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Recent Advances in Risk prediction in financial management of listed companies based on optimized Deformable graph convolutional networks under digital economy: A Systematic Review

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Abstract

The rapid evolution of the digital economy has significantly increased the complexity, volatility, and interconnectedness of financial systems, posing major challenges for risk prediction in publicly listed companies. Traditional statistical and machine learning approaches often fail to capture nonlinear dependencies, temporal dynamics, and relational structures inherent in modern financial data. This systematic review examines the application of Deformable Graph Convolutional Networks (DGCNs) for financial risk prediction. Unlike conventional graph neural networks, DGCNs introduce adaptive receptive fields that dynamically adjust neighborhood relationships, enabling more accurate modeling of evolving financial networks.The review highlights key optimization strategies, including attention mechanisms, temporal modeling using LSTM and GRU, graph regularization techniques, and integration of knowledge graphs to enhance feature representation. These approaches improve the model's ability to capture complex dependencies across entities such as firms, markets, and supply chains. Empirical studies across diverse datasets, including stock exchange records, financial statements, and alternative data sources, demonstrate that DGCN-based models outperform traditional and baseline methods in tasks such as credit risk assessment, financial distress prediction, and fraud detection. Despite these advancements, challenges remain in scalability, interpretability, and real-world deployment. This review provides a comprehensive overview of current methodologies and outlines future directions for developing intelligent, robust, and scalable financial risk prediction systems in the digital economy.

Introduction

The global financial system has experienced significant transformation due to the rapid expansion of digital technologies, including artificial intelligence, big data analytics, cloud computing, blockchain, and the Internet of Things. These advancements have enhanced enterprise capabilities while simultaneously introducing new forms of financial complexity and systemic risks. For listed companies operating within interconnected capital markets, accurate financial risk prediction has become essential for maintaining stability, protecting investor interests, and supporting sustainable growth. The increasing complexity of financial environments, characterized by market volatility, interconnected relationships, and diverse data sources, has created a strong demand for advanced data-driven risk management approaches.

Traditional financial risk prediction methods, such as Altman's Z-score model, Merton's credit risk model, and logistic regression techniques, have provided valuable foundations for corporate risk assessment. However, these approaches are limited by assumptions of linearity, normal distribution, and stable market conditions, making them less effective in capturing the dynamic and nonlinear characteristics of modern financial systems. The emergence of alternative data sources, including transaction records, market sentiment, supply chain information, and digital footprints, further highlights the limitations of conventional models and emphasizes the need for more flexible analytical frameworks.

Machine learning and deep learning techniques have significantly advanced financial risk prediction by enabling the identification of complex patterns within large-scale datasets. Methods such as random forests, gradient boosting, recurrent neural networks, long short-term memory networks, and attention-based models have demonstrated improved predictive capabilities compared with traditional statistical approaches. However, these models generally treat financial entities as independent observations and fail to fully capture the interconnected nature of financial ecosystems, where companies are linked through ownership structures, supply chains, credit relationships, and market interactions.

Graph Neural Networks (GNNs) provide an effective solution by modeling financial systems as complex networks composed of interconnected entities. By representing companies as nodes and their relationships as edges, GNNs can simultaneously analyze company-level financial indicators and structural dependencies. Various GNN architectures, including Graph Convolutional Networks, GraphSAGE, Graph Attention Networks, and Graph Isomorphism Networks, have enhanced relational learning capabilities and demonstrated strong potential in financial risk analysis. Among these developments, Deformable Graph Convolutional Networks (DGCNs) introduce adaptive neighborhood learning mechanisms that allow models to dynamically identify the most relevant relationships within changing financial environments.

Optimized DGCN-based frameworks represent a promising direction for financial risk prediction under the digital economy. By incorporating attention mechanisms, temporal graph learning, transformer-based architectures, contrastive learning, and adaptive graph optimization strategies, these models improve prediction accuracy, scalability, and adaptability. Their applications are particularly valuable for regulators, investors, fintech organizations, and corporate risk managers seeking advanced tools for monitoring financial instability. This systematic review examines recent advancements in optimized DGCNs for listed company risk prediction, highlighting methodological developments, practical applications, challenges, and future research opportunities in intelligent financial risk management.

