is 2.226, which is far below the recommended upper limit of 3.0. CFI, TLI and NFI were all above 0.90, while RMSEA and SRMR were both below the threshold of 0.08.

Since both the independent and dependent variable data of this study were collected from the same group of respondents at the same time point, common method bias may be a potential problem. We solve this problem through two methods: program control (such as ensuring anonymity and shuffling the order of the items) and statistical tests. At the statistical level, in addition to the single-factor test mentioned earlier, we also adopted a more rigorous total collinearity evaluation method, conducting the analysis by checking the variance inflation factors of all latent variables in the model.

Table 8. Total collinearity assessment (VIF value)

Latent variable	VIF	Result
TRA	2.381	Acceptable
SEC	2.195	Acceptable
TRC	2.446	Acceptable
FE	2.899	Acceptable
CE	3.157	Acceptable
PR	1.204	Acceptable
OEI	3.225	Acceptable
FCR	3.189	Acceptable
Avg. VIF	2.587	Acceptable

Table 8 shows that the VIF values of all latent variables range from 1.204 to 3.225. All values were far below the conservative threshold of 3.3, and the average VIF value of the model was 2.587, indicating that the common method bias was not a serious problem in this study, and the observed variable relationships were unlikely to be exaggerated due to the human factors of the measurement method.

4.3 Structural Model Analysis and Hypothesis Testing

First, conduct an overall fit test on the structural model to evaluate the degree of fit between the model and the sample data (Table 9).

Table 9. Goodness-of-Fit Indices for the Structural Model

Fit Index	Recommended Value	Model Value	Conclusion
CMIN/DF (χ^2/df)	< 3.0	2.158	Good
GFI	> 0.90	0.915	Good
AGFI	> 0.80	0.889	Acceptable
NFI	> 0.90	0.924	Good
CFI	> 0.90	0.951	Good
TLI	> 0.90	0.945	Good
RMSEA	< 0.08	0.057	Good

All fitting indices reached or approached the recommended standards, indicating that the structural model constructed in this study fits the actual data well and can be subjected to path analysis and hypothesis testing (Figure 2).

