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Research on Blockchain Consensus Mechanism and Risk Pricing Methods for Multi-Institution Financial Credit

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Abstract

In the field of financial credit, the phenomenon of credit data silos among institutions severely hinders the improvement of risk control effectiveness. This study proposes a multi-institution collaborative credit solution that integrates a consortium blockchain consensus mechanism with an innovative risk pricing model. A distributed credit information sharing platform was constructed based on Hyperledger Fabric, and an analytical dataset comprising 543,217 credit records was established. The risk pricing model developed in this study is based on logistic regression, combined with graph structure relationship modeling, achieving an AUC value of 0.917 on the test set and reducing the prediction error rate by 8.9% compared to traditional centralized models. Furthermore, the credit approval process based on the blockchain consensus mechanism reduced the average approval cycle from T+3 days to T+0.4 days. The study demonstrates that the proposed solution can significantly enhance the accuracy of risk assessment and the efficiency of approval processes in multi-institution financial credit.

Keywords **Blockchain Consensus Mechanism; Credit Risk Pricing; Multi-Institution Collaboration; Consortium Blockchain; Credit Reporting System**

Introduction

In the operational framework of the modern economic system, financial credit functions as a core hub for resource allocation, fundamentally representing a process of credit risk assessment and capital allocation under conditions of information asymmetry [1]. This process concerns not only the financing activities of microeconomic entities but also has a profound impact on macroeconomic stability and development [2]. By the end of 2024, the balance of RMB loans by financial institutions in China had surged to 237.2 trillion yuan, underscoring the increasing importance of multi-institution collaborative credit [3,4]. However, the current closed and segmented nature of credit data sharing among financial institutions has become a critical bottleneck restricting the enhancement of risk control effectiveness, reflecting deeper structural contradictions and systemic flaws within the financial market [5]. From the perspective of institutional economics, the isolated status of credit data among financial institutions results from the combined effects of multiple factors. The ambiguity in the definition of data ownership leads to unclear rights demarcation during the data-sharing process, making it difficult to establish stable expectations for cooperation [6,7]. High costs associated with data sharing—including technical integration costs, security protection costs and potential commercial loss—further weaken the willingness of institutions to share data [8]. Moreover, the lack of a comprehensive incentive and constraint mechanism fails to effectively balance the distribution of benefits and risks, resulting in approximately 78% of financial

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institutions adopting a cautious and conservative stance toward credit data sharing due to concerns about data security and competitive interests [9,10]. The long-term persistence of such "data silos" significantly exacerbates information asymmetry in the financial market, making it difficult for financial institutions to obtain comprehensive and accurate credit information on borrowers, thereby giving rise to adverse selection and moral hazard problems [11]. According to statistics from a provincial financial regulatory authority, in 2023, 32% of identified non-performing loan cases involved borrowers who had engaged in multi-institution borrowing without timely detection [12]. This phenomenon fully reveals the serious shortcomings of traditional credit reporting models in information integration and risk warning, highlighting the urgent need to break down data barriers and achieve credit data sharing [13].

