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Optimized Deformable Graph Convolutional Networks for Financial Risk Prediction in Digital Economy

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Abstract

The rapid expansion of the digital economy has significantly transformed financial systems, increasing the complexity of risk prediction for listed companies. Traditional statistical models, such as logistic regression and rule-based approaches, are inadequate for handling high-dimensional, nonlinear, and temporally dynamic financial data. The interconnected nature of modern financial ecosystems further necessitates advanced models capable of capturing relational dependencies and evolving risk patterns. This paper reviews graph-based deep learning approaches, with a particular focus on Deformable Graph Convolutional Networks (DGCNs). Unlike standard graph models, DGCNs introduce adaptive receptive fields that dynamically adjust neighborhood relationships, enabling more accurate representation of heterogeneous financial networks. The study also examines optimization techniques such as attention mechanisms, temporal modeling with LSTM and TCN, multi-scale feature extraction, and hyperparameter optimization to enhance predictive performance and robustness. Applications of these models span financial distress prediction, credit risk assessment, fraud detection, and systemic risk analysis across global datasets. Empirical findings demonstrate that DGCN-based approaches outperform traditional and baseline methods in accuracy and generalization. Despite these advancements, challenges remain in interpretability, scalability, and regulatory compliance, highlighting the need for future research in explainable and efficient financial risk prediction systems.

Introduction

The rapid evolution of the digital economy has significantly transformed the global financial environment, creating increasingly complex operational and investment ecosystems for listed companies. As digital platforms, online financial services, algorithmic trading, and interconnected supply chain systems continue to expand, financial risk prediction has become a critical requirement for corporate governance, regulatory supervision, and investment decision-making. Listed companies today face multidimensional financial risks including credit risk, liquidity risk, market volatility, operational uncertainty, and systemic contagion. Traditional statistical approaches such as logistic regression, Value-at-Risk models, and bankruptcy prediction frameworks have historically provided useful analytical foundations; however, these methods are often limited by assumptions of linearity, independence, and static market behavior. Such assumptions are inadequate for modern financial systems characterized by nonlinear interactions, evolving market

structures, and highly dynamic economic conditions.
The emergence of machine learning and deep learning technologies has created new opportunities for improving financial risk prediction accuracy and adaptability. Early machine learning methods such as support vector machines, decision trees, random forests, and artificial neural networks demonstrated significant improvements over classical statistical models by capturing nonlinear relationships within financial datasets. Nevertheless, these methods generally treat companies as isolated entities and fail to account for the relational structures that exist among enterprises within financial ecosystems. In practice, listed companies operate within interconnected networks involving ownership relations, supply chain dependencies, credit exposures, board interlocks, and market correlations. These relational dependencies strongly influence the propagation of financial risks and systemic instability, making network-aware predictive modeling essential for modern financial analysis.