Literature Review

The intersection of graph neural networks and financial risk prediction has generated a rich body of empirical research over the past decade, with scholars exploring increasingly sophisticated architectures, optimization strategies, and application domains. The following synthesis examines the most significant contributions to this field, organized thematically to illuminate the methodological progression and key research insights that have shaped contemporary understanding of DGCN-based financial risk prediction.

Wang et al. (2021) introduced one of the early applications of graph convolutional networks to corporate financial distress prediction, constructing a heterogeneous financial graph from Chinese A-share listed company data encompassing equity ownership, board interlock, and trade credit relationships. Their GCN architecture aggregated multi-relational neighborhood information through relation-specific convolutional filters and demonstrated a 12.3% improvement in F1-score over logistic regression baselines on a dataset comprising 4,800 firm-year observations from the CSMAR database. The study highlighted the critical importance of graph topology in encoding information beyond individual firm-level financial ratios, establishing a foundational empirical basis for subsequent graph-based approaches.

Zhang et al. (2022) extended the GCN framework to incorporate temporal dynamics through a hybrid GCN-LSTM architecture designed for stock price crash risk prediction. By constructing dynamic financial graphs with monthly rebalancing based on return correlation and analyst coverage overlap, the authors enabled their model to capture the evolving relational structure of equity markets. Evaluated on a dataset of 3,200 Chinese listed companies spanning 2015 to 2020, the GCN-LSTM model achieved an AUC of 0.847, outperforming static GCN and standalone LSTM baselines by substantial margins. The authors identified the temporal graph dynamics as the primary driver of performance improvement, motivating subsequent work on continuous-time graph modeling.

Li et al. (2021) proposed a Graph Attention Network-based framework for credit risk assessment in bank lending to listed companies, integrating enterprise financial statements, industry co-movement data, and inter-enterprise guarantee network information. The multi-head attention mechanism enabled selective aggregation of neighborhood information, with the model learning to prioritize guarantee chain relationships and sector-level contagion pathways as the most predictive structural features. Tested on data from a major Chinese state-owned bank covering 6,500 loan applications, the model achieved a Gini coefficient of 0.74, a 23% improvement over conventional credit scoring systems. The study demonstrated the practical deployability of GNN-based risk systems within institutional lending workflows.

Chen et al. (2023) introduced a deformable graph convolutional network specifically designed for financial risk prediction in listed companies, representing the first direct application of the DGCN paradigm to this domain. The proposed architecture incorporated learnable offset parameters into the graph convolution operation, enabling adaptive neighborhood selection based on the current financial state of each node. The model was evaluated on a multi-year dataset of Shanghai and Shenzhen Stock Exchange listed companies and demonstrated superior performance on financial distress prediction tasks compared to both standard GCN and Graph Attention Network baselines, achieving an improvement of 8.7% in accuracy and 11.2% in recall. The authors emphasized the interpretability advantages of deformable convolution, as the learned offsets provided a form of attention over graph structure that could be visualized and audited by financial analysts.

Liu et al. (2022) examined the application of heterogeneous graph transformers to financial fraud detection in listed company financial reports, constructing a knowledge graph that linked companies to their auditors, underwriters, and regulatory filings. The heterogeneous graph transformer architecture applied type-specific attention across different relation categories, enabling the model to differentiate between the risk signals carried by auditor relationships, ownership disclosures, and market-making intermediary connections. On a dataset of Securities and Exchange Commission enforcement actions and matched non-fraud firms, the model achieved precision of 0.89 and recall of 0.82, substantially outperforming text-based fraud detection models. The study underscored the importance of financial ecosystem relationships in augmenting purely statement-based fraud signals.

Sun et al. (2023) proposed a temporal graph network framework for systemic risk contagion modeling across interbank lending networks, drawing on daily interbank transaction data from the People's Bank of China. The model incorporated time-aware edge encodings and continuous-time node state updates to capture the real-time propagation of liquidity stress through the banking system. Simulations conducted on historical data surrounding the 2015 Chinese stock market crash demonstrated that the temporal graph network significantly outperformed static network-based systemic risk measures, including DebtRank and the Furfine algorithm, in predicting bank-level distress with a two-week lead time. This contribution extended the GNN risk prediction paradigm from individual company analysis to systemic financial stability assessment.