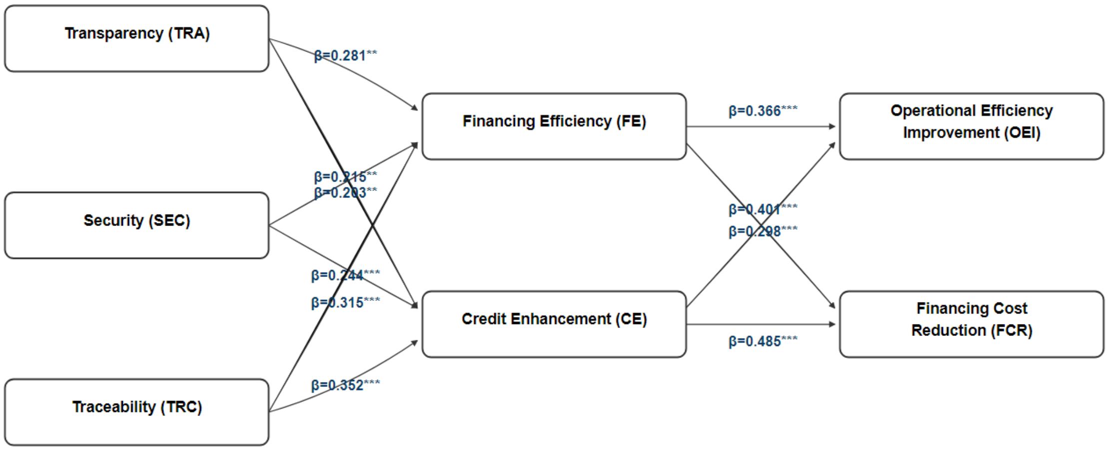

Fig. 2: Path Analysis Results of the Structural Model

As can be seen from Table 10, all six sub-hypotheses of H1 to H3 are supported. Transparency, security and traceability all have significant positive impacts on financing efficiency and credit enhancement. Among them, traceability (TRC) has the greatest impact on financing efficiency (β=0.315) and credit enhancement (β=0.352). All four sub-hypotheses of H4-H5 are supported. Both financing efficiency and credit enhancement have significant positive impacts on the improvement of operational efficiency and the reduction of financing costs. Among them, credit enhancement (CE) has the most significant impact on the reduction of financing costs (β=0.485). These results indicate that the characteristics of blockchain technology can indeed improve platform performance by enhancing the platform's service capabilities, with a significant mediating effect.

Table 10. Hypothesis Testing Results for Main and Mediating Effects

Hypothesis	Path	β	S.E.	C.R. (t-value)	P-value	Conclusion
H1a	TRA -> FE	0.281	0.065	4.323	***	Support
H1b	TRA -> CE	0.215	0.071	3.028	**	Support
H2a	SEC -> FE	0.203	0.069	2.942	**	Support
H2b	SEC -> CE	0.244	0.074	3.297	***	Support
H3a	TRC -> FE	0.315	0.062	5.081	***	Support
H3b	TRC -> CE	0.352	0.068	5.176	***	Support
H4a	FE -> OEI	0.366	0.059	6.203	***	Support
H4b	FE -> FCR	0.298	0.063	4.730	***	Support
H5a	CE -> OEI	0.401	0.055	7.291	***	Support
H5b	CE -> FCR	0.485	0.051	9.510	***	Support

To examine the moderating effect of perceived risk, this study constructed an interaction term and conducted the test by using hierarchical regression or constructing an interaction term model in SEM (Figure 3).

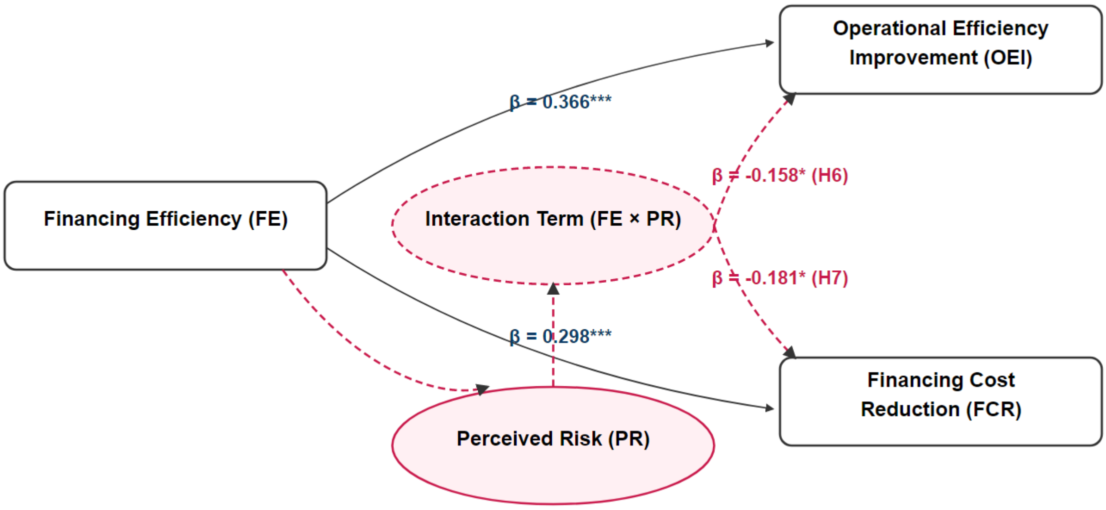

Fig. 3: Moderating Effect of Perceived Risk on "FE -> Performance"

