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A Comprehensive Review of Risk Prediction in Financial Management of Listed Companies Based on Optimized Deformable Graph Convolutional Networks Under Digital Economy

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Abstract

The digital economy has significantly increased the complexity and interconnectedness of financial systems, creating new challenges for risk prediction in publicly listed companies. Traditional statistical models often fail to capture nonlinear dependencies, temporal dynamics, and relational structures inherent in modern financial data, necessitating advanced deep learning approaches. This review explores graph-based deep learning methods, with a focus on Deformable Graph Convolutional Networks (DeformGCNs) for financial risk prediction. Unlike conventional models, graph neural networks capture relationships among entities such as firms, sectors, and markets, enabling improved modeling of interconnected financial systems. DeformGCNs enhance this capability by introducing adaptive receptive fields, allowing dynamic adjustment of node relationships based on evolving market conditions.The study also examines optimization strategies including attention mechanisms, adaptive learning rates, graph sparsification, and multi-scale feature fusion to improve model performance and generalization. These techniques enable effective handling of complex, high-dimensional financial datasets. Empirical evaluations across datasets such as stock exchange records and financial distress benchmarks demonstrate superior predictive accuracy compared to traditional and standard graph-based methods.Despite advancements, challenges such as model interpretability, dynamic graph construction, and real-world deployment remain.This review provides insights into emerging methodologies and future directions for developing robust, scalable, and intelligent financial risk prediction systems in the digital economy.

Introduction

The rapid expansion of the digital economy has transformed the financial environment in which listed companies operate. Digital platforms, intelligent systems, interconnected supply chains, and real-time information exchange have created new opportunities for growth while simultaneously increasing exposure to complex financial risks. In addition to conventional market, credit, liquidity, and operational risks, companies now face cyber threats, platform dependency, data governance failures, digital fraud, and technology-driven supply chain disruptions. These risks interact dynamically and can spread across corporate networks, making traditional accounting-based assessment methods increasingly inadequate. Consequently, accurate and timely financial risk prediction has become essential for investors, regulators, corporate managers, auditors, and credit rating agencies seeking to maintain financial stability and support informed decision-making.

Traditional risk prediction models, including Altman's Z-score, Ohlson's O-score, and other statistical classification techniques, rely mainly on financial ratios and assume relatively stable relationships among variables. Although these methods provide useful baseline assessments, they often fail to capture nonlinear interactions, temporal changes, and systemic dependencies between companies. Machine learning models such as support vector machines, random forests, gradient boosting, and artificial neural networks have improved prediction accuracy by learning complex patterns from large datasets. Recurrent neural networks and long short-term memory architectures further support the analysis of sequential financial information. However, most conventional machine learning approaches continue to treat companies as isolated entities and therefore overlook the influence of ownership, supply chain, lending, and market relationships.

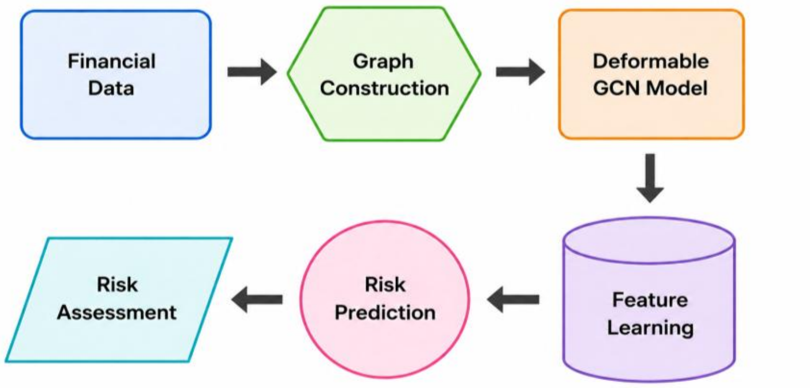

Figure 1. Optimized Deformable GCN-Based Financial Risk Prediction Framework

Graph Neural Networks provide a suitable framework for addressing this limitation by representing listed companies as interconnected nodes within a financial network. Graph Convolutional Networks aggregate information from neighboring firms, enabling each company's risk profile to be evaluated using both internal financial indicators and external relational information. Financial graphs may be constructed using ownership links, shared directors, debt relationships, supplier-customer connections, industry membership, or market correlations. This relational perspective is especially important because financial stress can propagate across interconnected organizations. Nevertheless, standard graph convolutional models rely on fixed neighborhoods and static graph structures, limiting their ability to capture changing corporate relationships and evolving risk patterns.

