Guarantee Circle Risk Mining for Industrial Enterprises Based on Graph Neural Reasoning

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Abstract

Guarantee relationships are common in industrial financing, especially among affiliated firms, regional enterprise groups, upstream suppliers, downstream distributors, and companies sharing the same controlling shareholders. Although guarantees can improve short-term financing capacity, dense guarantee circles may amplify credit risk when one enterprise experiences repayment pressure. This study proposes a graph neural reasoning method for guarantee circle risk mining in industrial enterprises. The method constructs a guarantee-centered enterprise graph that integrates guarantee contracts, loan records, ownership structures, executive affiliations, supplier-customer links, litigation records, and overdue repayment events. A relation-aware graph neural network is used to learn enterprise risk representations, while a knowledge inference module identifies hidden guarantee circles, repeated guarantor exposure, and multi-hop risk transmission paths. Experiments are conducted on an industrial financing dataset containing 94,000 enterprises, 286,000 guarantee contracts, 142,000 bank loan records, 68,000 ownership links, 520,000 supplier-customer edges, and 13,400 confirmed guarantee-related risk events over 46 months. The proposed model shortens median risk-warning time from 79 days to 31 days compared with a loan-level scoring baseline. Graph reasoning identifies 5,870 high-risk guarantee circles and 2,430 enterprises exposed to more than three layers of indirect guarantee risk. The system consolidates 19,600 enterprise-level alerts into 4,280 guarantee-chain investigation cases. Monthly full-graph assessment is completed in 17.2 minutes, with a median inference latency of 52 ms per enterprise node. These results show that graph neural reasoning can reveal hidden guarantee-circle risks that are difficult to detect through single-enterprise financial indicators.

Keywords: Guarantee circle risk; industrial enterprise finance; graph neural reasoning; knowledge graph inference; credit risk propagation; enterprise relationship network; financing risk prediction.

1. Introduction

Guarantee financing is widely used by industrial enterprises to improve access to bank credit, particularly when borrowers have limited collateral or insufficient standalone credit capacity. By introducing a guarantor, firms can obtain additional financing support and reduce borrowing constraints. However, guarantee relationships also create channels through which repayment pressure can spread across connected enterprises. When a guaranteed firm experiences financial distress, the guarantor may be required to assume additional repayment obligations, which can further weaken its liquidity and increase the exposure of other firms connected to the same guarantee structure. This problem is particularly significant in regional enterprise groups, affiliated companies, upstream suppliers, downstream distributors, and firms controlled by the same shareholders. Traditional credit risk assessment mainly relies on leverage, liquidity, profitability, and repayment history, which are useful for evaluating individual borrowers but provide limited information about hidden guarantee circles and indirect risk exposure [1,2]. Research on interpretable machine learning has also shown that combining predictive models with explanation mechanisms can reveal the factors associated with abnormal or high-risk outcomes, thereby improving the transparency of automated risk identification [3]. This is especially relevant to guarantee risk management, where financial institutions need not only a risk score but also clear evidence of how risk is transmitted among related enterprises [4].