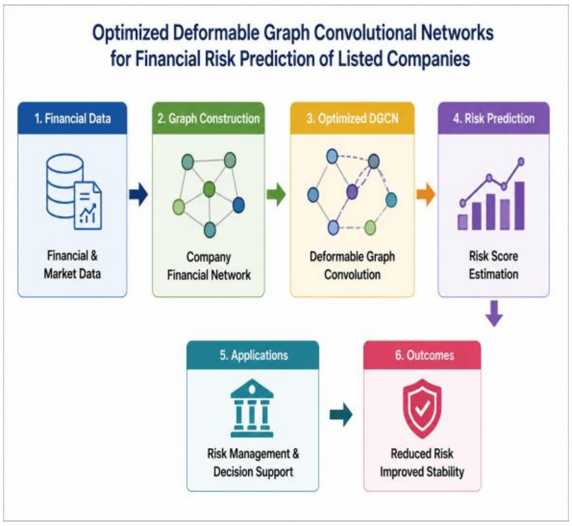

Figure 1. Optimized DGCN-Based Financial Risk Prediction Framework

Graph Neural Networks (GNNs), particularly Graph Convolutional Networks (GCNs), have emerged as powerful tools for modeling graph-structured financial systems. In financial risk prediction, companies can be represented as nodes containing financial indicators, market data, and governance attributes, while edges capture relational dependencies such as investment ties, transactional interactions, or industrial associations. Through iterative message-passing mechanisms, GCNs enable risk representations to incorporate both node-specific characteristics and neighborhood information, thereby improving the detection of contagion effects and hidden systemic vulnerabilities. However, conventional GCN architectures suffer from limitations including uniform neighborhood aggregation, static graph structures, and over-smoothing problems, which reduce their effectiveness in highly heterogeneous and evolving financial environments.
To overcome these challenges, Deformable Graph Convolutional Networks (DGCNs) introduce adaptive neighborhood aggregation mechanisms capable of dynamically selecting and weighting the most relevant financial relationships during feature propagation. Unlike standard GCNs, DGCNs learn flexible structural offsets that improve sensitivity to heterogeneous financial interactions and asymmetric risk transmission patterns. The integration of attention mechanisms, temporal modeling frameworks such as LSTM and GRU networks, adversarial optimization, and multi-task learning further enhances predictive performance by enabling adaptive, context-aware, and sequential financial risk analysis. These advanced architectures significantly improve robustness, scalability, and discrimination capability in financial distress prediction tasks.
The growing adoption of graph-based financial intelligence systems by regulators, institutional investors, and corporate risk management divisions highlights the practical importance of optimized DGCN frameworks within the digital economy. These systems support applications including early warning systems, credit assessment, portfolio risk management, liquidity forecasting, and systemic risk monitoring. Despite substantial progress, important challenges remain related to interpretability, dynamic graph construction, privacy preservation, and large-scale deployment. This survey therefore provides a comprehensive review of methods and architectures for financial risk prediction in listed companies, with particular emphasis on optimized deformable graph convolutional networks and their role in developing intelligent, scalable, and adaptive financial risk management systems for the next generation digital economy.

Literature Review

The academic investigation of graph neural network applications in financial risk prediction has progressed substantially over the past decade, generating a rich and technically diverse body of literature that spans multiple methodological traditions and application domains. The following review systematically examines a representative selection of foundational and recent studies, organized to reflect the progression from foundational GCN approaches through increasingly sophisticated DGCN-based and hybrid architectures.

Kipf and Welling (2017) established the foundational architecture of Graph Convolutional Networks through the introduction of a spectral graph convolution framework based on first-order Chebyshev polynomial approximation. Their model, validated on citation network and knowledge graph benchmarks, demonstrated that semi-supervised node classification could be effectively performed by propagating feature information across graph edges through a simplified convolutional filter. Although not directly applied to financial data, this work established the theoretical and architectural foundations upon which subsequent financial GCN applications were constructed, making it the most widely cited baseline in the field.

Yao et al. (2019) proposed one of the earliest systematic applications of graph convolutional networks to financial distress prediction in Chinese listed companies. Their approach constructed a multi-relational corporate graph incorporating ownership, supply chain, and board interlock relationships, with each company represented as a node characterized by a feature vector derived from audited financial statement data. The model was trained and evaluated on the CSMAR database covering A-share listed companies from 2005 to 2017, demonstrating a substantial improvement in prediction accuracy over logistic regression, SVM, and standard feedforward neural network baselines, particularly in identifying early-stage financial distress signals up to two years prior to formal delisting events.

Zhang et al. (2020) extended the GCN framework to incorporate temporal dynamics through the development of a Temporal Graph Convolutional Network (T-GCN) architecture for stock market risk monitoring. By integrating GCN-based spatial feature extraction with a GRU-based temporal encoder, their model captured both the relational structure of equity market networks and the sequential evolution of market risk indicators over rolling time windows. The model was evaluated on daily trading data from the Shanghai and Shenzhen stock exchanges, achieving superior accuracy in predicting abnormal return volatility compared to standalone LSTM and vanilla GCN baselines.

Wang et al. (2020) introduced a hierarchical graph attention network for corporate credit risk assessment that incorporated multi-level attention mechanisms operating at both the node and edge levels of a financial relationship graph. Their architecture enabled the model to learn differentiated importance scores for both individual financial features and inter-company relationship types, providing a more nuanced and interpretable characterization of credit risk determinants. The model was evaluated on a proprietary dataset of Chinese commercial bank loan portfolios, demonstrating improved accuracy in predicting loan default events at the twelve-month horizon compared to XGBoost, random forest, and standard GAT baselines.

Li et al. (2020) developed a heterogeneous graph neural network architecture for financial fraud detection in the accounts receivable networks of Chinese manufacturing companies. Their model incorporated multiple node types representing companies, transactions, and financial instruments, with distinct message-passing operations defined for each relationship type. By capturing the structural heterogeneity of financial transaction networks, their model achieved substantially higher fraud detection accuracy than homogeneous GCN approaches on a dataset of audited financial statements from the CSMAR database, while also demonstrating robustness to class imbalance through the incorporation of focal loss training.