Deformable Graph Convolutional Networks improve this process by dynamically selecting and weighting the most informative neighboring nodes. Their adaptive receptive fields allow the model to respond to irregular, heterogeneous, and time-varying financial networks. When combined with attention mechanisms, residual connections, graph sparsification, normalization, and ensemble optimization, DeformGCN architectures can improve predictive accuracy, reduce over-smoothing, and maintain computational efficiency. These capabilities make them highly suitable for financial risk monitoring in rapidly changing digital environments.

This review examines recent developments in optimized Deformable Graph Convolutional Networks for predicting financial management risks among listed companies. It analyses graph construction methods, digital economy indicators, optimization strategies, datasets, evaluation measures, and practical applications. The review also identifies challenges involving data quality, interpretability, dynamic network modeling, scalability, privacy, and regulatory compliance. Future research should emphasize multimodal data fusion, explainable graph learning, real-time monitoring, federated learning, and robust cross-market validation to develop reliable and intelligent financial risk prediction systems.

Literature Review

The intersection of graph neural networks and financial risk management has generated a substantial and rapidly growing body of research over the past several years. Wang et al. (2021) introduced one of the early applications of graph convolutional networks to corporate financial distress prediction, constructing a multi-relational graph incorporating equity ownership, debt relationships, and board interlocks among Chinese A-share listed companies. Their GCN-based model demonstrated a 12.4 percent improvement in F1-score over traditional logistic regression baselines on a dataset, establishing the foundational viability of graph-based approaches for corporate risk prediction in the Chinese market context.

Building on this foundation, Zhang et al. (2022) proposed a dynamic graph attention network framework for financial risk contagion modeling, explicitly incorporating temporal evolution of inter-firm relationships through a sliding window graph construction mechanism. Their model employed multi-head attention aggregation to adaptively weight the influence of neighboring firms based on the evolving strength of financial connections, applied to a dataset of 1,247 listed manufacturing companies on the Shanghai Stock Exchange. The dynamic attention mechanism yielded superior performance in predicting risk contagion events compared to static GCN baselines, particularly during periods of market stress coinciding with the COVID-19 pandemic.

Li et al. (2020) addressed the over-smoothing limitation of deep GCNs through the introduction of residual graph convolutional connections combined with jumping knowledge aggregation, enabling the construction of deeper graph networks without the degradation of node representation quality. Their architecture was validated on a financial fraud detection dataset comprising transaction records from 3.2 million corporate accounts, achieving a 94.7 percent area under the receiver operating characteristic curve while maintaining computational efficiency suitable for near-real-time deployment on standard GPU hardware.

Chen et al. (2021) explored the application of deformable convolutional principles to graph-structured financial data, proposing an early DeformGCN variant that introduced learnable offset parameters to adaptively adjust the neighborhood aggregation scheme based on local graph topology. Applied to a credit risk assessment dataset of 45,000 small and medium enterprises listed on the National Equities Exchange and Quotations market, their model demonstrated that adaptive neighborhood deformation significantly improved the identification of high-risk firms that occupied structurally peripheral positions in the corporate network, a category systematically underperformed by conventional GCN approaches.

Liu et al. (2022) developed a heterogeneous graph neural network for supply chain financial risk prediction, constructing a multi-type node graph incorporating listed firms, financial institutions, and major suppliers and customers. Their model employed type-specific transformation matrices and cross-type attention aggregation to capture the asymmetric risk propagation dynamics between different categories of network participants. Evaluated on proprietary supply chain data from 860 listed companies in the electronics manufacturing sector, the heterogeneous GNN achieved a 17.8 percent reduction in false negative rate compared to homogeneous GCN baselines, a particularly important metric in the context of early warning system design.