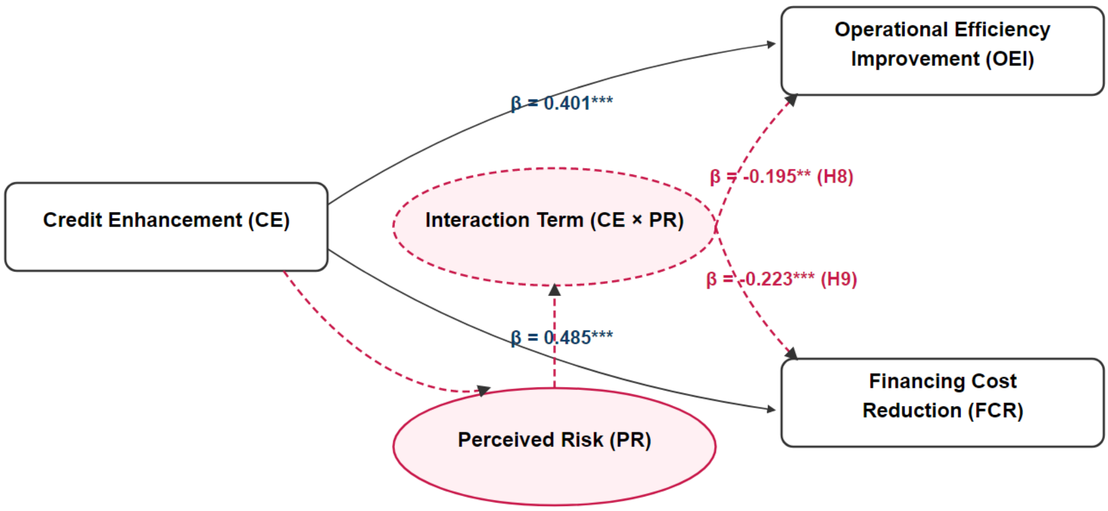

Fig. 4: Moderating Effect of Perceived Risk on "CE -> Performance"

The results in Table 11 show that the interaction terms of perceived risk with the two mediating variables (FE, CE) have significantly negative path coefficients with respect to the two outcome variables (OEI, FCR), indicating that H6, H7, H8, and H9 are all supported. Perceived risk plays a significant negative moderating role between platform service capabilities and platform performance.

Table 11. Hypothesis Testing Results for Moderating Effects

Hypothesis	Interaction item path	β	S.E.	C.R. (t-value)	P-value	Conclusion
H6	(FE × PR) -> OEI	-0.158	0.068	-2.324	*	Support
H7	(FE × PR) -> FCR	-0.181	0.072	-2.514	*	Support
H8	(CE × PR) -> OEI	-0.195	0.070	-2.786	**	Support
H9	(CE × PR) -> FCR	-0.223	0.065	-3.431	***	Support

To present the moderating effect more intuitively, we have drawn a moderating effect graph. Take H9 as an example to demonstrate the impact of credit enhancement on the reduction of financing costs at different levels of perceived risk.