Traditional centralized credit reporting models exhibit inherent limitations in both technical architecture and institutional design [14]. In terms of data governance, the average data update cycle ranges from 7 to 15 days, a significant lag that conflicts sharply with the highly dynamic nature of financial markets, thereby exposing credit decision-making processes to increased risks of misjudgment [15]. From a system security perspective, centralized architectures heavily rely on a limited number of core nodes; if these key nodes are subjected to cyberattacks or system failures, the entire credit reporting system faces a risk of paralysis [16]. In 2022, a major credit reporting agency experienced a system failure that resulted in a 12-hour service interruption, directly affecting the approval of over one million credit transactions, serving as a clear warning about the vulnerability of centralized models [17,18]. Regarding data management, the highly centralized control places data ownership predominantly in the hands of a few institutions, leading to a high risk of data misuse and privacy breaches [19]. According to the 2023 Financial Data Security White Paper, approximately 41% of financial data leakage incidents were associated with management vulnerabilities in centralized institutions, seriously undermining the legitimate rights of data subjects and severely damaging the trust foundation of the financial market [20]. The emergence of blockchain technology has provided a highly promising pathway to address the challenges of credit reporting in the financial credit sector. Its core technological features, including distributed ledger systems, consensus mechanisms and cryptographic algorithms, fundamentally reconstruct the modes of data storage, transmission and verification [21]. The decentralized architecture of blockchain enables multiple institutions to achieve trusted data sharing and collaborative operations without relying on intermediaries, effectively reducing trust costs and coordination costs in data sharing [22]. Taking Ant Group's “AntChain” as an example, it has successfully enabled data collaboration among more than 200 financial institutions, improving data verification efficiency by 60%, fully demonstrating the application value of blockchain technology in the financial sector [23]. In financial credit scenarios, blockchain technology is expected to build a transparent, secure and efficient credit reporting ecosystem [24]. Through real-time and accurate data sharing, it can reduce the degree of information asymmetry and enhance the overall risk control capabilities of financial institutions. Risk pricing, as a core component of financial credit operations, essentially involves the quantitative evaluation and value judgment of a borrower's future credit risk [25]. Traditional credit scoring models based on financial indicators, such as the Z-score model, rely excessively on the borrower's historical financial data, resulting in narrow evaluation dimensions and rigid methodologies, making it difficult to capture the complex and evolving features of credit risk [26]. As the financial market continues to innovate and develop, financial products are becoming increasingly diversified, and financial transaction relationships are growing more complex. Unstructured data such as borrower relationship networks, online behavior, and social network data are playing an increasingly significant role in influencing credit risk [27]. Related studies have shown that incorporating social network data into risk assessment models can improve prediction accuracy by 15%–

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20%. These findings fully illustrate that under the new market environment, it is necessary to break through the limitations of traditional models and integrate emerging technologies and diversified data sources to construct a more scientific and comprehensive risk pricing model, capable of meeting the evolving needs of financial credit operations and effectively mitigating credit risk [28]. Against the backdrop of rapid fintech development and increasingly stringent financial regulation, this study focuses on the collaborative innovation of consortium blockchain consensus mechanisms and risk pricing models, bearing important theoretical significance and practical value. Through in-depth research on the application mechanisms of blockchain technology in multi-institutional credit collaboration and the construction methods of innovative risk pricing models, this study aims to break traditional credit reporting barriers, reconstruct trust mechanisms and risk evaluation systems for multi-institution financial credit, and provide theoretical support and practical guidance for promoting the high-quality development of the financial industry.

2. Methodology

2.1 Consortium Blockchain Architecture Based on Hyperledger Fabric

This study adopts the open-source Hyperledger Fabric framework to construct a consortium blockchain system. The platform features a modular architecture design and demonstrates good adaptability in multi-institution collaboration scenarios. Previous studies have shown that supply chain finance systems built on Hyperledger Fabric can control data synchronization delays between nodes within 500 milliseconds [29]. In this system, each financial institution participates as a network node, achieving consistent data storage and sharing through distributed ledger technology and ensuring data integrity and reliability through the consensus mechanism. For data security and privacy protection, the system employs an identity authentication mechanism based on digital certificates, verifying node identities according to the X.509 certificate standard. In the data storage phase, the AES-256 encryption algorithm is applied, and during data transmission, encryption is performed based on the TLS 1.3 protocol. This encryption scheme has been certified by the State Cryptography Administration's commercial cryptography testing standards and can effectively resist data theft and tampering attacks.

2.2 Credit Information Sharing Protocol Design

Within the blockchain network, financial institutions encrypt customer credit information and encapsulate it into transaction blocks, which are broadcast through the peer-to-peer (P2P) network [30]. Upon receiving the block, other nodes verify it using the Practical Byzantine Fault Tolerance (PBFT) consensus algorithm. PBFT can achieve rapid consensus while tolerating up to one-third of malicious nodes, with an average consensus time of approximately 200–300 milliseconds. Nodes validate the legality of transactions based on the ISO 20022 financial messaging standard. Once verified, the block is incorporated into the local ledger, thereby realizing real-time synchronization and sharing of credit information among multiple institutions.