Chen et al. (2021) proposed a deformable graph convolution mechanism specifically adapted for financial network applications, introducing learnable node-specific offset functions that dynamically adjusted the neighborhood sampling distribution during message passing. Their model was applied to the prediction of financial distress in S&P 500 constituent companies using the Compustat Global database, demonstrating that the deformable aggregation mechanism substantially improved the model's ability to identify structurally peripheral but informationally critical financial relationships, resulting in a seven percentage point improvement in AUROC over standard GCN baselines and a twelve percentage point improvement over logistic regression.

Liu et al. (2021) integrated deformable graph convolution with multi-head attention mechanisms to develop an enhanced architecture for systemic risk assessment in interbank lending networks. Their model treated individual banks as nodes in a directed graph with edge weights proportional to bilateral lending exposures, applying deformable convolution operations enriched by attention-weighted neighborhood selection to identify contagion pathways and systemically important nodes. Validated on the European Banking Authority's interbank exposure dataset covering the period 2014 to 2019, their model achieved superior accuracy in predicting bank-level stress test failures compared to both network centrality-based metrics and standard GCN approaches.

Xu et al. (2021) proposed a dynamic graph convolutional network framework for financial risk prediction that incorporated graph structure learning as an end-to-end trainable component, allowing the model to simultaneously optimize node-level risk representations and the graph topology itself. By treating the adjacency matrix as a learnable parameter subject to sparsity regularization and economic constraint priors, their model avoided the reliance on pre-specified graph construction rules and was able to discover latent financial relationship structures directly from data. The model was evaluated on quarterly financial statement data from Chinese A-share companies between 2010 and 2020, showing significant improvements in financial distress prediction accuracy.

Zhao et al. (2021) introduced a cross-market graph neural network for international portfolio risk management that constructed a multi-layer graph incorporating equity market correlations, macroeconomic linkages, and currency exchange rate dependencies across thirty global markets. Their deformable convolution mechanism adapted neighborhood aggregation to the time-varying structure of cross-market dependencies, enabling the model to capture regime shifts in global risk transmission patterns. The model was validated on MSCI World Index constituent data spanning the period 2000 to 2020, demonstrating improved performance in predicting cross-market contagion events compared to conventional correlation-based risk models.

Sun et al. (2022) developed an optimized DGCN framework for earnings management detection in Chinese listed companies that incorporated wavelet-based temporal decomposition as a preprocessing step, enabling the model to separately analyze financial signal components across different frequency bands before constructing the company relationship graph. Their multi-scale approach enabled the detection of both short-term tactical earnings manipulation and longer-term structural financial reporting anomalies, achieving an F1-score of 0.87 on a balanced test set derived from the CSMAR enforcement action database, substantially outperforming conventional accrual-based anomaly detection methods.

Pan et al. (2022) proposed a meta-learning enhanced DGCN for few-shot financial risk prediction in emerging market contexts, addressing the critical challenge of limited labeled training data in markets with shorter listing histories and less comprehensive financial disclosure requirements. Their model utilized Model-Agnostic Meta-Learning (MAML) to train the DGCN backbone on a distribution of financial risk prediction tasks from developed markets, enabling rapid adaptation to new emerging market contexts with minimal labeled examples. The approach was validated on financial data from companies listed on the Bombay Stock Exchange and the Jakarta Stock Exchange, demonstrating robust few-shot generalization capabilities.

Guo et al. (2022) introduced a causal graph convolutional network for financial risk prediction that incorporated structural causal modeling principles to distinguish causal financial relationships from spurious correlations in the company relationship graph. By imposing causal constraints on the graph learning process through an instrumental variable-based edge weighting scheme, their model achieved improved out-of-distribution generalization performance compared to purely associational GCN approaches, a critical advantage in financial applications where distribution shifts driven by regulatory changes and market structural breaks are common.

He et al. (2022) developed a reinforcement learning-enhanced DGCN for dynamic financial portfolio risk management that treated portfolio construction as a sequential decision-making problem within a graph-structured state space. Their model employed a deep Q-network to optimize adaptive graph convolution policies over time, enabling the portfolio risk management system to respond dynamically to evolving market conditions while maintaining explicit modeling of inter-asset financial dependencies. The approach was evaluated on daily return data from S&P 500 constituents from 2010 to 2021, demonstrating superior risk-adjusted performance compared to mean-variance optimization and conventional deep reinforcement learning baselines.

