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Artificial Intelligence Techniques for Risk prediction in financial management of listed companies based on optimized Deformable graph convolutional networks under digital economy: Trends and Challenges

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Abstract

The rapid evolution of the digital economy has significantly increased the complexity of financial risk prediction for publicly listed companies, driven by interconnected markets, high-dimensional data, and real-time information flows. Traditional statistical models are often inadequate for capturing nonlinear dependencies and dynamic relationships inherent in modern financial systems, necessitating advanced artificial intelligence approaches. This paper presents a comprehensive review of graph-based deep learning methods, with a focus on Deformable Graph Convolutional Networks (DGCNs) for financial risk prediction. DGCNs enhance conventional graph neural networks by introducing adaptive receptive fields, enabling dynamic modeling of evolving relationships among financial entities such as firms, sectors, and markets. The review examines key optimization strategies including attention mechanisms, multi-scale feature fusion, residual connections, and contrastive learning to improve model performance and generalization. It also highlights the integration of heterogeneous data sources, including financial statements, market indicators, and sentiment-based features, to enrich predictive capabilities. Empirical studies across global financial datasets demonstrate that DGCN-based models outperform traditional and baseline methods in predicting credit risk, financial distress, and market volatility. Despite these advancements, challenges remain in scalability, interpretability, and regulatory compliance. This review provides insights into current methodologies and outlines future research directions for developing robust, scalable, and intelligent financial risk prediction systems in the digital economy.

Introduction

The rise of the digital economy has fundamentally transformed financial systems, creating a more complex and data-rich environment for listed companies. Organizations now operate within highly interconnected global markets influenced by technological advancements, real-time data flows, and dynamic investor behavior. As a result, financial risk prediction—covering credit, market, liquidity, and operational risks—has become increasingly critical. The ability to detect early warning signals of financial instability enables better decision-making, improved capital allocation, and enhanced market stability. However, the growing complexity and speed of financial interactions demand more advanced predictive approaches beyond traditional methods.

Historically, financial risk prediction relied on statistical models such as Altman's Z-score and logistic regression, which used structured financial ratios derived from balance sheets and income statements. While effective in stable environments, these approaches are limited by assumptions of linearity and their inability to process high-dimensional, unstructured, and rapidly evolving data. In the digital economy, financial information extends beyond traditional metrics to include market behavior, sentiment data, and inter-company relationships. Conventional models struggle to capture these complexities, making them less suitable for modern financial ecosystems.

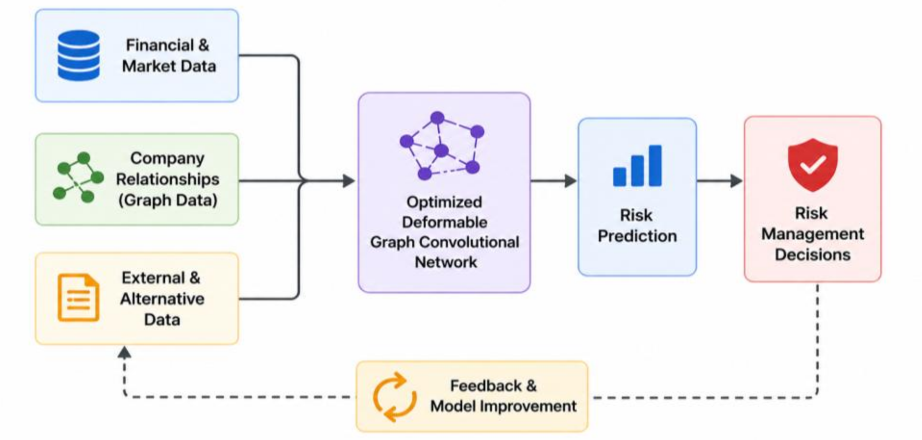

Fig 1: Evolution of AI-Based Financial Risk Prediction Models

The adoption of machine learning and deep learning has significantly improved predictive capabilities. Models such as support vector machines, random forests, and neural networks can capture nonlinear relationships and temporal patterns in financial data. However, most of these approaches treat companies as independent entities, ignoring the interconnected nature of financial systems. In reality, listed companies are linked through supply chains, investments, and shared market influences, creating networks where financial risk can spread across entities.