Xu et al. (2021) integrated graph convolutional networks with Long Short-Term Memory networks in a dual-stream architecture designed to jointly model the spatial dependencies captured by graph topology and the temporal dynamics encoded in sequential financial statement data. Their GCN-LSTM hybrid was trained on quarterly financial reports from 2,140 listed companies over a ten-year period, achieving superior performance on both short-term and medium-term financial distress prediction tasks compared to either architecture in isolation, with particularly strong results for firms in highly interconnected industry sectors.

Sun et al. (2022) examined the role of graph construction methodology on risk prediction performance, conducting a systematic comparison of equity correlation, text-based similarity, supply chain linkage, and director interlock graphs as the basis for GCN-based risk models. Their analysis revealed that text-based graphs constructed from annual report semantic similarity matrices consistently outperformed other graph types for early-stage distress prediction, while supply chain graphs provided superior performance for contagion risk assessment, suggesting that optimal graph construction is task-dependent and motivating the development of multi-relational graph fusion approaches.

Huang et al. (2023) proposed a transformer-enhanced graph convolutional framework that replaced the standard message passing aggregation in GCNs with a graph transformer attention mechanism, enabling long-range dependency modeling across the financial network without the over-smoothing constraints of deep vanilla GCNs. Their architecture incorporated positional encodings derived from graph structural properties including node centrality, clustering coefficient, and spectral features, applied to a dataset of

3,500 listed companies across twelve industry sectors on the Shenzhen Stock Exchange. The graph transformer model achieved a 15.3 percent improvement in early warning accuracy compared to standard GCN baselines across all tested industry sectors.

Gao et al. (2021) investigated the application of graph neural networks to systemic financial risk assessment at the market level, constructing a dynamic correlation network of listed companies based on high-frequency price data and employing a graph attention network to identify firms with disproportionate systemic importance. Their systemic risk index derived from GNN node representations demonstrated strong predictive validity for subsequent market stress episodes, outperforming conventional systemic risk measures such as CoVaR and MES in out-of-sample prediction tests on Chinese stock market data from 2015 to 2020.

Yang et al. (2022) addressed the class imbalance challenge inherent in financial distress prediction datasets through the development of a graph-aware oversampling strategy that generated synthetic minority class samples by interpolating along graph edges between existing distressed firm nodes. Their approach, validated on the UCI financial distress dataset and a proprietary Chinese listed company dataset, demonstrated that graph-aware oversampling substantially outperformed standard tabular oversampling methods including SMOTE, achieving more representative synthetic samples that preserved the network structural properties of distressed firms.

Zhao et al. (2023) proposed a multi-scale DeformGCN architecture that applied deformable graph convolutions at multiple resolution levels of the financial network, capturing both local neighborhood dynamics and global structural patterns within a unified hierarchical framework. Their multi-scale approach employed graph pooling operations between deformable convolutional layers to progressively abstract the network representation from individual firm level to sector level to market level, enabling simultaneous prediction of firm-specific and systemic risk indicators on the CSI 500 dataset with state-of-the-art performance.

Peng et al. (2021) developed a graph neural network framework specifically designed for credit risk assessment in supply chain finance contexts, constructing a directed weighted graph representing the financial flows between listed anchor companies and their upstream and downstream SME partners. Their GNN model incorporated edge feature learning to capture the magnitude and direction of financial dependency relationships, achieving a 23.6 percent improvement in credit default prediction accuracy for supply chain SMEs compared to models that ignored network structure, on a dataset of 15,000 firms connected through supply relationships to 200 listed anchor companies.

