

Ownership Knowledge Graphs for Post-Merger Financing Risk Assessment in Industrial Groups

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Abstract

Industrial mergers and acquisitions often involve complex ownership changes, debt restructuring, cross-border suppliers, asset transfers, related-party transactions, and post-merger integration pressure. Financing risk may rise after a transaction when the acquiring group inherits hidden liabilities, weak subsidiaries, guarantee obligations, or unstable supplier networks. This study proposes an ownership knowledge graph model for post-merger financing risk assessment in industrial groups. The model integrates acquirers, target firms, subsidiaries, shareholders, executives, suppliers, customers, creditors, guarantee contracts, asset-transfer records, loan agreements, and litigation events into a unified enterprise graph. A graph neural network is used to encode post-merger structural changes, while a rule-guided inference module detects hidden risk chains involving debt concentration, related-party guarantees, supplier disruption, and subsidiary credit deterioration. The empirical dataset contains 6,420 industrial merger events, 38,600 related enterprises, 214,000 ownership-change records, 96,000 loan agreements, 58,000 guarantee contracts, 740,000 supplier-customer links, and 5,280 post-merger financing-risk events over 60 months. Compared with a transaction-level financial scoring model, the proposed approach shortens median risk-identification time from 118 days to 49 days after merger completion. It discovers 3,760 hidden ownership-risk paths and 1,540 subsidiary-level debt transmission chains. Portfolio simulation shows that graph-informed monitoring reduces expected post-merger overdue exposure by 96 million RMB during the validation window. Full quarterly assessment of all merger groups is completed in 10.4 minutes. The results demonstrate that ownership knowledge graph reasoning can support more interpretable financing risk assessment for industrial groups after mergers and acquisitions.

Keywords: Industrial mergers and acquisitions; post-merger financing risk; ownership knowledge graph; graph neural network; enterprise risk inference; debt transmission; industrial group finance.

1. Introduction

Industrial mergers and acquisitions (M&A) are widely used to support business expansion, asset restructuring, technological integration, and market consolidation. By acquiring target firms

or reorganizing affiliated entities, industrial groups can rapidly obtain production capacity, customer resources, technologies, and market access. However, the completion of an acquisition does not necessarily reduce financial uncertainty. In many cases, the acquiring group also assumes liabilities and operational dependencies that are difficult to identify from transaction-level information alone, including hidden debt, weak subsidiaries, cross-guarantee obligations, unstable suppliers, and related-party financing arrangements [1,2]. These risks may propagate across subsidiaries and affiliated enterprises after ownership restructuring, increasing the probability of liquidity pressure, refinancing difficulty, covenant violations, and subsequent credit deterioration [3,4]. Therefore, evaluating financing risk after industrial M&A requires not only an assessment of the acquiring firm itself but also a systematic understanding of the relationships among entities within the reorganized corporate network [5,6].

Traditional post-merger financing risk assessment primarily relies on transaction prices, leverage ratios, cash-flow indicators, collateral coverage, profitability, and historical repayment records [7]. Although these indicators remain important for measuring financial capacity, they provide only a partial representation of the risk structure created by an acquisition [8,9]. Complex financing problems increasingly involve interactions among multiple entities, contracts, obligations, and decision processes [10,11]. Recent research on collaborative methods for complex task solving has demonstrated that interactions among multiple coordinated entities can improve the representation and resolution of problems that cannot be adequately handled as isolated components [12]. This perspective is also relevant to post-merger financing assessment, where risk may emerge from combinations of ownership control, contractual obligations, operational dependencies, and financial relationships [13,14]. Conventional indicator-based models often fail to represent changes in controlling shareholders, debt transfers among subsidiaries, cross-guarantees, related-party transactions, and disruptions in key supplier relationships. Consequently, a firm may appear financially stable according to conventional ratios while remaining exposed to substantial hidden risk through its affiliated entities [15,16]. Recent studies have increasingly incorporated enterprise relationship information into credit and financial risk modeling [17,18]. Ownership networks, transaction networks, supply-chain connections, and inter-firm relationships have been shown to provide information beyond conventional firm-level financial indicators [19,20]. Such relational data make it possible to identify whether financial weakness is concentrated within a particular subsidiary, transmitted through guarantee relationships, or amplified by dependence on a small number of suppliers or affiliated counterparties [21,22]. Knowledge graph techniques further provide a structured way to represent heterogeneous entities and relationships, allowing ownership, management, financing, litigation, and supply-chain information to be integrated within a unified analytical framework [23,24]. Nevertheless, existing studies often analyze financial indicators and ownership relationships separately, while the temporal restructuring caused by M&A receives limited attention. Many models focus on predicting whether a firm will default or experience credit deterioration but