2.3 Risk Pricing Model Construction

The risk pricing model adopts a combination of logistic regression and graph structure relationship modeling. The logistic regression model is used to analyze the nonlinear relationships between borrower attributes, such as age and income, and the probability of default. Parameter optimization is conducted using the maximum likelihood estimation

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method, with a convergence accuracy reaching 10^-6. In addition, graph structure relationship modeling is introduced to construct a borrower relationship graph, and an improved PageRank algorithm is applied to extract potential risk features within the relationship network. Compared with the traditional PageRank algorithm, the improved algorithm achieves a 22% increase in the accuracy of abnormal node identification within financial relationship networks, enabling more effective capture of associated risks among borrowers.

3. Results and Discussion

3.1 Experimental Design and Data Description

This study collected 543,217 credit records from five financial institutions covering the period from 2020 to 2023, encompassing both personal and corporate credit businesses. The dataset was divided into training, validation, and test sets in a ratio of 70%, 15%, and 15%, respectively. The experimental environment was configured with an Intel Xeon E5-2620 v4 processor and 32 GB of memory, running the Ubuntu 18.04 operating system. A blockchain network consisting of 10 nodes was deployed to simulate a multi-institution scenario. The data preprocessing procedures included standardization, multiple imputation of missing values, and one-hot encoding to ensure that the data quality met the requirements for model training.

3.2 Performance Analysis of the Risk Pricing Model.

Table 1. Comparison of Risk Pricing Performance Across Different Models

Model Type	AUC Value	Prediction Error Rate	Contribution of Network Features
Proposed Model	0.917	11.2%	37%
Traditional Logistic Regression Model	0.832	12.3%	–
Random Forest Model	0.865	–	–
Other Single Logistic Regression Models *	0.885	–	–
Other Models with Simple Graph Features *	0.892	–	–
Average Performance of Traditional Risk Pricing Models **	Around 0.85	–	–

*Note: * indicates models from related studies; ** indicates the average level under complex financial scenarios.

The test results show that the risk pricing model constructed in this study achieved an AUC value of 0.917 on the test set, significantly outperforming the traditional logistic regression model (AUC = 0.832) and the random forest model (AUC = 0.865). The prediction error rate was reduced by 8.9% compared with centralized models. The network features extracted

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through graph structure modeling contributed 37% to the overall model performance, indicating that the model can effectively capture the complex interrelations among borrowers and improve the accuracy of risk assessment.

3.3 Analysis of Credit Approval Efficiency Improvement

Table 2 Comparison of Credit Approval Efficiency

Approval Mode	Average Approval Time	Efficiency Improvement	Daily Processing Volume
Traditional Approval Process	T+3 days	–	120 cases
Blockchain-Enabled Process (Proposed)	T+0.4 days	86.7%	450 cases
Industry Average Level *	T+2.5 to T+4 days	–	–

*Note: * indicates the average approval time of traditional credit processes.

Based on the blockchain consensus mechanism, the proposed credit approval process reduced the average approval time from T+3 days to T+0.4 days, resulting in an efficiency improvement of 86.7%, and increased the daily processing volume from 120 cases to 450 cases. By eliminating information asymmetry and redundant verification procedures, this process significantly enhanced credit approval efficiency, showing a clear advantage over the industry average level. From a macro perspective, the multi-institutional credit collaboration solution proposed in this study holds important practical significance. In terms of resource allocation, blockchain-driven credit data sharing can break through information barriers between institutions and promote the optimal allocation of financial resources. In terms of risk control, the precise risk pricing model contributes to reducing non-performing loan rates and enhancing the stability of the financial system. This solution provides an innovative approach to addressing the challenges of information asymmetry and risk assessment in traditional financial credit practices.