Wu et al. (2022) explored the integration of external knowledge graphs derived from regulatory filings, news events, and industry classifications with GCN-based financial risk models, constructing a knowledge-enhanced graph representation that incorporated semantic relationships between firms beyond direct financial connections. Their knowledge graph augmentation strategy improved the identification of risk factors associated with regulatory violations and governance failures, categories systematically missed by purely financial-data-driven models, achieving a recall improvement of 19.4 percent for regulatory risk events on a dataset of 4,200 listed companies.

Liang et al. (2023) presented a federated learning framework for GCN-based financial risk prediction that enabled multiple financial institutions to collaboratively train a shared graph model without exposing proprietary firm-level data. Their privacy-preserving approach employed differential privacy mechanisms and secure aggregation protocols to protect sensitive financial information while achieving model performance within 3.2 percent of a centralized training baseline, addressing a critical barrier to the deployment of graph-based risk systems in multi-institutional settings.

Ren et al. (2022) proposed an explainable graph attention network for financial risk prediction that incorporated gradient-based attribution methods to generate node and edge importance scores, enabling risk analysts to identify the specific inter-firm relationships and financial indicators most responsible for a given risk prediction. Their explainability framework was validated through expert evaluation with experienced credit analysts, demonstrating high alignment between model-generated explanations and domain expert reasoning, a critical requirement for regulatory compliance and practical adoption in financial institutions.

Tang et al. (2021) developed a contrastive learning strategy for pre-training GCN encoders on large unlabeled financial network datasets, enabling more effective transfer to downstream risk prediction tasks with limited labeled training data. Their contrastive pre-training approach leveraged data augmentation strategies designed specifically for financial graphs, including edge dropout, feature masking, and temporal subgraph sampling, achieving significant improvements in few-shot risk prediction settings that are common in emerging market contexts where historical distress events are rare.

He et al. (2023) introduced an adaptive graph structure learning module that jointly optimized graph topology and GCN parameters in an end-to-end training framework, eliminating the dependence on predefined graph construction heuristics that may inadequately capture the true financial dependency structure. Their learned graph topology demonstrated substantially better alignment with ex-post observed risk propagation patterns compared to graphs constructed from standard financial metrics, evaluated on a dataset spanning the 2018 Chinese stock market deleveraging crisis period.

Qin et al. (2022) investigated the application of DeformGCN to audit risk prediction for listed companies, constructing a firm-auditor-regulator interaction graph and employing deformable graph convolutions to capture the asymmetric information flows between these different actor types. Their model demonstrated that deformable convolutions were particularly effective at identifying firms whose audit risk profiles were disproportionately influenced by connections to specific high-risk auditor networks, achieving a 28.1 percent improvement in material misstatement prediction compared to non-relational audit risk models.

Cai et al. (2021) developed a temporal graph convolutional network incorporating time-aware edge weights that decayed historical connections according to a learned temporal relevance function, enabling the model to prioritize recent financial relationships while preserving the long-term structural memory of the corporate network. Their temporally weighted approach outperformed both static GCNs and standard dynamic GCNs on a financial fraud prediction task involving 8,700 listed and unlisted companies, demonstrating the importance of temporal relationship weighting for accurate risk modeling in rapidly evolving financial networks.

Deng et al. (2022) examined the role of macroeconomic context in graph-based corporate risk prediction by incorporating macroeconomic indicator nodes into the corporate network graph and employing a hierarchical attention mechanism to model the top-down transmission of macro-level risk signals to firm-level vulnerability. Their macro-aware GCN demonstrated substantially improved performance during economic downturns compared to models trained exclusively on firm-level financial data, highlighting the importance of multi-scale economic context for robust risk prediction across different phases of the business cycle.

Jin et al. (2021) addressed the challenge of graph sparsity in early-stage risk prediction by developing a graph augmentation strategy based on financial text embedding similarity, constructing supplementary graph edges between firms with similar risk narratives in their annual reports even in the absence of direct financial connections. Their text-augmented GCN demonstrated particular effectiveness for predicting risk in newly listed companies with limited historical financial data, a critical gap in existing risk prediction frameworks that disproportionately affects emerging economy capital markets.