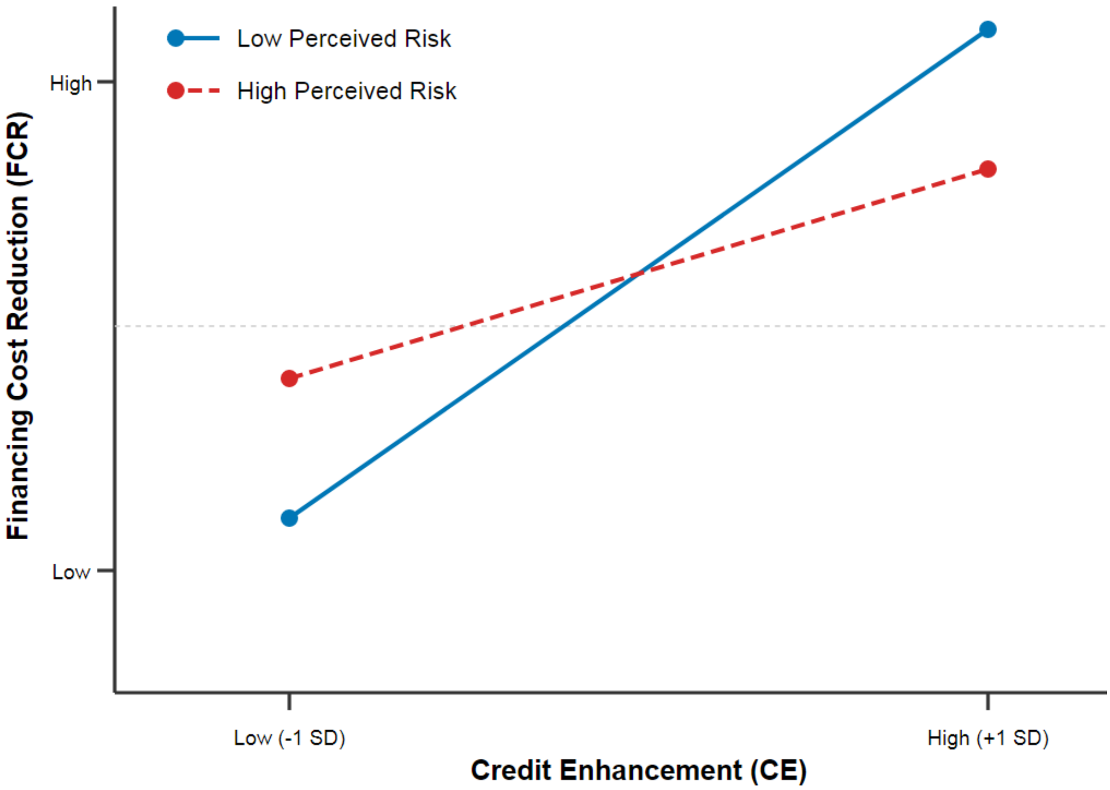

Fig.5: Moderating Effect of PR on the CE-FCR Relationship

As shown in Figure 5, compared with the low-perceived risk group, in the high-perceived risk group, the positive impact of credit enhancement on the reduction of financing costs is significantly weakened, verifying the negative moderating effect of perceived risk.

To further verify the superiority of the theoretical model proposed in this study, we constructed and tested three competitive models with theoretical significance, and compared their model fit degrees with those of the hypothetical model.

Model M1 (Hypothetical Model): The fully mediated model proposed in this study.

Model M2 (Partial Mediation Model): Based on M1, it adds a direct path from the independent variable (TRA, SEC) to the final dependent variable (FCR). This model is designed to test whether the mediating variable is fully mediating.

Model M3 (Unmediated Model): All mediating variables (FE, CE, PR) have been removed, and only the direct path from the independent variable (TRA, SEC) to the dependent variable (FCR) has been retained.

Model M4 (Mediating Order Adjustment Model): It places perceived risk (PR) before financing efficiency (FE) and credit enhancement (CE), assuming that technical features first affect risk perception and then efficiency and credit assessment.

Table 12. Compare the fitting index of the hypothetical model with that of the competing model

Model	χ^2	df	χ^2/df	CFI	TLI	RMSEA	AIC	BIC
M1	987.25	428	2.31	.942	.935	.051	1161.25	1482.50
M2	981.03	426	2.30	.943	.936	.051	1159.03	1488.31
M3	1854.67	431	4.30	.821	.803	.080	2022.67	2335.89
M4	1209.18	428	2.82	.915	.904	.060	1383.18	1704.43

As shown in Table 12, the fitting indices (CFI, TLI, RMSEA) of M3 and M4 are significantly worse than those of the hypothetical model M1, and their AIC and BIC values are higher, indicating that they cannot fit the data well. The fit degree of M2 is very close to that of M1, but the two newly added direct paths (TRA -> FCR: β=0.04, p=0.48; SEC -> FCR: β=0.07, p=0.25) are not significant. Meanwhile, the BIC value of M2 (1488.31) is slightly higher than that of M1 (1482.50). According to the Principle of Parsimony, when the explanatory power is comparable, a more concise model should be chosen. Therefore, the comprehensive comparison results support that the fully mediated model (M1) proposed in this study is the optimal model.