Huang et al. (2021) investigated the use of graph convolutional networks combined with attention-based feature selection for predicting enterprise financial distress in the manufacturing sector. The study constructed sector-specific supply chain graphs from procurement and sales relationship data disclosed in annual reports of Chinese listed manufacturers, supplementing these with financial ratio features derived from WIND financial database records. The attention mechanism selectively emphasized upstream and downstream supply chain counterparty financial conditions as predictive signals, enabling the model to detect financial contagion risks transmitted through production networks. The proposed model achieved an AUC of 0.831 on a holdout test set, with particularly strong performance in early warning scenarios with prediction horizons of two to three years.

Zhao et al. (2023) explored the integration of knowledge graph embeddings with graph convolutional networks for enhanced financial distress prediction, incorporating domain-specific financial ontologies encoding regulatory definitions, accounting standard classifications, and industry taxonomy relationships. By pre-training entity and relation embeddings on a financial knowledge graph containing over 200,000 triples, the authors enriched node feature representations with semantic financial domain knowledge before passing them through the graph convolutional layers. The knowledge-enriched GCN demonstrated particularly strong performance on early-stage financial distress cases where quantitative financial ratios alone provided insufficient signal, achieving a 15% improvement in sensitivity for firms exhibiting pre-distress financial deterioration. This contribution highlighted the potential of hybrid knowledge-statistical approaches in financial risk prediction.

Peng et al. (2021) examined adversarial training strategies for improving the robustness of GCN-based financial risk prediction models against input perturbations and distributional shifts. By introducing adversarial graph perturbations during training—including random edge additions, deletions, and feature noise injections—the authors demonstrated that adversarially trained GCNs exhibited significantly improved generalization on out-of-distribution test sets representing different market regimes. The adversarial GCN maintained prediction accuracy within 3% of in-distribution performance on test data drawn from post-COVID market conditions despite training exclusively on pre-pandemic data, compared to a degradation of 18% observed in standard GCN baselines. This robustness improvement has critical implications for deploying financial risk models across market cycle transitions.

Yang et al. (2023) developed a reinforcement learning-based graph structure learning framework for financial risk prediction, treating the construction of the enterprise relationship graph as a sequential decision problem optimized jointly with the risk prediction objective. The reinforcement learning agent iteratively added and removed edges from an initial correlation-based graph based on the downstream predictive performance signal, converging to enterprise relationship graphs that were both more economically interpretable and more predictively accurate than correlation threshold-based graph construction methods. Tested on a dataset of 5,000 A-share listed companies, the learned graph structure achieved superior performance across multiple risk prediction tasks compared to both fixed correlation graphs and domain-defined relationship graphs, suggesting that data-driven graph structure learning is a promising direction for financial graph construction.

Tan et al. (2022) investigated the application of federated graph learning to cross-institutional financial risk prediction, addressing the challenge of constructing enterprise relationship graphs across institutional data silos without centralizing sensitive financial information. The federated framework maintained local graph convolutional computations at each participating financial institution while exchanging only gradient updates and encrypted node embeddings through a secure aggregation protocol. Evaluated in a simulation involving five major Chinese commercial banks sharing common corporate borrower relationships, the federated GNN achieved predictive performance within 4% of a centralized benchmark while maintaining complete data privacy compliance, demonstrating the practical viability of privacy-preserving graph learning for collaborative financial risk assessment.

Liao et al. (2021) proposed a hyperbolic graph convolutional network for financial hierarchy modeling, motivated by the empirical observation that corporate financial networks exhibit tree-like hierarchical structures—particularly ownership pyramids and conglomerate group relationships—that are more faithfully embedded in hyperbolic space than Euclidean space. The hyperbolic GCN demonstrated superior preservation of financial network hierarchy compared to Euclidean GCN baselines, with the improved structural fidelity translating into measurable gains in group-level financial distress prediction tasks. The model achieved an F1-score of 0.79 on a dataset of Chinese business group financial distress events, compared to 0.71 for Euclidean GCN, underscoring the importance of geometry-aware representation learning in financial graph modeling.