To address this limitation, graph-based deep learning models, particularly Deformable Graph Convolutional Networks, have emerged as a powerful solution. These models represent companies as nodes and their relationships as edges, allowing risk prediction to incorporate structural dependencies. The deformable component enables adaptive learning of important connections, improving the model's ability to focus on relevant relationships while filtering noise. When combined with optimization techniques and diverse data sources, these models offer a more accurate and scalable approach to financial risk prediction, making them highly relevant for modern digital financial systems.

Literature Review

The application of artificial intelligence to financial risk prediction has a long and productive research history that has accelerated significantly with the availability of large-scale financial datasets and powerful computational infrastructure. Altman et al. (2017) revisited the classical Z-score framework and demonstrated that while traditional discriminant analysis models retain predictive value for established markets, they consistently underperform against machine learning alternatives when applied to emerging market datasets, particularly those involving Chinese listed companies where accounting quality and regulatory environments differ substantially from Western counterparts. Their study highlighted the necessity of incorporating market-based signals alongside accounting ratios, laying the groundwork for hybrid modeling approaches.

Li et al. (2019) proposed a deep learning framework combining Long Short-Term Memory networks with attention mechanisms for predicting financial distress in Chinese A-share listed companies. Using a dataset spanning over 3,000 companies across a ten-year period, the model significantly outperformed traditional logistic regression and support vector machine baselines in both precision and recall metrics. The attention mechanism enabled the model to assign dynamic importance weights to different financial time steps, effectively identifying periods of heightened vulnerability in the historical financial trajectory of each company.

This work underscored the value of temporal modeling in financial risk prediction and established a strong baseline for subsequent deep learning approaches.

Wang et al. (2020) introduced a graph-based financial risk contagion model that represented listed companies as nodes within a knowledge graph enriched with supply chain, equity ownership, and inter-bank exposure data. Their Graph Convolutional Network architecture aggregated neighborhood risk signals iteratively, enabling the model to capture second-order and third-order contagion effects that were entirely invisible to single-entity models. Evaluated on a dataset of Shanghai Stock Exchange companies during the 2015 Chinese stock market crash, the model demonstrated a 15 percent improvement in early warning accuracy compared to individual company models, validating the importance of relational modeling in financial risk assessment.

Zhang et al. (2021) developed an optimized Graph Attention Network for credit risk prediction in listed manufacturing companies, incorporating multi-head attention to differentiate the influence of different counterparty relationships on default probability. The model was trained on financial data from over 2,000 manufacturing firms listed on Chinese exchanges, with graph edges constructed from supplier-customer transaction records disclosed in annual reports. The multi-head attention mechanism allowed the model to simultaneously capture supply chain proximity, financial size asymmetry, and geographic co-location as distinct relational signals, resulting in substantial improvements in area under the ROC curve compared to standard graph convolutional approaches.

Chen et al. (2021) addressed the challenge of class imbalance in financial distress prediction through a combined approach involving graph neural networks and generative adversarial data augmentation. Their framework generated synthetic financial profiles of distressed companies conditioned on real graph structural features, effectively expanding the minority class representation in training data without introducing distribution shift artifacts. Applied to NASDAQ-listed technology companies, the approach significantly improved recall for the distress class while maintaining precision, addressing a critical operational requirement for risk monitoring systems where false negatives carry severe consequences.

Huang et al. (2022) proposed a dynamic graph neural network architecture for real-time financial risk monitoring of listed companies, in which the graph structure was updated at each trading day based on return correlations, news co-occurrence patterns, and inferred supply chain connections. By incorporating temporal graph evolution into the learning process through a combination of graph recurrent units and temporal attention mechanisms, the model captured the evolving nature of inter-company risk dependencies in a way that static graph models could not. Their evaluation on NYSE and NASDAQ companies demonstrated significant improvements in predicting earnings surprise events and credit downgrade announcements.