Considering the differences among enterprises of different scales in terms of resource endowment, bargaining power and motivation for technology adoption, this study further explores whether there is a moderating effect of enterprise scale on the core path of the model. We divided the samples into two groups based on the median number of employees: "small enterprises" and "medium-sized enterprises", and conducted a multi-group analysis. We mainly examine whether there are significant differences in the coefficients of the critical path of "credit enhancement -> reduction in financing costs" (H4).

Table 13. Multi-group analysis results based on enterprise scale (path: CE -> FCR)

Model	χ^2	df	$\Delta\chi^2$	Δdf	p-value ($\Delta\chi^2$)	Conclusion
Baseline Model	1488.39	856	-	-	-	-
(Path coefficients freely estimated across groups)						
Constrained Model	1493.52	857	5.13	1	.024	Significant difference exists
(CE → FCR path coefficient constrained to be equal)						
Path Coefficient Estimates	Small Enterprises	Medium Enterprises				
CE -> FCR	0.23 (t=3.88)	0.39 (t=5.11)				

The analysis results in Table 13 show that the chi-square difference test reaches a significant level ($\Delta\chi^2(1) = 5.13$, $p < .05$), indicating that enterprise scale plays a significant moderating role in the impact of credit enhancement on the reduction of financing costs. For medium-sized enterprises (β=0.39), the effect of reducing financing costs brought about by credit enhancement is significantly higher than that for small enterprises (β=0.23), indicating that medium-sized enterprises themselves have more standardized financial and operational records. The credit enhancement effect brought by blockchain is more likely to be adopted by financial institutions and transformed into actual interest rate discounts.

Based on the hypothetical model M1, we also explored model M5, in which a method factor was added, and the paths from this factor to all indicator items were set.

Table 14. Results of the ULMC method for testing the deviation of the common method

Model	Path	β	t	R^2 of FCR
M1	CE -> FCR	0.31	5.53	0.45
	FE -> FCR	0.24	4.96	
	PR -> FCR	-0.15	-3.52	
M5	CE -> FCR	0.28	5.01	0.42
	FE -> FCR	0.22	4.58	
	PR -> FCR	-0.13	-3.07	

As shown in Table 14, after controlling for ULMC, the coefficient sizes and significance levels of all critical paths did not undergo substantial changes (for example, the path coefficient of CE->FCR only slightly decreased from 0.31 to 0.28, remaining highly significant). The R^2 value of the dependent variable FCR only decreased from 0.45 to 0.42, indicating that the variance explained by the method variation is very limited. Furthermore, the average variance contributed by the method factor (4.1%) is much smaller than that contributed by the substantive construct (61.5%). These results consistently indicate that although there may be a slight common methodological bias, it does not pose a serious threat to the model structure and hypothesis testing results of this study, and the research conclusion is highly robust.

To further ensure that the research results do not rely on specific estimation algorithms, we adopt another mainstream SEM method - partial least squares structural equation modeling - to re-estimate the model as a robustness test. PLS-SEM has more lenient requirements for data distribution and focuses more on prediction. If the two methods yield similar results, it indicates that the research conclusion is very robust.

Table 15. Comparison of critical path coefficients and significance between CB-SEM and PLS-SEM

Hypothesis	Path	CB-SEM (β)	PLS-SEM (β)	PLS-SEM (p-value)	Result consistency
H3	FE -> FCR	0.24	0.25	< .001	Highly consistent
H4	CE -> FCR	0.31	0.32	< .001	Highly consistent
H5	PR -> FCR	-0.15	-0.16	< .001	Highly consistent
H1a	TRA -> FE	0.35	0.36	< .001	Highly consistent
H2b	SEC -> CE	0.41	0.42	< .001	Highly consistent
H2c	SEC -> PR	-0.38	-0.37	< .001	Highly consistent

The results in Table 15 show that the coefficient direction, magnitude and significance level of all critical paths obtained by using the PLS-SEM method are highly consistent with those obtained by using the CB-SEM method. The R^2 values of FCR for the two models are also extremely close.