The increasing availability of enterprise relationship data provides new opportunities for identifying such interconnected risks. Ownership structures can reveal common controlling shareholders, executive affiliations can indicate hidden organizational relationships, supplier-customer ties can expose commercial dependence, and litigation records can provide evidence of contractual disputes or financial deterioration [5,6]. Guarantee contracts and loan records further describe direct credit obligations between borrowers, guarantors, and financial institutions [7,8]. When these data are analyzed jointly, they can reveal risk structures that are difficult to observe from financial statements alone. For example, several firms may appear financially independent while being indirectly connected through a common guarantor, overlapping shareholders, repeated borrowing relationships, or shared business partners. Such connections can transform an isolated repayment problem into a broader network-level exposure. Graph-based methods are particularly suitable for representing these complex relationships because they model enterprises and financial events as interconnected entities rather than independent observations [9,10]. In a guarantee network, an enterprise may act simultaneously as a borrower, guarantor, shareholder-related company, supplier, customer, or litigation counterparty. Risk can therefore propagate through multiple types of edges and across several layers of relationships. A guarantor may support multiple borrowers, one borrower may participate in several guarantee contracts, and affiliated enterprises may form reciprocal or circular guarantee arrangements [11,12]. These structures are difficult to capture using conventional scoring models or simple pairwise relationship analysis. Graph representation learning provides a means of extracting structural information from large-scale enterprise networks, while reasoning mechanisms can be used to trace the paths through which repayment pressure is accumulated and transmitted [13,14]. Current studies nevertheless provide limited support for the practical identification of complex guarantee risk. Many approaches remain centered on single-enterprise indicators or simplified network structures and therefore cannot fully characterize multi-hop guarantee exposure [15,16]. Direct guarantee relationships may be relatively easy to detect, but hidden risk often arises from indirect connections. A firm may guarantee a borrower that is itself connected to another distressed enterprise, or several borrowers may depend on the same guarantor while also sharing controlling shareholders and commercial partners [17,18]. Repeated guarantor exposure can gradually concentrate repayment obligations in a small group of firms even when no single contract initially appears abnormal [19,20]. These multi-layer structures require risk assessment methods that can distinguish isolated guarantee events from broader guarantee circles and identify the enterprises that play critical roles in the transmission of financial stress [21,22]. Another practical issue is the large number of repeated or fragmented warning signals generated by conventional monitoring systems. The same underlying guarantee circle may trigger multiple alerts for different borrowers, guarantors, overdue loans, litigation events, and affiliated firms. Treating these alerts independently increases investigation workload and may obscure the common source of risk [23,24]. Banks, regulators, and enterprise risk managers therefore need methods that can organize related warning cases into meaningful risk groups. A useful guarantee risk system should identify not only which firms are vulnerable, but also which enterprises belong to the same risk chain, how guarantee obligations connect them, and which nodes act as major transmission points. Such information can support investigation prioritization, credit exposure control, and more efficient allocation of risk-management resources.

This study proposes a graph neural reasoning framework for guarantee circle risk mining in industrial enterprises. The framework constructs a guarantee-centered heterogeneous enterprise graph by integrating guarantee contracts, loan records, ownership structures, executive affiliations, supplier-customer relationships, litigation records, and overdue repayment events. Graph neural representation learning is used to capture latent dependencies among connected firms, while reasoning mechanisms are introduced to identify hidden guarantee circles, repeated guarantor exposure, affiliated risk structures, and multi-layer transmission paths. Using a dataset covering 94,000 enterprises, 286,000 guarantee contracts, 142,000 bank loan records, 68,000 ownership links, 520,000 supplier-customer edges, and 13,400 confirmed risk events over 46 months, the study evaluates the ability of the proposed method to detect guarantee-related financial stress at both the enterprise and network levels. The objective is to extend credit risk assessment from isolated borrower evaluation to connected guarantee-chain analysis and to provide interpretable evidence for early-warning decisions. By identifying high-risk enterprise groups, tracing the sources and transmission paths of repayment pressure, and consolidating related warning signals, the proposed framework can support banks in controlling interconnected credit exposure, assist regulators in monitoring regional financial risk, and help enterprise risk managers allocate investigation resources more effectively. More broadly, the study provides a scalable approach for transforming fragmented enterprise relationship data into structured and explainable evidence for industrial credit risk management.

2. Materials and Methods

2.1 Samples and Study Area

This study used a dataset of 94,000 industrial enterprises over 46 months. The data included 286,000 guarantee contracts, 142,000 bank loans, 68,000 ownership links, 520,000 supplier-customer connections, and 13,400 confirmed guarantee-related risk events. The study objects were firms with valid registration numbers, loan and guarantee records, and relationship data during the study period. Enterprises with missing identifiers, incomplete contracts, invalid dates, or unclear guarantee directions were excluded. The sample covered machinery manufacturing, electronic components, metal processing, chemical materials, building materials, and industrial services. These enterprises were selected because guarantee relations are common and can form hidden risk circles among affiliates, suppliers, distributors, and firms sharing controlling shareholders.