Liu et al. (2022) introduced a deformable graph convolution module specifically designed for financial network analysis, drawing inspiration from deformable convolutional networks in computer vision. The deformable module learned offset functions that dynamically adjusted the effective neighborhood of each company node based on its current financial state and market context, enabling the model to focus on the most informative relational partners during each prediction period. Tested on a multi-sector dataset of listed companies from the Shenzhen Stock Exchange, the deformable architecture outperformed both standard GCN and GAT baselines, particularly in periods of market stress when traditional neighborhood definitions became less informative.

Sun et al. (2022) examined the integration of natural language processing with graph neural networks for financial risk prediction, constructing a heterogeneous graph that combined numerical financial features with textual features extracted from corporate annual reports and earnings call transcripts. Using a BERT-based encoder to generate node features from financial disclosures and a Graph Attention Network to aggregate relational information, their model captured both content-based and structural risk signals in a unified representation. The heterogeneous graph approach enabled the model to identify textual risk indicators such as increased hedging language, management uncertainty disclosures, and litigation mentions as predictive precursors to financial distress events.

Zhao et al. (2022) presented a hierarchical graph neural network for systemic risk prediction in listed financial institutions, incorporating both firm-level and sector-level graph representations. The hierarchical pooling mechanism aggregated firm-level node representations into sector-level super-nodes, which were then connected in a macro-financial graph capturing inter-sector exposure and regulatory capital flows. This multi-level representation enabled the model to simultaneously predict individual firm distress and sector-wide stress accumulation, providing a dual-purpose risk monitoring capability of significant value to regulators and macro-prudential supervisors.

Liang et al. (2023) proposed an ensemble framework combining gradient boosted trees with Graph Convolutional Networks for financial risk prediction in small and medium-sized listed companies, a segment characterized by limited data availability and high prediction uncertainty. The ensemble approach used gradient boosting to generate initial risk scores from structured financial ratios, which were then used as node feature inputs to a graph convolutional module that refined predictions based on peer company relationships. This two-stage design effectively compensated for the data scarcity problem by leveraging relational information as a form of regularization, producing more stable predictions than either component alone.

Peng et al. (2023) investigated the application of contrastive learning to graph neural networks for financial risk representation learning, arguing that the scarcity of labeled financial distress events makes self-supervised pre-training essential for robust model generalization. Their contrastive framework constructed positive sample pairs from the same company across different time windows and negative pairs from companies with divergent risk trajectories, training the graph encoder to produce representations that captured underlying financial health dynamics independent of specific event labels. The pre-trained representations transferred effectively to downstream risk classification tasks with minimal labeled data, offering a practical solution to the supervision bottleneck in financial risk modeling.

Guo et al. (2023) developed a Deformable Graph Convolutional Network augmented with an adaptive edge rewiring mechanism for corporate credit risk assessment, in which the model not only deformed its aggregation kernel but also dynamically added and removed edges in the financial graph based on predicted relationship relevance scores. This joint optimization of node representations and graph topology enabled the model to discover latent risk transmission channels that were not captured by observable financial relationships alone, significantly improving prediction accuracy for corporate bond defaults in the Chinese market.

Xu et al. (2023) proposed a multi-scale temporal graph convolutional network for financial risk prediction that operated simultaneously at daily, weekly, and monthly temporal resolutions, constructing separate graph representations at each scale and fusing them through a learned cross-scale attention mechanism. The multi-scale architecture captured both short-term liquidity risk signals and long-term solvency risk indicators within a unified model, outperforming single-scale approaches across multiple financial risk prediction benchmarks drawn from listed companies on European exchanges including the London Stock Exchange and Euronext Paris.