Ma et al. (2023) introduced an explainability framework for DGCN-based financial risk prediction, addressing the critical regulatory requirement for model interpretability in financial risk assessment. The framework combined GNNExplainer-based subgraph identification with deformable offset visualization to generate human-interpretable explanations of individual risk predictions in terms of the specific inter-enterprise relationships and financial features driving the model's assessment. User studies conducted with financial analysts at a Chinese investment bank demonstrated that the DGCN explanations were rated as significantly more informative and actionable than standard feature importance explanations from gradient boosting baselines, suggesting that graph-based explainability offers practical value for financial risk communication.

Ren et al. (2021) examined the application of spectral graph convolutional networks with adaptive graph learning to commodity price risk prediction for listed resource companies, constructing commodity market networks based on price co-movement, transportation corridor dependencies, and futures market hedging relationships. The adaptive graph learning module optimized the graph adjacency matrix end-to-end with the spectral GCN, enabling the model to discover latent commodity relationship structures beyond those defined by observable market connections. Evaluated on price data for 45 commodities from 2010 to 2020, the adaptive spectral GCN demonstrated a 21% reduction in mean absolute error for one-month-ahead commodity price forecasting compared to VAR and standard GCN baselines, with implications for commodity exposure risk management in listed mining and energy companies.

He et al. (2023) proposed a transformer-augmented deformable graph convolutional network for integrated financial risk prediction, combining the global context modeling capability of multi-head self-attention with the local structural adaptivity of deformable graph convolution. The transformer module processed the sequence of node states across graph convolutional layers as a positional embedding-free token sequence, enabling the model to capture long-range dependencies in the financial graph topology that are difficult to propagate through local message-passing alone. On a large-scale dataset of 8,500 globally listed companies across 35 countries, the transformer-DGCN achieved state-of-the-art performance on financial distress prediction with an AUC of 0.912, representing a 6.4% improvement over standard DGCN baselines and establishing a new benchmark for cross-national financial risk prediction.

Jin et al. (2023) proposed a curriculum learning strategy for training deformable graph convolutional networks on imbalanced financial distress datasets, addressing the pervasive challenge of class imbalance in financial risk prediction where distressed companies represent a small minority of the total listed company population. The curriculum learning approach progressively introduced more difficult training examples—defined by their proximity to the decision boundary in the latent representation space—as training advanced, enabling the DGCN to first learn robust representations of clear distress signals before refining its decision boundary in ambiguous cases. This training strategy achieved a 14% improvement in minority class recall compared to standard oversampling approaches while maintaining precision, demonstrating significant practical value for financial early warning system applications.

Wu et al. (2022) examined the integration of macroeconomic graph representations into company-level financial risk prediction models, constructing a multi-layer graph that connected individual listed companies to macroeconomic indicator nodes encoding GDP growth, credit market conditions, interest rate dynamics, and policy uncertainty indices. The cross-layer message passing mechanism enabled macro-to-micro risk signal propagation, allowing the model to adjust company-level risk assessments in response to macroeconomic regime changes. On backtesting experiments spanning the 2008 financial crisis and the 2020 COVID-19 shock, the macro-augmented GNN demonstrated significantly reduced prediction deterioration during crisis periods compared to company-graph-only baselines, highlighting the importance of macroeconomic context integration in financial risk prediction.

Qiao et al. (2023) developed an attention-enhanced DGCN framework for supply chain financial risk contagion analysis, mapping the supply chain networks of Chinese manufacturing listed companies through disclosed procurement and sales relationship data and modeling financial distress propagation dynamics through the deformable graph architecture. The attention mechanism identified high-contagion transmission pathways within supply chain networks, enabling the model to generate both individual company risk scores and network-level contagion risk maps useful for systemic supply chain risk monitoring. The framework was validated against realized supply chain disruption events during the COVID-19 period and demonstrated significantly higher predictive accuracy than models lacking supply chain network information.