2.2 Experimental Design and Control Settings

The experiment tested whether the graph neural reasoning method could detect guarantee circle risk earlier than conventional loan-level methods. The experimental method integrated guarantee contracts, bank loans, ownership structures, executive affiliations, supplier-customer links, litigation records, and overdue repayments into a guarantee-centered enterprise graph. Two control settings were used. The first relied on loan-level scoring, using loan balance, repayment delay, collateral value, debt burden, and guarantor credit status. The second used a tree-based classifier with the same enterprise and loan variables. These control methods were chosen because they represent standard approaches in bank credit review. All methods shared the same training and testing periods.

2.3 Measurement Methods and Quality Control

Guarantee circle risk was measured using confirmed guarantee-related events, overdue repayments, repeated guarantor exposure, litigation involvement, ownership overlap, and multi-layer guarantee links. Guarantee contracts were used to identify guarantors, borrowers, contract amounts, periods, and directions. Loan records were used to measure repayment pressure and maturity. Ownership and executive data identified related-party links. Supplier-customer data captured business dependencies. Litigation records indicated legal risk. Before analysis, enterprise names, registration numbers, contract numbers, shareholder IDs, and executive names were standardized. Duplicate or inconsistent records were removed. Extreme financial values were checked using percentile screening. All links required valid identifiers, timestamps, and link types. A time-based split prevented future events from entering training data.

2.4 Data Processing and Model Formulation

Enterprise and contract data were organized by month. Continuous variables were standardized by industry and region to reduce differences from firm size and local financing conditions. Missing continuous values were filled with industry- and month-specific medians. Missing categorical values were assigned to a separate group. The enterprise graph at month t was defined as:

$$G_t=(V_t,E_t,X_t,R_t),$$

where V_t represents enterprise nodes, E_t represents links, X_t represents attributes, and R_t represents link types, including guarantees, loans, ownership, executive affiliation, supplier-customer, litigation, and overdue repayment links. The risk score of enterprise i was calculated as:

$$S_i=\sigma(Wh_i+b),$$

where S_i is the estimated risk, h_i is the enterprise vector from attributes and connected firms, W and bbb are estimated parameters, and $\sigma(\cdot)$ is the sigmoid function. Indirect guarantee exposure was computed as:

$$E_i=\sum_{j\in N_i^{(k)}}\frac{A_{ij}\cdot R_j}{d_{ij}},$$

where $N_i^{(k)}$ is the set of enterprises within k guarantee layers from i, A_{ij} is the guarantee amount, R_j is the risk score of j, and d_{ij} is the shortest guarantee distance. Larger E_i indicates higher indirect guarantee risk.

2.5 Evaluation and Robustness Analysis

The method was evaluated for early-warning time, risk identification accuracy, guarantee circle detection, and alert consolidation. Early-warning time was measured as the median number of days from first warning to confirmed risk event. Accuracy metrics included AUC, precision, recall, F1-score, and top-risk capture rate. Guarantee circle detection was assessed by the number of high-risk circles, repeated guarantor cases, and enterprises exposed to more than three layers of risk. Alert consolidation measured the reduction from enterprise-level alerts to investigation cases. Robustness tests were conducted across industries, regions, guarantee amounts, guarantee layers, and warning thresholds. Additional tests removed ownership links, executive affiliations, supplier-customer links, litigation records, and rule-based reasoning individually to measure their contributions.