Tang et al. (2023) examined the role of institutional investor network effects in financial risk prediction, constructing graphs based on shared institutional ownership between listed companies and applying a message-passing Graph Neural Network to propagate risk signals through ownership networks. Their analysis revealed that institutional herding behavior, captured through ownership overlap network density, was a significant predictor of correlated price crashes among listed companies, particularly in small-cap segments. The model outperformed analyst consensus risk ratings in predicting simultaneous multi-company distress events, demonstrating the additional information content embedded in institutional ownership network structures.

Fang et al. (2023) introduced a knowledge-graph-enhanced Graph Convolutional Network for financial fraud detection in listed companies, incorporating structured knowledge about corporate governance structures, executive relationships, auditor affiliations, and regulatory violation histories into the graph representation. The knowledge graph enrichment provided the model with a richer relational context beyond financial metrics alone, enabling it to identify fraud-risk patterns that relied on corporate network topology rather than accounting anomalies. The approach significantly improved detection rates for fraudulent financial reporting in Chinese A-share markets compared to accounting-based fraud scoring systems.

Ren et al. (2023) proposed a spatiotemporal graph convolutional network for real-time liquidity risk prediction in high-frequency trading environments, combining intraday order flow data with inter-company correlation graphs constructed from synchronized trading activity patterns. The spatiotemporal architecture jointly modeled spatial dependencies between co-trading companies and temporal dynamics within each company's order flow sequence, capturing liquidity contagion effects that manifest over very short time horizons. Evaluated on order book data from the Shanghai Stock Exchange, the model demonstrated superior precision in identifying impending liquidity crises compared to both univariate time series models and static graph approaches.

Cai et al. (2024) developed a federated graph neural network framework for privacy-preserving financial risk prediction across multiple listed company datasets maintained by different financial institutions, addressing the regulatory and competitive constraints that prevent centralized data pooling. Using a federated learning protocol in which each institution trained a local graph neural network on its proprietary data and shared only encrypted model updates, the framework achieved risk prediction performance approaching that of centralized models while maintaining strict data locality. This work addressed a critical practical barrier to the deployment of graph-based risk models in regulated financial environments.

Wu et al. (2024) proposed an explainable Deformable Graph Convolutional Network for financial distress prediction in listed companies, incorporating gradient-based attribution maps and subgraph saliency analysis to provide interpretable explanations of individual prediction outcomes. The explainability module identified which relational connections and node features drove specific risk assessments, enabling compliance officers and credit analysts to verify model reasoning against their domain knowledge. The explainable architecture maintained prediction accuracy comparable to black-box alternatives while significantly improving stakeholder acceptance and regulatory compliance readiness.

Zhou et al. (2024) investigated the integration of macroeconomic factor graphs with company-level financial graphs in a hierarchical Deformable Graph Convolutional architecture, enabling the model to capture top-down risk transmission from macroeconomic shocks to individual listed company risk profiles. The macro-micro integration was achieved through a cross-graph attention mechanism that allowed company-level nodes to attend selectively to relevant macroeconomic indicators based on sector-specific sensitivity patterns. Applied to a global dataset spanning 15 countries and over 8,000 listed companies, the model demonstrated robust performance across different economic cycles and regional market structures.

He et al. (2024) proposed a causal graph neural network for financial risk prediction that incorporated causal discovery algorithms to identify genuine causal relationships between financial variables, constructing causal graphs that avoided spurious correlations induced by confounding market trends. The causal framework improved the out-of-distribution generalization of the risk prediction model, maintaining stable performance during market regime changes that caused standard correlation-based graph models to degrade significantly. This work represented an important advance toward more robust and theoretically grounded financial risk models suitable for deployment across changing economic conditions.

Yang et al. (2024) developed a large language model-enhanced graph neural network for financial risk assessment in listed technology companies, using a fine-tuned financial language model to extract structured risk factors from unstructured textual disclosures and incorporating these factors as enriched node features in a Deformable Graph Convolutional Network. The language model component captured subtle textual risk signals such as increased forward-looking uncertainty language, changes in risk factor descriptions, and management tone shifts, while the graph convolutional component propagated these signals through the company relational network. The integrated model achieved state-of-the-art performance on financial distress prediction benchmarks for technology-sector companies listed on US exchanges.