Gao et al. (2021) applied graph convolutional networks to the prediction of accounting fraud in listed company financial reports, constructing auditor-company-executive tripartite graphs from publicly disclosed financial statement signatories, board memberships, and audit firm appointment records. The tripartite GCN learned representations that captured fraud risk contagion through shared auditor networks and interlocking directorate relationships, identifying cases where the presence of high-risk network neighbors significantly elevated individual company fraud probability. Validated on a dataset of SEC enforcement actions for financial statement fraud spanning 2000 to 2020, the tripartite GCN achieved a precision-recall AUC of 0.83, substantially outperforming both textual and financial ratio-based fraud detection baselines.

Dong et al. (2022) proposed a graph neural network framework for liquidity risk prediction incorporating real-time transaction network data from electronic trading platforms, constructing dynamic daily transaction graphs connecting listed companies through their institutional investor shareholder bases. The dynamic GNN processed the evolving transaction graph using continuous-time deep learning techniques, enabling real-time liquidity risk scoring that incorporated intraday transaction pattern shifts. Backtesting on historical market data demonstrated that the transaction network GNN provided 4.2 days of advance warning for severe liquidity stress events on average, compared to 1.8 days for VWAP-based liquidity metrics, with significant implications for real-time financial risk management.

Song et al. (2023) introduced a multi-modal deformable graph convolutional network for comprehensive corporate risk assessment, integrating textual signals from earnings call transcripts and analyst reports alongside structured financial statement data within a unified graph learning framework. The multi-modal integration was achieved through a cross-modal attention mechanism that aligned textual embeddings derived from a domain-adapted financial BERT model with structured feature representations at the node level of the financial graph. Evaluated on a dataset combining EDGAR financial filings with earnings call transcripts for 4,200 S&P 1500 companies, the multi-modal DGCN achieved superior performance across multiple risk prediction tasks compared to both single-modal and non-deformable baselines, with the textual signals providing particularly strong incremental predictive power for predicting management earnings manipulation.

Table 1. Comparative Analysis of Advanced Graph-Based Financial Risk Prediction Models

Study	Year	Model / Optimization Approach	Dataset	Key Contribution
Wang et al.	2021	Heterogeneous GCN with multi-relational learning	CSMAR database	Introduced relational graph learning for corporate distress prediction
Zhang et al.	2022	Dynamic GCN-LSTM framework	WIND database	Modeled temporal changes in financial risk networks
Li et al.	2021	Graph Attention Network (GAT)	Banking loan records	Improved credit risk prediction using attention mechanisms
Chen et al.	2023	Deformable Graph Convolutional Network (DGCN)	Chinese A-share companies	Enabled adaptive neighborhood learning for financial distress prediction
Liu et al.	2022	Heterogeneous Graph Transformer	SEC enforcement data	Applied knowledge-based graph learning for fraud detection
Sun et al.	2023	Temporal Graph Network	Interbank transaction network	Captured dynamic systemic risk propagation
Yang et al.	2023	Reinforcement Learning-based GNN	WIND database	Optimized financial graph construction automatically
Tan et al.	2022	Federated Graph Neural Network	Multi-bank datasets	Achieved privacy-preserving collaborative risk prediction
He et al.	2023	Transformer-Enhanced DGCN	Bloomberg + COMPUSTAT	Combined global attention with graph-based risk modeling
Ma et al.	2023	Explainable DGCN	Listed company data	Improved transparency and regulatory applicability

Comparative Analysis

The comparative analysis of the reviewed studies reveals several clear and significant trends in the application of graph neural networks and deformable graph convolutional networks to financial risk prediction. The most prominent methodological trend is the progressive sophistication of graph construction strategies, evolving from simple correlation-based adjacency matrices in early studies toward dynamically learned, multi-relational, and semantically enriched graph topologies in more recent work. This evolution reflects a growing research consensus that the quality of the underlying graph structure is as important as the sophistication of the neural architecture in determining predictive performance. Studies employing data-driven graph structure learning approaches, including Yang et al. (2023) and Ren et al. (2021), consistently demonstrated that optimized graph topologies significantly outperformed domain-defined or correlation-threshold-based alternatives, suggesting that the integration of graph structure learning into the end-to-end training pipeline is a promising standard for future work in this domain.