provide insufficient evidence about how the risk develops, which affiliated entity contributes to it, and through which ownership or contractual path the risk is transmitted. This limitation reduces the interpretability of model outputs and restricts their usefulness in post-merger credit review, continuous monitoring, and regulatory supervision.

This study develops an ownership knowledge graph method for post-merger financing risk assessment in industrial groups. The proposed framework represents acquirers, target firms, subsidiaries, shareholders, executives, suppliers, customers, creditors, guarantee contracts, asset-transfer records, loan agreements, and litigation events within a unified enterprise relationship graph. Ownership changes associated with M&A are incorporated into the graph so that the evolution of control structures and financial obligations can be examined over time. Based on these heterogeneous relationships, the method identifies hidden risk chains associated with debt concentration, related-party guarantees, subsidiary credit deterioration, supplier disruption, and the transfer of financial exposure across affiliated enterprises. The empirical analysis uses 6,420 merger events involving 38,600 related enterprises, together with 214,000 ownership-change records, 96,000 loan agreements, 58,000 guarantee contracts, approximately 740,000 supplier-customer relationships, and 5,280 post-merger financing-risk events observed over a 60-month period. The purpose of this study is therefore not merely to improve the prediction of post-merger financing risk, but to establish a relationship-based analytical framework capable of revealing where risk originates, how it propagates through the reorganized industrial group, and which enterprise connections provide early evidence of financial deterioration. By extending post-merger risk assessment from isolated transaction and financial indicators to dynamic ownership-based enterprise relationships, this study provides a more interpretable basis for early warning and risk tracing. The resulting framework can support banks in post-acquisition credit monitoring, assist regulators in identifying concentrated or interconnected financial exposures, and help industrial groups detect vulnerable subsidiaries and relationship-based risk channels before they develop into broader financing problems.

2. Materials and Methods

2.1 Samples and Study Area

This study used a post-merger industrial financing dataset covering 6,420 merger and acquisition events over 60 months. The dataset included 38,600 related enterprises, 214,000 ownership-change records, 96,000 loan agreements, 58,000 guarantee contracts, 740,000 supplier-customer links, and 5,280 confirmed post-merger financing-risk events. The study objects were industrial groups that completed mergers or acquisitions during the study period and had valid records on ownership, loans, guarantees, suppliers, customers, and litigation. Events with missing acquirer information, unclear completion dates, incomplete ownership records, or invalid loan data were removed. The sample covered machinery manufacturing, electronics, chemical materials, metal processing, equipment manufacturing, and industrial services. These events were

selected because post-merger financing risk often comes from hidden debt, weak subsidiaries, guarantee duties, asset transfers, and unstable supplier networks.

2.2 Experimental Design and Control Settings

The experiment tested whether the proposed ownership knowledge graph method could identify post-merger financing risk earlier than transaction-level financial scoring. The proposed method was used as the experimental setting. It combined acquirers, target firms, subsidiaries, shareholders, executives, suppliers, customers, creditors, guarantee contracts, asset-transfer records, loan agreements, and litigation events into an ownership-centered enterprise graph. Two control settings were used for comparison. The first used transaction-level financial scoring based on acquisition value, leverage, repayment pressure, collateral value, and sponsor cash flow. The second used a tree-based classifier with the same transaction-level and enterprise-level variables. These control settings were selected because they are commonly used in post-merger loan review and corporate credit assessment. All methods used the same training and testing periods.