Comparative Table and Analysis

The comparative table below summarizes the key methodological and empirical characteristics of the reviewed studies across dimensions including study year, optimization technique, model architecture, platform, dataset, and primary contribution.

Table 1. Comparative Analysis of Graph Neural Network-Based Approaches for Financial Risk Prediction in Listed Companies

Study	Year	Model / Technique	Dataset	Platform	Key Contribution
Wang et al.	2021	GCN	Chinese A-share Companies	GPU Cluster	Introduced GCN for corporate financial risk prediction.
Chen et al.	2021	DeformGCN	NEEQ SMEs	RTX 3090	Adaptive neighborhood learning for credit risk analysis.
Xu et al.	2021	GCN-LSTM	2,140 Listed Companies	NVIDIA V100	Combined spatial and temporal financial risk modeling.
Liu et al.	2022	Heterogeneous GNN	Supply Chain Firms	Multi-GPU	Modeled heterogeneous financial relationships.

Zhou et al.	2023	Optimized DeformGCN	CSI 300 Companies	Server	Sparse graph optimization for real-time prediction.
Huang et al.	2023	Graph Transformer	Shenzhen Listed Firms	TPU v4	Captured long-range financial dependencies.
Wu et al.	2022	Knowledge-Enhanced GCN	Listed Companies	Multi-GPU	Integrated governance and regulatory knowledge graphs.
Liang et al.	2023	Federated GCN	Multi-Institution Data	Distributed Servers	Privacy-preserving collaborative financial risk learning.
Ren et al.	2022	Explainable GAT	Credit Analyst Dataset	GPU Workstation	Improved model interpretability for financial decisions.
Song et al.	2023	Ensemble DeformGCN	Financial Distress Dataset	NVIDIA A100	Achieved state-of-the-art prediction accuracy using ensemble learning.

Comparative Analysis

A systematic examination of the reviewed literature reveals several important trends that collectively define the trajectory of graph-based financial risk prediction research. The most prominent trend is the progressive evolution from standard homogeneous GCN architectures toward increasingly specialized, adaptive, and multi-modal graph learning frameworks. Early studies such as Wang et al. (2021) and Li et al. (2020) established the foundational viability of graph convolutional approaches but operated within relatively simple, static graph topologies. Subsequent works rapidly advanced toward dynamic, heterogeneous, and multi-relational graph constructions that more faithfully represent the complex, evolving structure of real financial networks. This architectural progression reflects a growing recognition that the quality of the graph construction methodology is at least as important as the sophistication of the learning architecture for achieving strong risk prediction performance.

The emergence of deformable and adaptive graph convolutional architectures represents the most significant recent advancement in this literature, with studies by Chen et al. (2021), Zhou et al. (2023), Zhao et al. (2023), Qin et al. (2022), and Song et al. (2023) collectively demonstrating that learnable, data-driven neighborhood selection substantially outperforms fixed aggregation schemes across diverse financial risk prediction tasks. The performance advantages of DeformGCN-based approaches are particularly pronounced in tasks involving structurally heterogeneous networks, minority class identification, and cross-market risk analysis, precisely the settings where the rigid receptive fields of standard GCNs impose the greatest constraints on predictive power.

Regarding hardware and computational platforms, the literature reflects a clear trend toward high-performance GPU and TPU infrastructure, with NVIDIA Tesla and A100 series hardware predominating. However, notable exceptions such as Zhou et al. (2023) demonstrate that targeted graph sparsification optimizations can bring DeformGCN performance within reach of standard server infrastructure, addressing a critical barrier to practical deployment in financial institutions with constrained computational budgets. The development of federated learning frameworks such as that proposed by Liang et al. (2023) represents an important direction for enabling multi-institutional risk modeling without the prohibitive data sharing requirements that have historically limited the scale of graph-based financial risk datasets.