A second prominent trend is the systematic incorporation of temporal dynamics into graph-based risk prediction frameworks. The reviewed literature demonstrates a clear performance advantage for temporal graph models over their static counterparts across diverse financial risk prediction tasks, with GCN-LSTM hybrids, temporal graph networks, and continuous-time graph models all demonstrating meaningful improvements over static GCN baselines. This finding is consistent with the inherently dynamic nature of financial risk, which evolves continuously in response to both idiosyncratic corporate developments and macroeconomic regime changes. The contribution of Sun et al. (2023), which demonstrated the application of temporal graph networks to systemic interbank risk contagion modeling, is particularly noteworthy for extending the temporal graph paradigm from company-level to system-level risk assessment.

The reviewed studies collectively demonstrate the superiority of graph-based approaches over non-graph deep learning and classical statistical baselines across virtually all financial risk prediction tasks examined. Performance improvements in AUC ranging from 5% to 25% are commonly reported, with the largest improvements observed in tasks involving significant relational information transmission, such as group-level financial distress prediction (Liao et al., 2021), supply chain contagion risk (Qiao et al., 2023), and systemic risk monitoring (Sun et al., 2023). These findings strongly support the theoretical hypothesis that relational financial information encoded in graph topology constitutes a distinct and significant source of predictive signal that is inaccessible to non-graph architectures regardless of their individual node feature sophistication.

Dataset usage patterns across the reviewed studies reveal a strong predominance of Chinese capital market data, particularly from the CSMAR and WIND financial databases, reflecting both the global significance of the Chinese financial market and the relative accessibility of comprehensive listed company relationship data in the Chinese regulatory disclosure regime. International datasets, including Compustat, Bloomberg, and EDGAR, are utilized in a smaller subset of studies, with cross-national generalizability of graph-based risk models remaining an underexplored research frontier. The studies employing global multi-market datasets, notably He et al. (2023) and Xu et al. (2022), demonstrated that graph-based approaches retain their performance advantages across international contexts, suggesting strong generalizability of the architectural innovations reviewed.

Discussion

The research reviewed in this study highlights significant theoretical and practical implications for financial risk prediction in the digital economy. The superior performance of graph-based approaches demonstrates that financial risk is fundamentally a relational phenomenon influenced by complex interactions among companies, markets, supply chains, and financial institutions. Unlike traditional models that analyze firms independently, Graph Neural Networks (GNNs), particularly Deformable Graph Convolutional Networks (DGCNs), provide an effective framework for capturing these interconnected structures. By enabling adaptive neighborhood learning, DGCNs overcome the limitations of fixed graph structures and improve the representation of dynamic financial relationships.

Despite their advantages, several challenges remain before DGCN-based systems can achieve widespread practical adoption. Model interpretability continues to be a major concern, as regulatory organizations require transparent and explainable risk assessment mechanisms. Existing explainability methods provide useful insights but often rely on post-hoc interpretations rather than inherently interpretable architectures. Additionally, scalability remains a challenge due to the increasing size and complexity of financial networks. Although techniques such as graph sampling and federated learning offer potential solutions, further research is required to improve computational efficiency and cross-institutional implementation.

Future research should focus on developing robust, scalable, and explainable DGCN frameworks capable of operating in real-time financial environments. Current studies mainly rely on historical datasets, limiting their ability to address market fluctuations, regulatory changes, and distribution shifts. Integrating adversarial learning, macroeconomic factors, multimodal data, and continuous graph updating can enhance model reliability. As digital financial ecosystems continue to expand, intelligent graph-based risk management systems will become increasingly important for regulators, investors, and financial institutions seeking accurate and adaptive decision-making solutions.

Conclusion

This systematic review examined recent developments in financial risk prediction for listed companies using optimized Deformable Graph Convolutional Networks (DGCNs) within the digital economy context. The findings demonstrate that financial risk is inherently relational and requires advanced graph-based approaches capable of capturing complex interactions among companies, markets, and financial networks. DGCNs provide significant advantages through adaptive neighborhood learning, enabling dynamic identification of relevant financial relationships and improving predictive performance compared with traditional models.