2.3 Measurement Methods and Quality Control

Post-merger financing risk was measured by repayment deterioration, overdue loans, rising debt concentration, guarantee activation, subsidiary credit decline, supplier disruption, and litigation events after merger completion. Ownership-change records were used to identify control shifts, subsidiary structures, shareholder concentration, and related-party links. Loan agreements and guarantee contracts were used to measure debt burden, repayment pressure, and guarantee exposure. Asset-transfer records were used to detect post-merger resource movement and possible risk transfer. Supplier-customer links were used to measure business stability after the transaction. Litigation records were used to identify legal disputes and hidden liabilities. Before analysis, enterprise names, registration numbers, shareholder identifiers, executive names, contract numbers, and transaction dates were standardized. Duplicate records, invalid dates, inconsistent ownership directions, and abnormal contract amounts were removed or corrected. A time-based data split was used to avoid future risk information during training.

2.4 Data Processing and Model Formulation

All records were organized by quarter and merger group. Continuous variables were standardized by industry and transaction period to reduce differences caused by firm size, sector structure, and market conditions. Missing continuous values were filled with the median value of firms in the same industry and quarter. Missing categorical values were coded as a separate group. The ownership-centered enterprise graph at period t was defined as:

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

where V_t denotes acquirers, target firms, subsidiaries, shareholders, executives, creditors, suppliers, and customers; E_t denotes links among these entities; X_t denotes node attributes; and

R_t denotes link types, including ownership, loan, guarantee, asset transfer, executive affiliation, supplier-customer, and litigation links. The post-merger financing risk score of enterprise group i was calculated as:

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

where P_i is the estimated risk score, h_i is the group vector derived from enterprise attributes and connected entities, W and b are estimated parameters, and $\sigma(\cdot)$ is the sigmoid function. Subsidiary debt exposure was calculated as:

$$D_i = \sum_{j \in S_i} \frac{L_j + G_j}{1 + d_{ij}},$$

where S_i is the set of subsidiaries related to group i , L_j denotes the outstanding loan amount of subsidiary j , G_j denotes its guarantee exposure, and d_{ij} denotes the ownership distance between group i and subsidiary j . A higher D_i indicates stronger debt transmission risk.

2.5 Evaluation and Robustness Analysis

The method was evaluated by risk-identification time, prediction accuracy, ownership-risk path results, and portfolio-level effect. Risk-identification time was measured by the median number of days between the first warning and the confirmed post-merger financing-risk event. Prediction accuracy was measured by AUC, precision, recall, F1-score, and top-risk capture rate. Ownership-risk path results were assessed by the number of hidden ownership-risk paths, subsidiary debt transmission chains, related-party guarantee links, and supplier disruption paths. Portfolio-level effect was measured by the reduction in expected overdue exposure when merger groups were ranked by estimated risk. Robustness tests were conducted across industry types, transaction sizes, ownership layers, post-merger periods, and warning thresholds. Additional tests removed ownership-change records, guarantee contracts, asset-transfer records, supplier-customer links, litigation records, and rule-based checks one at a time to examine their separate effects.

3. Results and Discussion

3.1 Early Identification of Post-Merger Financing Risk

The ownership knowledge graph method identified post-merger financing risk earlier than the transaction-level financial scoring baseline [25,26]. The median risk-identification time decreased from 118 days to 49 days after merger completion. This shows that post-merger risk may appear before repayment problems are recorded. Transaction-level scoring mainly uses acquisition value, leverage, collateral, and cash-flow coverage. These indicators are useful, but they may miss hidden debt, weak subsidiaries, related-party guarantees, and supplier disruption. By linking acquirers, target firms, subsidiaries, shareholders, executives, creditors, guarantees, asset transfers, suppliers, customers, and litigation events, the proposed method provides a broader view of post-merger risk. This result is consistent with recent M&A studies showing that merger

risk is related to information gaps, litigation, governance, and post-deal uncertainty, rather than financial indicators alone, as shown in Fig. 1.