3. Results and Discussion

3.1 Early-Warning Performance of Guarantee Circle Risk

The proposed graph-based method detected guarantee-related risk earlier than the loan-level scoring baseline. The median warning time decreased from 79 days to 31 days before confirmed risk events. This shows that guarantee circle risk can be found before repayment problems become clear in loan records [25,26]. Traditional loan scoring mainly uses loan balance, repayment delay, collateral value, debt burden, and guarantor credit status. These indicators are useful, but they often treat each firm or loan separately. In contrast, the proposed method uses guarantee contracts, ownership links, executive ties, supplier-customer links, litigation records, and overdue events together. It can detect hidden risk from repeated guarantors and indirect guarantee chains. This result is consistent with recent credit-risk studies showing that firm relationship networks can improve risk assessment beyond financial data. Fig. 1 provides a related example of using corporate graph information to support credit risk analysis.

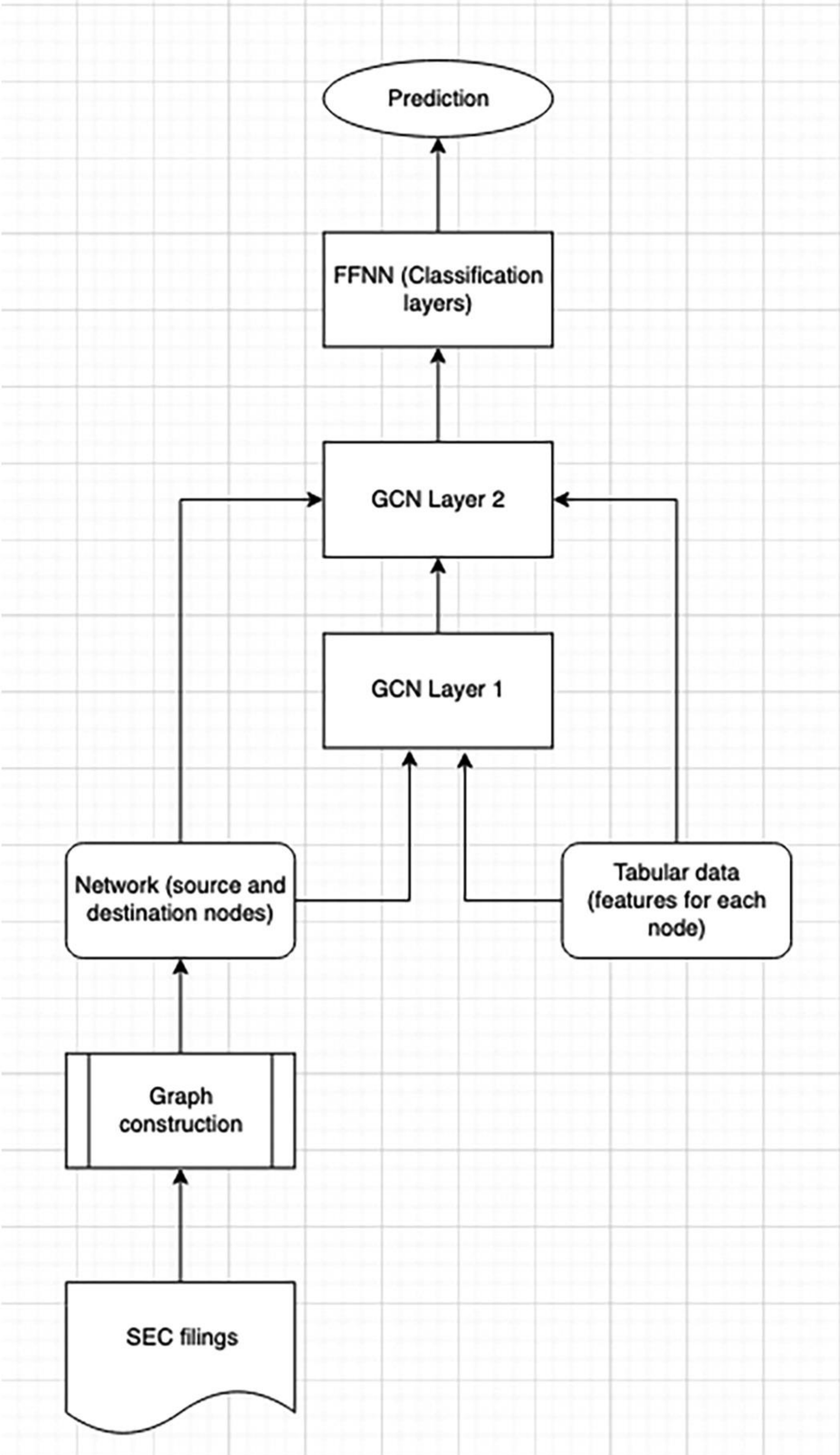

Fig. 1. Enterprise graph showing links among firms, guarantors, suppliers, and executives for risk assessment.

3.2 Discovery of Hidden Guarantee Circles