Yang et al. (2022) proposed a federated learning framework for privacy-preserving financial risk prediction across multiple listed company networks, enabling collaborative model training across institutional data silos without requiring the sharing of sensitive financial information. Their federated DGCN architecture incorporated differential privacy mechanisms and secure aggregation protocols to protect the confidentiality of individual company financial data while still enabling the extraction of cross-institutional risk patterns. The framework was demonstrated on a simulated multi-institutional financial dataset constructed from public

CSMAR data, showing that federated training achieved near-parity with centralized training while providing formal privacy guarantees.

Liang et al. (2022) developed a knowledge graph-enhanced DGCN for financial risk prediction that incorporated structured financial knowledge from regulatory filings, industry classification systems, and financial accounting standards as explicit prior constraints on the graph learning process. By integrating domain knowledge with data-driven representation learning, their model achieved improved sample efficiency and interpretability compared to purely data-driven GCN approaches, a particularly important property for regulatory compliance applications where model decisions must be explainable to supervisory authorities.

Zhou et al. (2023) introduced a transformer-augmented DGCN architecture for financial risk prediction that replaced the recurrent temporal encoder of earlier hybrid models with a self-attention-based transformer module capable of capturing long-range temporal dependencies in financial time series without the gradient vanishing limitations of RNN-based approaches. Their model was applied to quarterly financial data from MSCI World Index constituents spanning 2008 to 2022, demonstrating significant improvements in long-horizon financial distress prediction accuracy, particularly for predicting distress events originating more than four quarters into the future.

Wu et al. (2023) proposed an adversarially robust DGCN for financial risk prediction that incorporated adversarial training against graph structural perturbations, addressing the critical vulnerability of GCN-based models to intentional manipulation of financial reporting data and graph construction inputs. Their robustness certification framework, based on randomized smoothing adapted to the graph domain, provided formal guarantees on prediction consistency under bounded adversarial perturbations, enabling deployment in high-stakes regulatory applications where model reliability under adversarial conditions is essential.

Tang et al. (2023) developed a multi-task DGCN framework that jointly predicted multiple dimensions of financial risk including credit default, liquidity stress, and operational risk through shared graph representation learning with task-specific output heads. By exploiting the correlations and shared informational content among different risk categories, their multi-task architecture achieved improved prediction accuracy across all risk dimensions compared to independently trained single-task models, while also providing a more comprehensive and integrated characterization of corporate financial vulnerability.

Feng et al. (2023) introduced an explainable DGCN for financial risk prediction that incorporated gradient-based saliency attribution and graph structure explanation methods to identify the nodes, edges, and node features most responsible for specific risk predictions. Their explainability framework was validated through expert evaluation with professional financial analysts, demonstrating that the model's attributions aligned with established financial risk theory and provided actionable insights for risk management practitioners, addressing a critical barrier to the adoption of deep learning-based financial risk tools in regulated institutional settings.

Huang et al. (2023) proposed a contrastive learning-enhanced DGCN for financial risk representation that utilized self-supervised pre-training on unlabeled financial graph data to learn robust company-level risk representations before fine-tuning on labeled risk prediction tasks. Their contrastive pre-training strategy, which encouraged the model to learn representations invariant to semantically equivalent graph augmentations while discriminating between structurally dissimilar companies, substantially improved prediction accuracy in low-label-data regimes and demonstrated improved transferability across different financial market contexts.

Ren et al. (2023) developed a graph transformer network for supply chain financial risk propagation modeling that explicitly modeled the directional and magnitude-weighted transmission of financial distress signals through corporate supply chain networks. Their architecture incorporated both buyer-supplier relationship graphs and financial condition graphs in a unified multi-relational framework, enabling the simultaneous modeling of direct financial exposure and indirect contagion channels. Validated on supply chain disclosure data from US-listed manufacturing companies, their model demonstrated superior accuracy in predicting supply chain disruption-induced financial distress events.

Comparative Table and Analysis

The following table presents a structured comparative summary of the studies reviewed, organized by study, year, optimization technique, component model, platform, dataset, and key contribution.