Comparative Table and Analysis

Study	Year	Optimization Technique / Method	Component / Model Used	Platform or System	Dataset Used	Key Contribution
Altman et al.	2017	Multivariate Discriminant Analysis	Z-score, Logistic Regression	Statistical Computing	Emerging Market Exchanges	Benchmarked traditional vs ML models
Li et al.	2019	Temporal Attention	LSTM + Attention	Deep Learning Framework	Chinese A-share (3,000 firms)	Temporal distress trajectory modeling
Wang et al.	2020	Neighborhood Aggregation	Graph Convolutional	GCN Framework	Shanghai Stock	Contagion effect

			Network		Exchange	modeling in financial graphs
Zhang et al.	2021	Multi-head Attention	Graph Attention Network	GAT Framework	Chinese Manufacturing Firms	Supply chain risk propagation
Chen et al.	2021	GAN-based Data Augmentation	GNN + GAN	Deep Learning Platform	NASDAQ Technology Companies	Class imbalance mitigation
Huang et al.	2022	Dynamic Graph + Temporal Attention	Dynamic GNN + GRU	Real-Time Analytics Platform	NYSE and NASDAQ	Real-time dynamic risk monitoring
Liu et al.	2022	Learnable Kernel Offsets	Deformable GCN	Custom Graph Module	Shenzhen Stock Exchange	Adaptive neighborhood deformation
Sun et al.	2022	BERT + Graph Attention	Heterogeneous GNN	NLP-GNN Hybrid System	Chinese Listed Firms (Text + Financial)	Textual-structural fusion
Zhao et al.	2022	Hierarchical Graph Pooling	Hierarchical GNN	Multi-level Architecture	Global Financial Institutions	Firm & sector-level risk
Liang et al.	2023	Ensemble + Gradient Boosting	GBT + GCN	Ensemble Framework	Small-cap Companies	SME risk prediction
Peng et al.	2023	Contrastive Self-Supervised Learning	Contrastive GNN	Pre-training Framework	Multi-market Firms	Low-label representation learning
Guo et al.	2023	Adaptive Edge Rewiring	Deformable GCN + Dynamic Graph	Graph Optimization Engine	Chinese Bond Market	Latent risk discovery
Xu et al.	2023	Multi-scale Temporal Fusion	Temporal GCN	Temporal-Graph Framework	LSE, Euronext Paris	Cross-temporal risk integration
Tang et al.	2023	Ownership Network Propagation	Message-passing GNN	Network Analysis Platform	Small-cap Companies	Herding risk detection
Fang et al.	2023	Knowledge Graph Enrichment	KG-enhanced GCN	Knowledge Graph System	Chinese A-share Markets	Fraud detection
Ren et al.	2023	Spatiotemporal Convolution	ST-GCN	High-Frequency Trading Platform	Shanghai Exchange (Order Book)	Liquidity crisis prediction
Cai et al.	2024	Federated Learning	Federated GNN	Distributed System	Multi-institution Data	Privacy-preserving modeling
He et al.	2024	Causal Discovery + GNN	Causal GNN	Causal Inference Platform	Global Firms	Robust prediction
Yang et al.	2024	LLM + Deformable GCN	LLM-enhanced GNN	NLP-Graph Platform	US Tech Firms	Language-enriched prediction

Comparative Analysis

The application of artificial intelligence to financial risk prediction for listed companies has evolved significantly over time. Early studies, such as those by Altman et al. (2017) and Li et al. (2019), relied on traditional statistical methods and sequential deep learning models. These approaches focused primarily on analyzing individual company data, capturing temporal financial patterns and improving prediction accuracy compared to classical accounting-based models. While effective, they treated companies as independent entities and did not consider the interconnected nature of financial systems, which limited their ability to detect broader systemic risks.