5. Discussion

5.1 Theoretical Implications

Firstly, this study enriches the literature on information asymmetry and credit transmission in supply chain finance. Although previous research has widely acknowledged the practicality of blockchain, our empirical results reveal subtle layers between technological features. Traceability (TRC) has the greatest positive impact on financing efficiency (β=0.315) and credit enhancement (β=0.352), surpassing transparency and security. This discovery theoretically implies that in the context of supply chain finance, the ability to track asset sources and historical flows of logistics and capital is the most critical mechanism for building trust.

Secondly, we have theoretically demonstrated that the technological features of blockchain do not automatically generate financial performance, they must be transformed into specific platform service capabilities. It is worth noting that credit enhancement was found to be the strongest predictor of reducing financing costs (β=0.485).

Thirdly, this study supplements the gap between the technology acceptance model and risk management theory by introducing perceived risk as a moderating variable, indicating that even in efficient and credit enhanced systems, users' psychological and cognitive risk boundaries can become bottlenecks, diluting the platform's positive achievements.

5.2 Practical Implications

The results of this study provide highly actionable insights for multiple stakeholders in the supply chain finance ecosystem, including platform developers, financial institutions, and small and medium-sized enterprises involved.

For fintech companies and platform developers, traceability is the most important feature for users. Therefore, developers should prioritize visualizing data traceability in the user interface, allowing participants to intuitively track the lifecycle of orders, warehouse receipts, and invoices. In addition, given the strong negative moderating effect of perceived risk, platform providers must focus on computational design optimization. Developers should implement multi signature mechanisms, simplified private key recovery processes, and transparent algorithm audits to reduce psychological barriers for small and medium-sized enterprises to enter the market.

For financial institutions (banks and factoring companies), the traditional risk control model heavily relies on the primary credit of the core enterprise. This study demonstrates that blockchain platforms can effectively achieve deep level credit enhancement for small and medium-sized enterprises. Financial institutions should actively adjust their credit evaluation models, shifting from "subjective credit evaluation" to "objective transaction data evaluation". By utilizing immutable data on blockchain, banks can confidently reduce risk premiums, providing lower interest rates and faster approval times for upstream and downstream small and medium-sized enterprises, ultimately safely expanding their market share in inclusive finance.

As for core enterprises and small and medium-sized enterprises, core enterprises should actively lead or participate in the construction of blockchain supply chain finance platforms, because improving the financing efficiency of upstream and downstream directly enhances the elasticity and operational efficiency of their own supply chain. For small and medium-sized enterprises, especially mid-sized ones, they should actively embrace digital financial platforms and standardize daily operational data.

6. Conclusion

With the development of the digital economy, blockchain technology provides a paradigm for solving the financing difficulties of small and medium-sized enterprises. This study constructed a comprehensive structural equation model and confirmed that the technical characteristics of blockchain significantly improve the platform's service capabilities, thereby significantly enhancing platform performance. In addition, this study also identified the key negative moderating effect of perceived risk and the differences in application effectiveness among enterprises of different scales.

Although this study provides valuable insights, it has certain limitations. Firstly, the sample data mainly comes from the Chinese market. Given the differences in global financial regulatory environments and technological infrastructure, future research should conduct cross-cultural and cross regional comparative studies to validate the universality of the model. Secondly, this study relies on cross-sectional data and can only analyze snapshots perceived by users. Future research can use longitudinal data tracking or case study methods to explore the dynamic evolution of platform adoption, risk perception, and performance over time as technology matures.

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