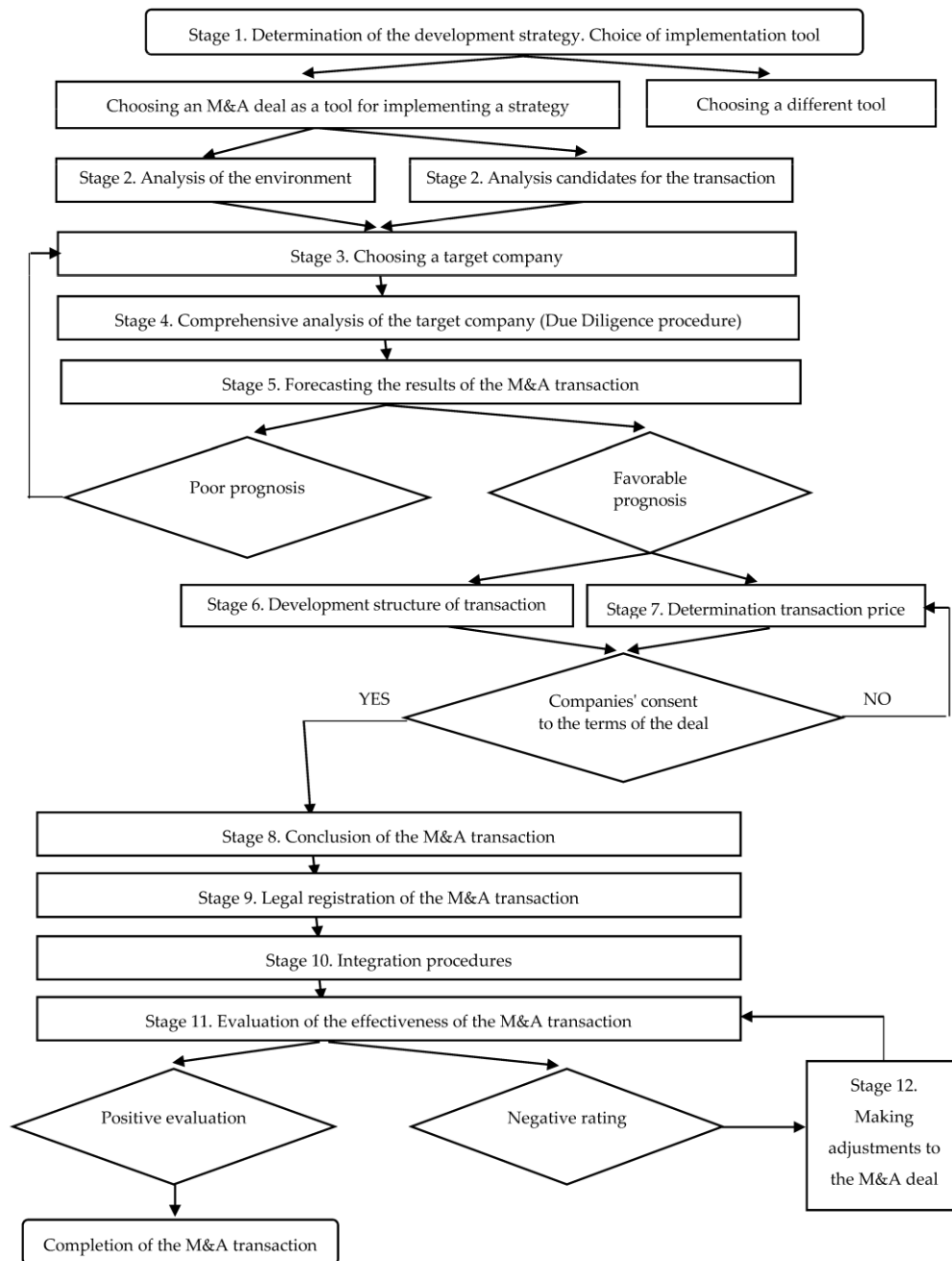


Fig. 1. Post-merger enterprise graph linking acquirers, targets, subsidiaries, and related firms for risk assessment.