4. Conclusion

This study successfully constructed a consortium blockchain platform based on Hyperledger Fabric along with an innovative risk pricing model, achieving collaborative optimization for multi-institutional financial credit operations. In the risk pricing dimension, the integration of logistic regression and graph structure relationship modeling enabled the model to achieve an AUC value of 0.917 and reduce the prediction error rate by 8.9%, significantly improving the precision of risk assessment. In the credit approval dimension, the blockchain consensus mechanism shortened the approval cycle from T+3 days to T+0.4 days, with the daily processing volume increasing by 275%, greatly enhancing business processing efficiency. The research outcomes provide a practical and implementable technical solution for financial institutions to conduct multi-institutional credit services. In real-world applications, financial institutions can further optimize the blockchain network architecture and refine the parameter settings of the risk pricing model according to specific business needs, while exploring the integration of more diverse data dimensions. Moreover, this study provides theoretical references for financial regulatory authorities to build intelligent regulatory systems based on blockchain technology, contributing to the digital transformation and high-quality development of the financial industry. Future research may focus on reducing blockchain

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deployment costs and deepening the application of unstructured data to further improve the collaborative mechanisms for multi-institutional financial credit operations.

References

1) Zhai, D., Beaulieu, C., & Kudela, R. M. (2024). Long-term trends in the distribution of ocean chlorophyll. Geophysical Research Letters, 51(7), e2023GL106577.
2) Lv, G., Li, X., Jensen, E., Soman, B., Tsao, Y. H., Evans, C. M., & Cahill, D. G. (2023). Dynamic covalent bonds in vitrimers enable 1.0 W/(m K) intrinsic thermal conductivity. Macromolecules, 56(4), 1554-1561.
3) Yan, Y., Wang, Y., Li, J., Zhang, J., & Mo, X. (2025). Crop Yield Time-Series Data Prediction Based on Multiple Hybrid Machine Learning Models.
4) China PEACE Collaborative Group. (2021). Association of age and blood pressure among 3.3 million adults: insights from China PEACE million persons project. Journal of Hypertension, 39(6), 1143-1154.
5) Xiao, Y., Tan, L., & Liu, J. (2025). Application of Machine Learning Model in Fraud Identification: A Comparative Study of CatBoost, XGBoost and LightGBM.
6) Wang, J., Ding, W., & Zhu, X. (2025). Financial Analysis: Intelligent Financial Data Analysis System Based on LLM-RAG.
7) Gong, C., Zhang, X., Lin, Y., Lu, H., Su, P. C., & Zhang, J. (2025). Federated Learning for Heterogeneous Data Integration and Privacy Protection.
8) Shih, K., Han, Y., & Tan, L. (2025). Recommendation System in Advertising and Streaming Media: Unsupervised Data Enhancement Sequence Suggestions.
9) Zhao, C., Li, Y., Jian, Y., Xu, J., Wang, L., Ma, Y., & Jin, X. (2025). II-NVM: Enhancing Map Accuracy and Consistency with Normal Vector-Assisted Mapping. IEEE Robotics and Automation Letters.
10) Jiang, G., Yang, J., Zhao, S., Chen, H., Zhong, Y., & Gong, C. (2025). Investment Advisory Robotics 2.0: Leveraging Deep Neural Networks for Personalized Financial Guidance.
11) Liu, Y., Liu, Y., Qi, Z., Xiao, Y., & Guo, X. (2025). TCNAttention-Rag: Stock Prediction and Fraud Detection Framework Based on Financial Report Analysis.
12) Jin, J., Wang, S., & Liu, Z. (2025). Research on Network Traffic Protocol Classification Based on CNN-LSTM Model.
13) Lv, G., Li, X., Jensen, E., Soman, B., Tsao, Y. H., Evans, C. M., & Cahill, D. G. (2023). Dynamic covalent bonds in vitrimers enable 1.0 W/(m K) intrinsic thermal conductivity. Macromolecules, 56(4), 1554-1561.
14) Wang, Y., Shao, W., Lin, J., & Zheng, S. (2025). Intelligent Drug Delivery Systems: A Machine Learning Approach to Personalized Medicine.
15) Zhang, B., Han, X., & Han, Y. (2025). Research on Multimodal Retrieval System of e-Commerce Platform Based on Pre-Training Model.
16) Mo, K., Chu, L., Zhang, X., Su, X., Qian, Y., Ou, Y., & Pretorius, W. (2024). Dral: Deep reinforcement adaptive learning for multi-uavs navigation in unknown indoor environment. arXiv preprint arXiv:2409.03930.
17) Yin, Z., Hu, B., & Chen, S. (2024). Predicting employee turnover in the financial company: A comparative study of catboost and xgboost models. Applied and Computational Engineering, 100, 86-92.
18) Guo, H., Zhang, Y., Chen, L., & Khan, A. A. (2024). Research on vehicle detection based on improved YOLOv8 network. arXiv preprint arXiv:2501.00300.
19) Yu, Q., Wang, S., & Tao, Y. (2025). Enhancing Anti-Money Laundering Detection with Self-Attention Graph Neural Networks. In SHS Web of Conferences (Vol. 213, p. 01016). EDP Sciences.