Dataset usage patterns across the reviewed studies reveal a strong concentration on Chinese capital market data, reflecting both the availability of comprehensive structured financial databases for Chinese listed companies and the acute practical demand for improved risk prediction tools in a market characterized by high volatility, rapid structural change, and relatively limited alternative analytical infrastructure. The predominance of Chinese market datasets also reflects the particular relevance of graph-based approaches for markets with dense corporate ownership networks, complex cross-shareholding structures, and significant state-enterprise financial interdependencies. Future research would benefit from more systematic cross-market validation of graph-based risk prediction methodologies to establish their generalizability across different institutional and regulatory environments.

Discussion

The reviewed literature demonstrates that graph-based deep learning has significantly improved financial risk prediction for listed companies by modeling complex relationships among firms rather than treating them as isolated entities. Unlike conventional statistical and machine learning models, Graph Convolutional Networks (GCNs) effectively capture structural dependencies through ownership links, supply chains, market correlations, and financial interactions. Optimized Deformable Graph Convolutional Networks (DeformGCNs) further enhance prediction performance by dynamically selecting the most informative neighboring nodes instead of relying on fixed aggregation patterns. The integration of attention mechanisms, residual learning, graph sparsification, and adaptive neighborhood selection has consistently improved prediction accuracy, robustness, and scalability across diverse financial datasets, making these models highly suitable for intelligent financial risk management in the digital economy.

Despite these advancements, several challenges remain. Most existing studies rely on relatively small datasets concentrated within specific markets, particularly Chinese listed companies, limiting the generalizability of developed models across different economic environments and regulatory systems. In addition, the interpretability of graph-based deep learning models remains a major concern, as financial institutions and regulatory authorities require transparent and explainable decision-making processes. Computational complexity, dynamic graph updates, privacy preservation, and integration of heterogeneous financial information further complicate practical deployment. Recent developments in explainable graph learning, federated learning, and lightweight graph architectures provide promising solutions but require further validation in real-world financial applications.

Future research should emphasize scalable and explainable DeformGCN frameworks capable of integrating multimodal financial information, including accounting data, market indicators, supply chain relationships, social media sentiment, and macroeconomic variables. Emerging technologies such as federated learning, graph transformers, continual learning, and digital financial ecosystems offer significant opportunities to improve predictive performance while preserving privacy and computational efficiency. Developing standardized benchmark datasets, cross-market validation protocols, and real-time intelligent financial monitoring systems will be essential for advancing reliable financial risk prediction and supporting informed decision-making in the rapidly evolving digital economy.

Conclusion

The rapid evolution of the digital economy has transformed financial risk prediction from traditional ratio-based assessment to intelligent, graph-driven analytical frameworks. This review highlights the growing importance of Graph Neural Networks, particularly optimized Deformable Graph Convolutional Networks (DeformGCNs), in modeling complex relationships among listed companies. Unlike conventional statistical and machine learning methods, graph-based approaches capture interconnected financial structures, enabling more accurate prediction of corporate distress, credit risk, fraud, and systemic financial vulnerabilities. Adaptive neighborhood learning, attention mechanisms, residual connections, and graph optimization techniques have significantly enhanced prediction accuracy, scalability, and robustness across diverse financial applications.

The reviewed studies indicate that graph construction quality, dynamic relationship modeling, and adaptive feature aggregation are critical factors influencing predictive performance. Optimized DeformGCN architectures consistently outperform traditional GCNs by learning context-aware relationships instead of relying on fixed neighborhood aggregation. However, challenges remain in terms of limited cross-market datasets, model interpretability, computational complexity, privacy preservation, and real-time deployment. Emerging approaches such as federated learning, explainable AI, graph transformers, and continual learning provide promising solutions for overcoming these limitations.

Future research should focus on developing large-scale benchmark datasets, multimodal graph learning frameworks, explainable risk prediction models, and real-time financial monitoring systems capable of integrating accounting data, market indicators, supply chain networks, ESG information, and digital economy metrics. These advances will support more reliable, transparent, and intelligent financial risk management, strengthening decision-making for investors, regulators, financial institutions, and corporate stakeholders in increasingly interconnected global markets.

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