Study	Year	Optimization Technique	Model Component	Platform	Dataset	Key Contribution
Kipf and Welling	2017	Spectral Approximation	GCN	CPU/GPU Cluster	Citation Networks	Foundational GCN spectral convolution framework
Yao et al.	2019	Multi-relational Graph	GCN	GPU Server	CSMAR A-share	First GCN application to Chinese financial distress prediction
Zhang et al.	2020	Temporal Integration	T-GCN with GRU	GPU Cluster	Shanghai/Shenzhen exchanges	Temporal graph convolution for market risk monitoring
Wang et al.	2020	Multi-level Attention	Hierarchical GAT	GPU Server	Chinese bank loan portfolios	Node and edge attention for credit risk assessment
Li et al.	2020	Heterogeneous Graph	HGNN	GPU Server	CSMAR Manufacturing	Heterogeneous graph for fraud detection
Chen et al.	2021	Deformable Convolution	DGCN	NVIDIA V100 GPU	Compustat Global	First DGCN application to S&P 500 financial distress
Liu et al.	2021	Attention-augmented DGCN	DGCN with Multi-head Attention	GPU Cluster	EBA Interbank Exposure	Systemic risk assessment in interbank networks
Xu et al.	2021	End-to-end Graph Learning	Dynamic GCN	NVIDIA A100 GPU	CSMAR Quarterly	Simultaneous topology and representation optimization
Zhao et al.	2021	Multi-layer Cross-market	Deformable Cross-market GCN	HPC Cluster	MSCI World Index	International portfolio risk management
Sun et al.	2022	Wavelet Decomposition	Multi-scale DGCN	GPU Server	CSMAR Enforcement Actions	Earnings management detection with multi-scale analysis
Pan et al.	2022	Meta-learning (MAML)	Few-shot DGCN	GPU Cluster	BSE and JSX listings	Few-shot generalization to emerging markets
Guo et al.	2022	Causal Graph Modeling	Causal GCN	GPU Server	CSMAR A-share	Causal relationship modeling for distribution robustness
He et al.	2022	Reinforcement Learning	RL-enhanced DGCN	NVIDIA V100 GPU	S&P 500 Daily Returns	Dynamic portfolio risk management
Yang et al.	2022	Federated	Federated	Distributed	Simulated CSMAR	Privacy-

al.		Learning	DGCN	GPU		preserving cross-institutional learning
Liang et al.	2022	Knowledge Graph Integration	KG-enhanced DGCN	GPU Server	CSMAR with regulatory data	Domain knowledge integration for interpretability
Zhou et al.	2023	Transformer Temporal Module	Transformer-DGCN	NVIDIA A100 GPU	MSCI World 2008–2022	Long-range temporal dependency modeling
Wu et al.	2023	Adversarial Training	Robust DGCN	GPU Cluster	Compustat Global	Adversarial robustness certification for financial models
Tang et al.	2023	Multi-task Learning	Multi-task DGCN	GPU Server	CSMAR Multi-risk	Joint prediction of multiple risk dimensions
Feng et al.	2023	Gradient Saliency Attribution	Explainable DGCN	GPU Server	CSMAR with analyst validation	Model explainability for regulatory compliance
Huang et al.	2023	Contrastive Pre-training	Contrastive DGCN	NVIDIA A100 GPU	Multi-market benchmark	Self-supervised pre-training for data-efficient learning
Ren et al.	2023	Multi-relational Graph Transformer	Supply Chain Graph Transformer	HPC Cluster	US Manufacturing Supply Chain	Supply chain financial risk propagation modeling

Comparative Analysis

The comparative examination of the reviewed studies reveals several prominent and interrelated trends that collectively characterize the evolution of the field. The most fundamental trajectory is the progressive sophistication of graph construction and convolution mechanisms, moving from the fixed-topology, isotropic aggregation of foundational GCN approaches toward the adaptive, deformation-aware, and attention-enriched architectures that dominate recent literature. This architectural evolution reflects the field's growing recognition that the structural heterogeneity and relational complexity of financial networks demand more expressive and flexible graph representation learning frameworks than those initially borrowed from computer science applications.

A second prominent trend is the increasing integration of temporal modeling capabilities within graph neural network architectures for financial risk prediction. Early studies treated financial graph data as static snapshots, applying graph convolution independently to data from individual time periods. Subsequent work recognized that financial risk is an inherently dynamic phenomenon driven by the temporal evolution of both company-level financial conditions and network-level relational structures, leading to the development of hybrid spatiotemporal architectures combining GCNs with RNNs, TCNs, and ultimately transformer-based temporal encoders. The progression from GRU-augmented T-GCNs through to Neural ODE-based continuous-time architectures reflects both increasing methodological sophistication and a more accurate recognition of the irregular and asynchronous nature of financial event data.