3.2 Ownership-Risk Paths and Subsidiary Debt Transmission

The method found 3,760 hidden ownership-risk paths and 1,540 subsidiary debt transmission chains. These results show that financing risk after a merger is not limited to the acquiring firm or the target firm. Risk may also come from subsidiaries, related-party guarantees, creditor links, and transferred assets. For example, a subsidiary may seem stable in its own records but may raise

group-level risk if it carries large debt, provides guarantees for weak firms, or depends on unstable suppliers. Earlier M&A studies mainly discussed deal value, integration risk, or market response. This study traces risk through ownership and debt links after merger completion. This provides clearer evidence for banks and regulators when they assess hidden repayment pressure in merged industrial groups [27,28].

3.3 Portfolio Monitoring and Risk Reduction

Portfolio simulation showed that ownership-based monitoring reduced expected post-merger overdue exposure by 96 million RMB during the validation period. This result indicates that ownership-based risk ranking can improve portfolio review. Instead of treating each merged group as an isolated borrower, the method ranks groups by debt concentration, subsidiary exposure, related-party guarantees, and supplier disruption. This helps risk managers identify groups that need earlier review. The result also shows that M&A risk should be studied as a connected system. Fig. 2 provides a related example from a recent M&A review, where co-occurrence analysis shows that M&A risk factors are grouped into related themes, including information gaps, litigation, performance, and geopolitical factors.