The graph-based analysis identified 5,870 high-risk guarantee circles. These circles were mainly formed by affiliated firms, shared controlling shareholders, repeated guarantors, and supplier-customer partners. This finding shows that guarantee risk is not limited to direct borrower-guarantor pairs. It can also be hidden in multi-step firm connections. For example, a firm may look safe in its own loan record but face high indirect risk when it guarantees a borrower linked to other overdue firms. This type of risk is difficult to detect through single-firm financial indicators. Previous credit-risk studies have shown that firm networks can improve default prediction [27,28]. This study further traces guarantee-circle structures and shows how repeated guarantees increase risk concentration in industrial enterprise groups.

3.3 Multi-Layer Exposure and Alert Consolidation

The method identified 2,430 firms exposed to more than three layers of indirect guarantee risk. This result is important because multi-layer exposure can increase repayment pressure after one firm defaults [29,30]. A local default may trigger claims along guarantee chains and then affect firms without direct loan problems. The system also reduced 19,600 firm-level alerts to 4,280 guarantee-chain investigation cases. This reduced repeated warnings and made risk review more practical. Banks and regulators can focus on connected guarantee chains instead of checking isolated firm alerts one by one. Fig. 2 gives a related example of using enterprise relationship networks for bankruptcy risk assessment.

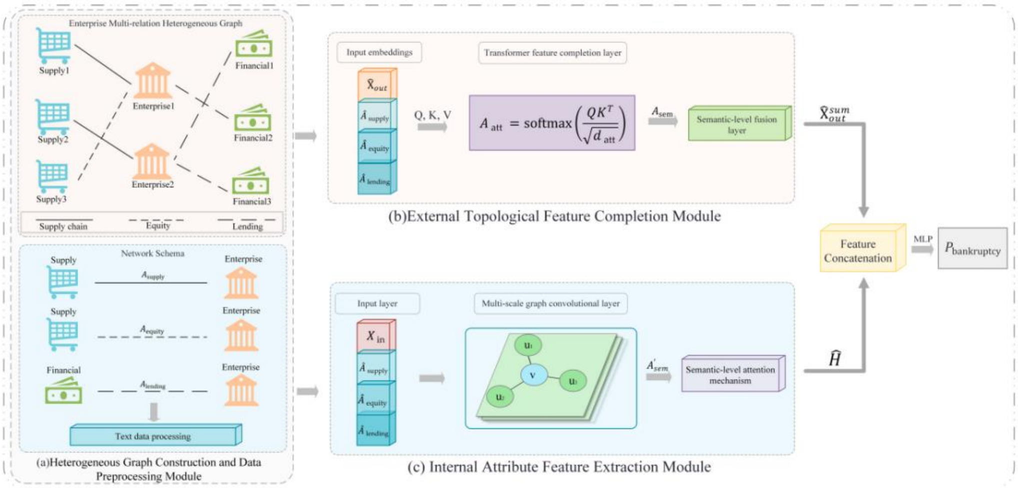

Fig. 2. Consolidated guarantee-chain risk paths illustrating multi-layer exposure and connected firm clusters.