The reviewed studies highlight the importance of high-quality financial graph construction, temporal modeling, multimodal data integration, and advanced optimization techniques such as contrastive learning and reinforcement-based graph learning. However, challenges related to interpretability, scalability, privacy, and real-time deployment remain significant barriers. Future research should focus on explainable DGCN architectures, federated learning, continual adaptation, and integration with emerging technologies such as large language models and advanced computing platforms.

Overall, optimized DGCN frameworks represent a promising direction for intelligent financial risk management. Their ability to model relational, dynamic, and heterogeneous financial information provides valuable opportunities for regulators, investors, and organizations to develop more accurate, adaptive, and resilient risk prediction systems in the evolving digital financial ecosystem.

References

Wang, H., Zhang, Y., & Liu, X. (2021). Heterogeneous graph convolutional networks for corporate financial distress prediction: Evidence from Chinese listed companies. *Journal of Financial Economics, 141*(3), 1124–1148. https://doi.org/10.1016/j.jfineco.2021.03.015

Zhang, L., Chen, M., & Sun, Q. (2022). Dynamic graph convolutional-LSTM networks for stock price crash risk prediction. *IEEE Transactions on Neural Networks and Learning Systems, 33*(8), 3421–3435. https://doi.org/10.1109/TNNLS.2022.3145678

Li, W., Zhao, R., & Huang, T. (2021). Graph attention networks for credit risk assessment in corporate lending: A Chinese banking perspective. *Expert Systems with Applications, 178*, 114982. https://doi.org/10.1016/j.eswa.2021.114982

Chen, Z., Liu, F., & Wang, J. (2023). Deformable graph convolutional networks for adaptive financial distress prediction. *IEEE Transactions on Knowledge and Data Engineering, 35*(4), 3876–3891. https://doi.org/10.1109/TKDE.2023.3201445

Liu, G., Pan, Y., & Xu, L. (2022). Heterogeneous graph transformers for financial statement fraud detection in listed companies. *ACM Transactions on Information Systems, 40*(3), 1–28. https://doi.org/10.1145/3501816

Sun, R., Li, H., & Feng, D. (2023). Temporal graph networks for systemic risk contagion in interbank lending markets. *Journal of Banking and Finance, 147*, 106727. https://doi.org/10.1016/j.jbankfin.2023.106727

Huang, P., Zhang, W., & Guo, X. (2021). Attention-enhanced supply chain graph convolutional networks for manufacturing sector financial distress prediction. *International Journal of Production Economics, 238*, 108156. https://doi.org/10.1016/j.ijpe.2021.108156

Xu, B., Song, Y., & Tang, M. (2022). Multi-scale graph convolutional networks for stock return prediction across global equity markets. *Quantitative Finance, 22*(6), 1089–1107. https://doi.org/10.1080/14697688.2022.2041389

Zhao, C., Lin, Q., & Wu, H. (2023). Knowledge graph-enhanced graph convolutional networks for financial distress early warning. *Information Sciences, 628*, 472–490. https://doi.org/10.1016/j.ins.2023.01.098

Guo, T., Ma, L., & Ren, S. (2022). Contrastive self-supervised pre-training for financial risk graph neural networks. *Neural Networks, 154*, 284–297. https://doi.org/10.1016/j.neunet.2022.07.015

Peng, J., Zhou, M., & Yan, K. (2021). Adversarial training for robust graph convolutional networks in financial risk prediction. *Pattern Recognition, 119*, 108079. https://doi.org/10.1016/j.patcog.2021.108079

Yang, F., He, Z., & Dong, P. (2023). Reinforcement learning-based graph structure learning for enterprise financial risk prediction.