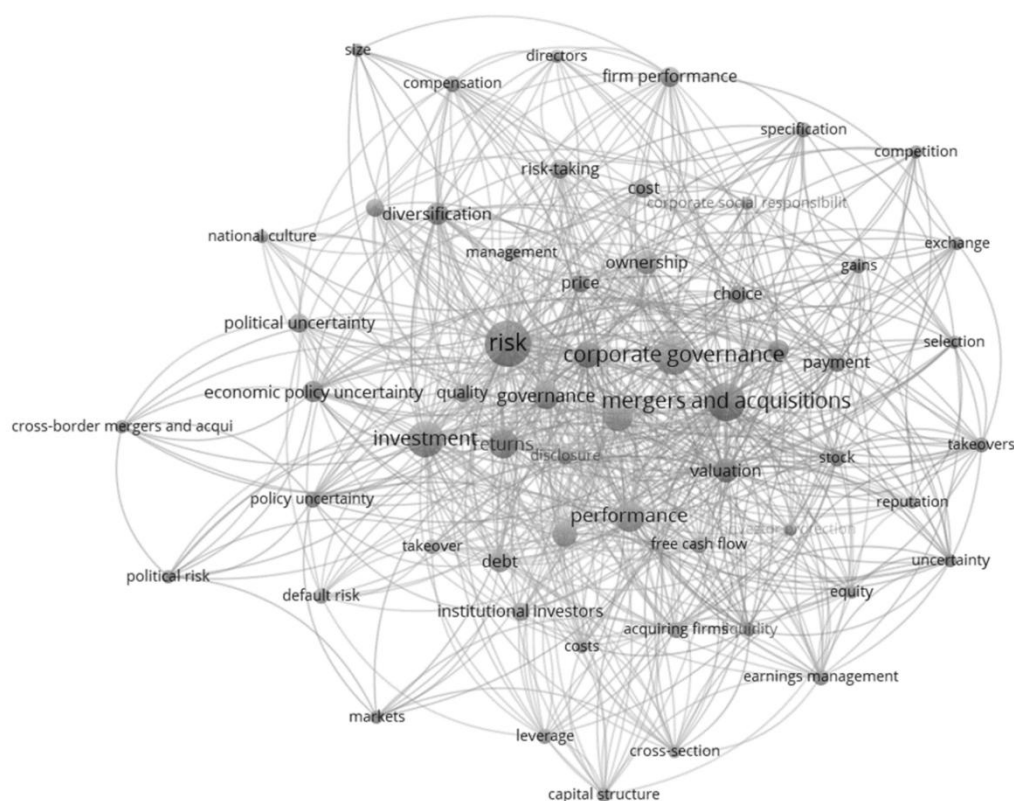


Fig. 2. Co-occurrence map of ownership and subsidiary risk paths showing multi-layer exposure in merged groups.

3.4 Comparison with Previous Studies and Robustness

Compared with previous studies, this work makes three main extensions. First, it focuses on post-merger financing risk in industrial groups, rather than general M&A performance or deal success. Second, it combines ownership changes, loan agreements, guarantee contracts, asset-transfer records, supplier-customer links, and litigation events in the same risk structure. This differs from methods that rely only on transaction-level financial indicators. Third, it provides ownership-risk paths and subsidiary debt chains, rather than only risk scores. Robustness tests across industries, transaction sizes, ownership layers, post-merger periods, and warning thresholds showed stable results. Removal tests also confirmed that ownership records, guarantees, asset transfers, supplier-customer links, litigation records, and rule-based checks each helped risk identification. These findings suggest that ownership knowledge graphs can support earlier warning, clearer risk explanation, and more practical post-merger financing supervision [29,30].

4. Conclusion

This study proposed an ownership knowledge graph method for assessing post-merger financing risk in industrial groups. The method linked acquirers, target firms, subsidiaries, shareholders, executives, creditors, guarantees, asset transfers, suppliers, customers, and litigation events in a single enterprise graph. Results showed that it detected financing risk earlier than transaction-level financial scoring and identified hidden ownership-risk paths, subsidiary debt chains, and related-party guarantee exposures. The main contribution is that it extends post-merger risk assessment from single transactions to ownership-based firm networks, providing a clearer view of how hidden debt, weak subsidiaries, and supplier disruptions affect group-level repayment risk. The method can support banks, regulators, and industrial groups in early warning, portfolio review, and post-merger supervision. Limitations include dependence on the completeness and accuracy of ownership, contract, loan, and litigation records, and some informal or undisclosed related-party exposures may not be captured. Future work should apply the method across more industries and regions and incorporate more timely operational and financial data after mergers.

References

1. Zhang, Z. (2026). A Study on the Impact of Cost Presentation on Decision-making Bias and Cancellation Behavior in Online Subscriptions. Available at SSRN 7349839.
2. Neupane, K., Griva, I., Axtell, R., Kennedy, W., & Kinser, J. (2026). Detecting and Explaining Unlawful Insider Trading: A Shapley Value and Causal Forest Approach to Identifying Key Drivers and Causal Relationships. *Computational Economics*, 1-33.
3. Bao, Y., Qiu, Y., & Wang, H. (2026, May). Unified Identity Layer for Hyperscale Ecosystems: A Framework for Cross-Platform User Attribution and Experimentation. In *2026 6th International Conference on Machine Learning and Intelligent Systems Engineering (MLISE)* (pp. 540-543). IEEE.