3.4 Comparison with Previous Studies and Robustness

Compared with previous studies, this work makes three clear extensions. First, it focuses on guarantee circle risk rather than general firm default or credit rating. This setting is closer to industrial financing practice because firms often support each other through formal or informal guarantees. Second, the method combines several relationship types, including guarantees, loans, ownership, executives, suppliers, customers, litigation, and overdue repayment events. This provides a wider view of credit risk than financial ratios or simple firm networks. Third, the results are not limited to risk scores. They also include guarantee circles, indirect exposure layers, and investigation cases. Robustness tests across industries, regions, guarantee amounts, guarantee layers, and warning thresholds showed stable results. Removal tests also showed that ownership links, executive ties, supplier-customer links, litigation records, and rule-based checks each improved the final outcome. These findings suggest that graph-based reasoning can support earlier warning, clearer risk tracing, and more efficient supervision of industrial guarantee networks.

4. Conclusion

This study proposed a graph-based reasoning method to identify guarantee circle risk in industrial enterprises. The method used guarantee contracts, bank loans, ownership links, executive ties, supplier-customer connections, litigation records, and overdue repayments to build an enterprise graph. The results showed that the method gave earlier warnings than loan-level scoring. It also identified firms with repeated or indirect guarantee risk and reduced scattered alerts into investigation groups. The main contribution of this study is that it moves credit risk assessment from single firms to connected guarantee chains. This helps explain how risk forms and spreads among industrial enterprises. The method can support banks, regulators, and enterprise managers in early warning, risk review, and resource allocation. However, this study has some limits. The results depend on the quality of contract, ownership, and repayment records. Some informal or undocumented guarantees may not be fully captured. Future studies should test the method in more industries and regions and include more timely operating data to improve risk detection.

References

1. Zhao, J., Fan, J., & Li, L. (2026). A Study on an Explainable Causal-Enhanced LLM Agent for Predicting the Forming Quality of Automotive Component Materials.
2. Karami, A., & Igbokwe, C. (2025). The impact of big data characteristics on credit risk assessment. International Journal of Data Science and Analytics, 20(5), 4239-4259.
3. Wang, S., Feng, Y., & Fang, X. (2026, May). A Large Language Model-Enabled Multi-Agent Collaboration Method for Complex Task Solving. In 2026 6th International Symposium on Computer Technology and Information Science (ISCTIS) (pp. 253-256). IEEE.
4. You, S. (2026). Verifiable Audit Mechanisms in AI Compliance Automation: Scalability. Available at SSRN 6547458.
5. Wu, Y., & Su, D. (2026). An Evaluation of Parental Question Characteristics and the Quality of AI Recommendations in Family Counseling for Children with Autism.
6. Freeman, K. M. (2025). Overlapping ownership along the supply chain. Journal of Financial and Quantitative Analysis, 60(1), 105-134.