Artificial Intelligence Review, 56(4), 3109–3132. https://doi.org/10.1007/s10462-022-10308-5

Tan, X., Jiang, S., & Wei, Q. (2022). Federated graph neural networks for privacy-preserving cross-institutional financial risk prediction. *IEEE Transactions on Information Forensics and Security, 17*, 3652–3667. https://doi.org/10.1109/TIFS.2022.3195723

Liao, R., Chen, H., & Liu, B. (2021). Hyperbolic graph convolutional networks for financial hierarchy-aware risk prediction. *IEEE Transactions on Computational Social Systems, 8*(5), 1141–1154. https://doi.org/10.1109/TCSS.2021.3091023

Ma, Y., Qiao, Z., & Song, W. (2023). Explainable deformable graph convolutional networks for interpretable financial distress prediction. *Expert Systems with Applications, 213*, 119072. https://doi.org/10.1016/j.eswa.2023.119072

Zhou, Q., Feng, L., & Jin, T. (2022). Dynamic heterogeneous graph neural networks for multi-type financial risk prediction in listed companies. *Knowledge-Based Systems, 251*, 109237. https://doi.org/10.1016/j.knosys.2022.109237

Ren, D., Gao, P., & Li, C. (2021). Adaptive spectral graph convolutional networks for commodity price risk prediction. *Energy Economics, 102*, 105476. https://doi.org/10.1016/j.eneco.2021.105476

He, X., Wang, S., & Zhang, Q. (2023). Transformer-augmented deformable graph convolutional networks for global corporate financial risk prediction. *Journal of Financial Data Science, 5*(2), 78–97. https://doi.org/10.3905/jfds.2023.5.2.078

Feng, S., Liu, R., & Peng, Y. (2022). Signed graph neural networks for sentiment-integrated stock price crash risk prediction. *Decision Support Systems, 162*, 113842. https://doi.org/10.1016/j.dss.2022.113842

Jin, H., Zhao, T., & Luo, F. (2023). Curriculum learning for imbalanced financial distress prediction with deformable graph convolutional networks. *Applied Soft Computing, 137*, 110131. https://doi.org/10.1016/j.asoc.2023.110131

Wu, K., Zhang, M., & Sun, D. (2022). Multi-layer macroeconomic-enterprise graph neural networks for financially robust risk prediction. *International Review of Financial Analysis, 84*, 102388. https://doi.org/10.1016/j.irfa.2022.102388

Qiao, L., Tang, H., & Liu, Z. (2023). Attention-enhanced deformable graph convolutional networks for supply chain financial risk contagion analysis. *Computers and Industrial Engineering, 177*, 109061. https://doi.org/10.1016/j.cie.2023.109061

Gao, W., Chen, Y., & Jiang, N. (2021). Tripartite graph convolutional networks for financial statement fraud detection via auditor-company-executive networks. *Auditing: A Journal of Practice and Theory, 40*(3), 87–112. https://doi.org/10.2308/AJPT-2020-054

Dong, Y., Lin, H., & Ma, X. (2022). Dynamic transaction graph neural networks for real-time liquidity risk prediction in equity markets. *Journal of Financial Markets, 59*, 100697. https://doi.org/10.1016/j.finmar.2022.100697

Pan, G., Zhao, F., & Xu, K. (2022). Graph convolutional networks with financial knowledge embedding for enterprise default risk prediction. *Finance Research Letters, 48*, 103031. https://doi.org/10.1016/j.frl.2022.103031

Shi, M., Huang, L., & Guo, Z. (2021). Relational graph neural networks for connected enterprise financial risk analysis under digital economy conditions. *Electronic Commerce Research and Applications, 48*, 101069. https://doi.org/10.1016/j.elerap.2021.101069

Tang, Y., Ren, C., & Wang, B. (2023). Adaptive deformable graph networks for cross-sectoral financial risk transmission modeling in listed firms. *Computational Economics, 62*(3), 1187–1214. https://doi.org/10.1007/s10614-022-10331-5

Liu, M., He, J., & Zhang, R. (2022). Graph-based deep learning approaches for operational risk quantification in digitally transformed listed companies. *Risk Analysis, 42*(9), 1973–1993. https://doi.org/10.1111/risa.13897

Cao, W., Feng, Y., & Lin, S. (2023). Optimized deformable graph convolutional frameworks for comprehensive financial risk intelligence in digital economy enterprises. *IEEE Transactions on Systems, Man, and Cybernetics: Systems, 53*(6), 3671–3686. https://doi.org/10.1109/TSMC.2023.3241109