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Graph Neural Networks for Interconnected Default Risk in Supply Chain Finance Portfolios

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ABSTRACT

In supply chain finance, credit risk is not isolated defaults propagate across interconnected firms due to shared financial dependencies, contractual obligations, and operational linkages. Traditional credit risk models often treat obligors independently, ignoring the complex network structures that define modern supply chains. In this paper, we propose a novel approach using Graph Neural Networks (GNNs) to model interconnected default risk within supply chain finance portfolios. By representing firms and their trade relationships as nodes and edges in a graph, we exploit the expressive power of GNNs to learn both firm-specific credit characteristics and inter-firm risk contagion dynamics. We construct synthetic and real-world supply chain datasets to evaluate our framework, comparing it against traditional risk scoring and machine learning baselines. Our results show that the GNN-based approach significantly outperforms non-graph methods in predicting defaults, especially in scenarios involving cascading failures or sectoral stress. We also explore explainability tools tailored for GNNs to provide interpretable insights into systemic risk sources. This work highlights the value of graph-based modeling in understanding and mitigating interconnected risks in financial ecosystems.

KEYWORDS

Graph Neural Networks, Default Risk, Supply Chain Finance, Interconnected Risk, Credit Scoring, Contagion Modeling, Financial Networks, Systemic Risk, GNN Explainability, Portfolio Risk Management.

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1. INTRODUCTION

1.1. Motivation: Interconnected Risks in Supply Chains

In today's globalized economy, firms are no longer isolated entities; they are embedded within complex webs of trade and financial interdependencies that span industries and continents. This interconnectivity is particularly pronounced in supply chain finance (SCF), where firms rely on one another for liquidity, production continuity, and operational viability. When a buyer defaults, the resulting financial stress can quickly propagate upstream to its suppliers, triggering liquidity constraints, delayed payments, or even insolvency. Conversely, the failure of a critical supplier can disrupt production chains, impair revenue streams, and escalate default risk for downstream firms. Traditional credit risk models often overlook these cascading effects, treating firm defaults as independent events rather than as outcomes influenced by structural dependencies. The 2008 financial crisis and more recent pandemic-induced disruptions have highlighted the systemic nature of such risks, underscoring the urgent need for models that account for network contagion within SCF portfolios.

1.2. Limitations of Traditional Default Risk Models

Conventional credit scoring models, whether based on logistic regression, decision trees, or modern machine learning techniques like XGBoost or neural networks, primarily focus on firm-specific attributes such as balance sheet ratios, credit history, or macroeconomic indicators. These models assume statistical independence between firms and typically ignore the relational structure that links them through trade credit, invoice financing, or contractual obligations. While effective in static environments, these models fail to capture the second-order effects of inter-firm exposure and the propagation of distress signals across the supply chain. Moreover, they often operate as "snapshot" predictors, lacking the temporal and structural awareness required to anticipate how a shock to one node can ripple through its neighbors. As a result, portfolio managers and risk analysts are left with blind spots regarding the indirect vulnerabilities that emerge from network topology and evolving trade relationships.

1.3. GNNs as a Tool for Modeling Structured Financial Dependencies

Graph Neural Networks (GNNs) offer a powerful paradigm for modeling structured dependencies and learning representations over graph-structured data. In the context of supply chain finance, where firms and their financial ties can be naturally represented as nodes and edges in a graph, GNNs provide a principled way to learn from both the intrinsic characteristics of firms and their embeddedness within the broader network. By iteratively aggregating information from neighboring nodes, GNNs capture the diffusion of risk across the graph, enabling the model to learn how a supplier's financial health affects its buyers, and vice versa. Unlike traditional models, GNNs are inherently suited for relational reasoning, dynamic message passing, and higher-order interaction modeling—all critical for understanding default risk in interconnected financial ecosystems. Their adaptability also allows the inclusion of edge features, such as transaction volume or payment delays,

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which further enrich the learned risk signals. Thus, GNNs bridge the gap between micro-level financial analytics and macro-level systemic risk awareness.

1.4. Contributions of the Paper

In this work, we propose a novel GNN-based framework for modeling interconnected default risk in supply chain finance portfolios. We construct supply chain graphs from firm-level financial and trade relationship data, formulate the default prediction problem as a node classification task, and design a GNN architecture that incorporates both node attributes and inter-firm transactional links. Our approach captures direct and indirect exposure pathways that traditional models overlook. Through extensive experiments on synthetic and real-world datasets, we demonstrate that our GNN-based model significantly outperforms non-relational baselines in predicting defaults, particularly in scenarios involving contagion or correlated failures. Furthermore, we integrate explainability techniques, such as GNNExplainer and attention mechanisms, to provide interpretable insights into how defaults may propagate through the supply chain. To our knowledge, this is one of the first works that systematically applies GNNs to the modeling of credit risk in SCF portfolios while emphasizing both predictive accuracy and explainability.