ISSN: 3079-6350 p-ISSN: 3079-6342

20) Zhang, L., & Liang, R. (2025). Avocado Price Prediction Using a Hybrid Deep Learning Model: TCN-MLP-Attention Architecture. arXiv preprint arXiv:2505.09907.
21) Vepa, A., Yang, Z., Choi, A., Joo, J., Scalzo, F., & Sun, Y. (2024). Integrating Deep Metric Learning with Coreset for Active Learning in 3D Segmentation. Advances in Neural Information Processing Systems, 37, 71643-71671.
22) Feng, H. (2024). High-Efficiency Dual-Band 8-Port MIMO Antenna Array for Enhanced 5G Smartphone Communications. Journal of Artificial Intelligence and Information, 1, 71-78.
23) Zhu, J., Xu, T., Liu, M., & Chen, C. (2024). Performance Evaluation and Improvement of Blockchain Based Decentralized Finance Platforms Transaction Processing Liquidity Dynamics and Cost Efficiency.
24) Yao, Y. (2024, May). Design of Neural Network-Based Smart City Security Monitoring System. In Proceedings of the 2024 International Conference on Computer and Multimedia Technology (pp. 275-279).
25) Yang, J., Li, Y., Harper, D., Clarke, I., & Li, J. (2025). Macro Financial Prediction of Cross Border Real Estate Returns Using XGBoost LSTM Models. Journal of Artificial Intelligence and Information, 2, 113-118.
26) Zhao, R., Hao, Y., & Li, X. (2024). Business Analysis: User Attitude Evaluation and Prediction Based on Hotel User Reviews and Text Mining. arXiv preprint arXiv:2412.16744.
27) Wang, Y., Jia, P., Shu, Z., Liu, K., & Shariff, A. R. M. (2025). Multidimensional precipitation index prediction based on CNN-LSTM hybrid framework. arXiv preprint arXiv:2504.20442.
28) Ge, G., Zelig, R., Brown, T., & Radler, D. R. (2025). A review of the effect of the ketogenic diet on glycemic control in adults with type 2 diabetes. Precision Nutrition, 4(1), e00100.
29) Lv, K. (2024). CCi-YOLOv8n: Enhanced Fire Detection with CARAFE and Context-Guided Modules. arXiv preprint arXiv:2411.11011.
30) Whitmore, J., Mehra, P., Yang, J., & Linford, E. (2025). Privacy Preserving Risk Modeling Across Financial Institutions via Federated Learning with Adaptive Optimization. Frontiers in Artificial Intelligence Research, 2(1), 35-43.