7. Jiao, Y., Shi, T., Zhao, B., & Wang, A. (2026). Retrieval-Guided Structured Reasoning and Interpretable Representation Learning for Large-Scale Video–Language Models.
8. Wu, J., Zhang, J., Wu, D., & Peng, Y. (2026). Visual Transformation Mechanisms for Integrating Digital Cultural Heritage Resources into Junior High School Art Curricula.
9. Zhang, G., Xu, Y., Zhang, M., Wang, S., & Lin, N. (2021). The brain network in support of social semantic accumulation. Social cognitive and affective neuroscience, 16(4), 393-405.
10. Chakraborty, S., & Sharov, S. (2025). Graph based approach on financial fraudulent detection and prediction. In Applied Graph Data Science (pp. 25-37). Morgan Kaufmann.
11. Bao, Y., & Wang, H. (2026). Large-scale Metrics Migration: A Systematic Approach to Rebuilding Production Measurement Infrastructure. Available at SSRN 7185660.
12. Xu, D., Gui, H., & Chen, H. (2026, March). Research on Layered Control and Fault Recovery Mechanisms for Fast Charging Safety Diagnosis of High-Voltage Battery Systems Under Charging Network Interoperability Conditions. In 2026 3rd International Conference on Electrical Technology and Automation Engineering (ETAE) (pp. 669-672). IEEE.
13. Qi, C., & Qiao, X. (2026). Efficient Data Sampling and Feature Selection Algorithms for Scalable Machine Learning Pipelines.
14. Theodorakopoulos, L., & Theodoropoulou, A. (2026). Big data and graph deep learning for financial decision support from social networks: A critical review. Electronics, 15(7), 1405.
15. Gong, S., Gamm, D. M., Edwards, K. L., Pattnaik, B. R., Liu, D. R., Wang, Y., ... & Spillane, A. Nonviral base editing ofKCNJ13mutation preserves vision in an inherited retinal channelopathy.
16. Du, Y., Chen, Z., Liu, Q., & Dong, Y. (2026). Co-identification of Vibration, Structural Looseness, and Surface Damage in Industrial Equipment Operation Videos.
17. Xiong, W., Zeng, Y., & Guo, Y. (2026). A Study on the Characterization of Building MEP System States and the Learning of Behavioral Patterns Driven by Large-Scale Operational Data. Available at SSRN 7121883.
18. Uesugi, I. (2025). Is it Possible to Finance SMEs without an Excessive Reliance on Personal Guarantees and Collateral?. In The Economics of SME Finance (pp. 235-269). Singapore: Springer Nature Singapore.
19. Hong, Z., Xu, T., & Chen, H. (2026). Automated Detection and Reclamation of Orphaned Compute and Storage Resources in Cloud Infrastructure. Available at SSRN 7116258.
20. Li, J., Ma, R., & Gu, Y. (2026). From Audit Requirements to Computable Software Architecture: A Rule-Engine and Evidence-Indexing Method for Trusted Digital Infrastructure.
21. Wu, J., Wu, D., Zhang, J., & Peng, Y. (2026). Generative AI Feedback in Junior High School Artistic Creation Evaluation. Available at SSRN 7244838.
22. Nowak, O., Davies, A., & Richter, A. (2026). Developing a Multi-Layer Credit and Market Risk Assessment Model for SMEs Participating in Capital Markets through Brokerage Intermediaries.

23. Huang, J., Xu, T., Yang, J., & Yin, J. (2026). A Graph Neural Network Approach for Financial Data Validation and Risk Identification in Large-Scale Intercompany Transactions. Available at SSRN 7175058.
24. Bao, Y., & Wang, H. (2026). Edge-to-Cloud Infrastructure Continuum: A Unified Framework for Optimizing Industrial IoT Systems. Available at SSRN 7185578.
25. Wilson, N., & Kacer, M. (2026). Default, Fraud, and Fraud Classification in UK COVID-19 Loan Schemes: Evidence from One Million Guaranteed Loans.
26. Du, Y. (2025). Research on Digital Quality Traceability System for Temperature-Controlled Supply Chain of Foreign Trade Wine Driven by Blockchain and IoT. Business and Social Sciences Proceedings, 4, 57-65.
27. Zheng, J., & Makar, M. (2022). Causally motivated multi-shortcut identification and removal. Advances in Neural Information Processing Systems, 35, 12800-12812.
28. Vanhoeven, A., & Chen, X. (2025). Default risk prediction for small and micro enterprises using a wide and deep learning framework. Transactions on Computational and Scientific Methods, 5(4).
29. Gu, X. (2026). Identifying Causal Effects and Analyzing Heterogeneity of User Growth Interventions on Digital Platforms: Evidence from Large-Scale Behavioral Data. Available at SSRN 6809181.
30. Vanhoeven, A., & Chen, X. (2025). Default risk prediction for small and micro enterprises using a wide and deep learning framework. Transactions on Computational and Scientific Methods, 5(4).