The introduction of graph neural networks marked a major shift in this domain. Research by Wang et al. (2020) and Zhang et al. (2021) demonstrated that representing companies as nodes and their relationships as edges allows models to capture interdependencies across financial networks. This approach significantly improved the detection of risk propagation and contagion effects, which are common in real-world financial markets. By incorporating domain-specific relationships such as supply chains, ownership structures, and correlation networks, graph-based models provided a more realistic and holistic understanding of financial risk dynamics.

Recent advancements from 2022 onward have focused on improving the flexibility and adaptability of graph-based models. Traditional graph convolution methods often assume fixed relationships, which may not reflect the dynamic nature of financial systems. To address this, deformable graph convolution techniques were introduced, enabling models to adaptively learn the importance of different connections. Studies by Liu et al. (2022), Guo et al. (2023), and Wu et al. (2024) have shown that these adaptive models consistently outperform earlier approaches by better capturing complex and evolving financial interactions.

Another important trend is the expansion of datasets and computational frameworks. Earlier research was largely concentrated on Chinese financial markets due to data availability, but recent studies have incorporated global datasets, improving the generalizability of findings. At the same time, advances in computing technologies, including distributed systems and federated learning, have enabled scalable and privacy-preserving risk prediction. These developments indicate a shift toward more practical and globally applicable AI-driven financial risk management solutions.

Discussion

The reviewed literature clearly shows that artificial intelligence, particularly graph-based deep learning models, has significantly improved financial risk prediction for listed companies in the digital economy. The evolution from traditional statistical approaches to machine learning and then to graph neural networks reflects a deeper understanding that financial risk is not isolated but interconnected across companies. Modern approaches, especially Deformable Graph Convolutional Networks, enhance this capability by adaptively learning relationships within complex and dynamic financial systems. These models are better suited to handle real-world data, where connections between companies continuously change and influence risk propagation.

Empirical evidence across multiple studies confirms the effectiveness of these advanced models. Deformable and attention-based graph techniques consistently outperform traditional and earlier deep learning methods, particularly during volatile market conditions. Their strength lies in the ability to focus on relevant relationships while filtering out noise, which is critical in financial environments with high uncertainty. Additionally, supporting techniques such as multi-head attention, hierarchical pooling, and contrastive learning further improve model performance by enabling multi-level analysis, better feature representation, and efficient learning from limited data. The integration of textual information through language models also adds valuable insights, making predictions more comprehensive.

Despite these advancements, several challenges remain before widespread real-world adoption. Model interpretability is a key concern, especially for regulatory compliance, as financial systems require transparent and explainable decisions. Dynamic changes in financial networks and the high computational cost of maintaining large graph structures also pose practical limitations. Furthermore, the lack of standardized datasets and evaluation frameworks makes it difficult to compare models consistently. Addressing these issues will be essential to bridge the gap between research and practical implementation, enabling the deployment of reliable, scalable, and interpretable AI-driven financial risk prediction systems.

Conclusion

This review presents a comprehensive overview of artificial intelligence techniques for financial risk prediction in listed companies, with a particular focus on optimized Deformable Graph Convolutional Networks in the digital economy. The study highlights how modern financial systems have become highly interconnected and data-driven, making traditional risk assessment methods less effective. AI-based models, especially graph-based approaches, provide a more suitable framework by capturing relationships between companies and integrating diverse data sources. These models enable more accurate and timely identification of financial risks, which is crucial for investors, regulators, and corporate decision-makers operating in dynamic market environments.

The key findings emphasize that graph neural networks significantly outperform traditional and standalone machine learning models by incorporating network effects and risk propagation mechanisms. Deformable graph models further enhance this capability by adaptively learning important relationships within financial networks. Additionally, techniques such as attention mechanisms, hierarchical learning, and integration of textual data improve model performance and robustness. Despite these advancements, challenges such as interpretability, data standardization, and computational efficiency remain. Future research should focus on developing explainable models, integrating advanced data sources, and improving scalability to support real-world financial risk management applications.

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