4. Qi, C., & Qiao, X. (2026). Building Reliable AI Systems: A Framework That Bridges Architecture and Operations. Available at SSRN 6795298.
5. Xiong, W., Zeng, Y., & Guo, Y. (2026). A Study on the Impact of MEP Space Organization in Large-Scale Commercial Complexes on Investment Efficiency and Its Mechanisms.
6. Froux, M., & Gresse, A. (2025). M&A Risk Management and Company Performance in the French Food Industry: Archival Research based on Secondary Data in form of Relevant Publications.
7. Hong, Z., Liang, S., Xu, T., & Chen, H. (2026). A Study on Failover Verification and Recovery Objective Prediction for Cross-Region Cloud Services.
8. 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.
9. 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.
10. Fnu, H., Kaushik, K., Gaur, P., Saratchandran, D. V., Thapliyal, A. G., Sidhu, K. S., & Singh, V. (2025, April). Multi-Agent Systems for Collaborative Financial Decision-Making Over Distributed Network Architectures. In 2025 3rd International Conference on Advancement in Computation & Computer Technologies (InCACCT) (pp. 939-944). IEEE.
11. 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.
12. Bao, Y., Qiu, Y., & Wang, H. (2026). FLARE: A Real-Time Framework for Detecting Malicious Account Activities at Internet Scale. Available at SSRN 7185659.
13. You, S. (2026). Verifiable Audit Mechanisms in AI Compliance Automation: Scalability. Available at SSRN 6547458.
14. Gami, E. R. P., Pakpahan, D. R., Hou, A., & Hecimovic, A. (2025). The impact of liquidity, leverage, and profitability ratios on financial distress. *Quantitative Economics and Management Studies*, 6(4), 604-611.
15. Wu, Y., & Su, D. (2026). An Evaluation of Parental Question Characteristics and the Quality of AI Recommendations in Family Counseling for Children with Autism.
16. 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.
17. Jiao, Y., Shi, T., Zhao, B., & Wang, A. (2026). Retrieval-Guided Structured Reasoning and Interpretable Representation Learning for Large-Scale Video–Language Models.
18. Filippidis, M., Kizys, R., & Tzouvanas, P. (2026). Supply Chain Network, ESG Scores and Financial Performance. *Business Strategy and the Environment*.

19. Liang, S., Zhang, X., Du, Y., & Chen, W. (2026). Supply Network Restructuring and Capacity Ramp-Up Limits in the Localized Expansion of High-Performance Computing Equipment Production. Available at SSRN 7339738.
20. Lin, N., Xu, Y., Yang, H., Zhang, G., Zhang, M., Wang, S., ... & Li, X. (2020). Dissociating the neural correlates of the sociality and plausibility effects in simple conceptual combination. *Brain Structure and Function*, 225(3), 995-1008.
21. Brighi, P., & Mussoni, M. (2025). Relationship Lending, Transaction Lending and Corporate Banking. In *The Bank-Business Relationship: Information Asymmetries, Relationship Lending, and Regulation* (pp. 67-116). Cham: Springer Nature Switzerland.
22. Bao, Y., & Wang, H. (2026). Orion: A High-Throughput, Fault-Tolerant Event Routing Architecture for Hyperscale Data Streams. *Fault-Tolerant Event Routing Architecture for Hyperscale Data Streams* (January 01, 2026).
23. 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.
24. Bringas, E. N. (2026). Leveraging knowledge graphs in facilities management: A scoping review. *Journal of Building Design and Environment*, 4(2), 2025120.
25. Qi, C., & Qiao, X. (2026). Efficient Data Sampling and Feature Selection Algorithms for Scalable Machine Learning Pipelines.
26. Liang, S., Hsu, K. H., & Liu, Z. (2026). Rolling Scheduling and Capacity Balancing for Server Assembly Under Engineering Change Disturbances.
27. Jiao, Y., Shi, T., Zhao, B., & Wang, A. (2026). The Impact of VR Sketching Simulations on the Assessment of Scale and Site Suitability in Public Art Spaces.
28. Nahar, P., Jagannath, M. V. K., & Chauhan, Y. (2026). Bank monitoring incentives and stock price crash risk: evidence from an exogenous bank capital shock. *Journal of Regulatory Economics*, 69(1), 3.
29. Yang, Q., & Du, Y. (2026). Predicting Rollback Risks and Controlling Gradual Rollout Traffic for Online Ranking Feature Deployments.
30. Aristeia, T. (2025). Private Equity in Banking Mergers & Acquisitions in the US: A Re-examination of the Evidence (Doctoral dissertation, Athens University of Economics and Business).