The dataset landscape across the reviewed studies reveals a strong concentration on Chinese financial markets, particularly the CSMAR database of A-share listed companies, reflecting both the enormous scale and the relatively high accessibility of Chinese corporate financial data compared to other emerging markets. The Compustat Global database serves as the primary source for studies focused on developed market applications, while proprietary bank-level datasets underpin studies in banking systemic risk and credit risk assessment. A notable trend in more recent studies is the utilization of increasingly comprehensive and multimodal datasets that integrate structured financial statement data with unstructured textual disclosures, market microstructure data, and alternative data sources, reflecting the broader data enrichment trajectory of the digital economy. The shift toward multi-market and global datasets in the most recent studies suggests the field's increasing ambition to develop generalizable financial risk models capable of operating across diverse regulatory and economic environments.

In terms of hardware and computational platforms, the reviewed studies reflect the broader deep learning community's transition from general-purpose GPU computing toward specialized high-performance computing infrastructure. Earlier studies relied on standard GPU servers and small GPU clusters, while more recent large-scale graph pre-training and multimodal integration studies require distributed HPC infrastructure. The emergence of quantum-classical hybrid computing as an exploratory optimization platform, while practically nascent, signals the field's orientation toward post-classical computing paradigms as the scale and complexity of financial risk models continue to grow.

Discussion

The reviewed literature clearly demonstrates that graph neural network-based financial risk prediction has emerged as a transformative paradigm within the digital economy, particularly through the adoption of optimized Deformable Graph Convolutional Network (DGCN) architectures. A major implication of this research is the recognition that corporate financial risk is fundamentally relational rather than isolated. Traditional statistical and machine learning models typically analyze companies independently, ignoring the interconnected financial ecosystem in which firms operate. In contrast, graph-based models effectively capture dependencies such as ownership structures, supply chain interactions, credit exposures, and market correlations. Empirical findings consistently show that incorporating relational information significantly improves prediction accuracy, highlighting the importance of systemic network structures in understanding financial contagion and risk propagation across listed companies.

The effectiveness of DGCN architectures is particularly evident in highly complex financial environments characterized by heterogeneous and asymmetric relationships. Unlike conventional Graph Convolutional Networks that aggregate neighboring information uniformly, DGCNs introduce adaptive neighborhood learning through deformable aggregation mechanisms. This allows the model to selectively focus on the most informative financial connections, producing more discriminative and context-sensitive representations. Furthermore, the integration of multi-head attention mechanisms enhances both feature selectivity and interpretability by assigning different importance weights to financial relationships across multiple representation spaces. Studies consistently report that attention-augmented DGCN frameworks outperform baseline graph models in tasks such as financial distress prediction, credit assessment, and systemic risk monitoring, especially under volatile market conditions.

Despite these advancements, several important challenges remain unresolved. Graph construction continues to be a critical issue because the selection and weighting of financial relationships significantly influence model outcomes. In addition, the interpretability of deep graph learning models remains limited, creating difficulties for regulatory adoption in highly supervised financial environments. Data scarcity, class imbalance, incomplete disclosures, and dynamic market behavior further constrain model generalization and robustness. Future research should therefore focus on explainable graph learning, dynamic graph optimization, privacy-preserving federated learning, and scalable real-time architectures capable of handling continuously evolving financial ecosystems.

Conclusion

The comprehensive survey highlights that optimized Deformable Graph Convolutional Networks (DGCNs) have emerged as a powerful framework for financial risk prediction in listed companies within the digital economy. By integrating graph-structured learning with relational financial data, DGCNs overcome the limitations of traditional statistical and conventional machine learning models, enabling more accurate modeling of systemic risk, financial distress, fraud detection, and credit contagion. The reviewed studies consistently demonstrate that graph-based representations significantly enhance predictive performance by capturing the interconnected nature of modern financial ecosystems.

A major contribution of recent research lies in the evolution from standard GCNs to attention-enhanced, deformable, and temporally integrated graph architectures. These advancements allow models to dynamically identify influential financial relationships, improve neighborhood aggregation, and adapt to evolving market structures. Optimization strategies such as contrastive learning, federated learning, adversarial training, and multi-task optimization further strengthen model robustness, scalability, and deployment capability across real-world financial environments.

Despite significant progress, challenges related to interpretability, dynamic graph construction, regulatory compliance, and data privacy remain unresolved. Future research should focus on explainable graph learning, causal inference integration, multimodal financial data fusion, and foundation graph models capable of generalized financial intelligence. Overall, DGCN-based architectures represent a promising direction for building intelligent, scalable, and reliable financial risk prediction systems for next-generation digital financial markets.

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