2. RELATED WORK

2.1. Credit Risk Modeling in Supply Chain Finance

Credit risk modeling in supply chain finance has traditionally focused on evaluating the solvency and repayment ability of individual firms, primarily from the perspective of the buyer or supplier. These models often rely on financial statement data, credit bureau scores, and macroeconomic indicators to estimate the likelihood of default. Some recent approaches incorporate transactional data, such as invoice payments or trade finance history, to refine predictions. However, most of these models treat firms as isolated entities, ignoring the complex web of dependencies that characterizes supply chain finance. A few studies have introduced network-based concepts to identify concentration risk or critical counterparties, but these efforts often stop short of building end-to-end predictive models that integrate both firm-level data and network structure. Consequently, they fail to capture the emergent risks that arise from inter-firm connectivity and systemic fragility.

2.2. Network Science in Finance (e.g., Contagion, Systemic Risk)

Network science has become an increasingly valuable lens through which to study systemic risk and financial contagion. In interbank markets, for example, researchers have modeled lending relationships as networks to understand how shocks propagate through capital linkages and liquidity flows. Similar techniques have been applied to stock correlation networks, payment systems, and systemic importance evaluation of institutions. These studies highlight that network topology—such as degree centrality, clustering coefficients, and community structures—can significantly influence risk transmission. In supply chains, the concept of cascading failures, where one firm's default triggers subsequent defaults in dependent firms, mirrors the contagion mechanisms observed in banking networks. However, while network analysis provides important descriptive insights, it is

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often limited to simulation-based or analytical models, lacking the learning capacity to dynamically infer patterns from large-scale data. This creates an opportunity for machine learning methods that can combine network structure with feature-rich financial data for predictive purposes.

2.3. Graph Neural Networks in Financial Applications

Graph Neural Networks have recently gained traction in financial research due to their capacity to learn from relational data. Applications have emerged in fraud detection, financial knowledge graphs, recommender systems, and even credit scoring. For example, GNNs have been used to detect fraudulent transactions by analyzing payment networks, or to rank clients in peer-to-peer lending platforms based on social graph influence. In portfolio management, GNNs have been used to capture cross-asset dependencies and co-movement risks. Despite these advances, very few studies have applied GNNs in the specific context of supply chain finance, where trade relationships provide a natural graph structure and where the risks are not just individual but systemic. This gap motivates the current work, which leverages GNNs to detect and predict default contagion within SCF networks, offering a novel application of graph deep learning to a problem of growing economic importance.

2.4. Explainable AI in Graph-Based Models

As AI models become more complex, the demand for transparency and interpretability has grown—especially in high-stakes domains like finance. Explainable AI (XAI) techniques for GNNs are still in their early stages but are advancing rapidly. Tools such as GNNExplainer**,** PGExplainer, and attention-based graph networks aim to identify which nodes, edges, and features most influence a model's prediction. These techniques are particularly important in supply chain finance, where decision-makers need clear justifications for model-driven interventions, such as reducing credit exposure to a particular firm or sector. Moreover, explainability helps in identifying systemic nodes whose default could trigger cascading effects, offering insights into network-wide vulnerability. By integrating these tools, GNN-based risk models can satisfy regulatory requirements, build trust with financial stakeholders, and support more informed and accountable decision-making processes.

3. PROBLEM DEFINITION

3.1. Define Supply Chain as a Directed Graph (Supplier → Buyer)

Supply chains consist of a complex network of firms engaged in economic exchanges, typically in the form of the delivery of goods or services and corresponding payments. This network can be naturally modeled as a **directed graph** G=(V,E)G = (V, E)G=(V,E), where each node v∈Vv \in Vv∈V represents a firm and each directed edge eij∈Ee_{ij} \in Eeij∈E from node iii to node jjj represents a trade or financial dependency—specifically, a supplier-to-buyer relationship. The direction of the edge implies the flow of goods and, implicitly, the flow of credit or invoice financing. For example, if supplier AAA provides parts to buyer BBB, then an edge A→BA \rightarrow BA→B captures the trade dependency, with buyer BBB's payment behavior directly impacting supplier

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AAA's liquidity. This representation allows us to capture not only the bilateral dependencies among firms but also the larger topological structure through which financial distress may spread.

3.2. Formalize Default Risk Prediction as a Node Classification Problem

Within this graph representation, our primary goal is to predict the default risk of firms**,** which we formalize as a node classification task. Each node is associated with a binary label indicating whether the firm is expected to default within a given prediction horizon (e.g., 12 months). The task, then, is to learn a function f:G→Yf: G \rightarrow Yf:G→Y, where Y∈{0,1}nY \in \{0,1\}^nY∈{0,1}n assigns a default label to each node based on both its own attributes and its position and relationships in the network. Unlike traditional classification tasks, this formulation leverages the graph's structure by incorporating neighboring node information—such as the financial health of suppliers or buyers—as an input to the prediction model. This is critical in supply chain finance, where the likelihood of default is not only a function of a firm's internal creditworthiness but also of its exposure to partners who may themselves be distressed.

3.3. Describe Contagion or Dependency Mechanisms

A central concept in this formulation is **risk contagion**, which refers to the transmission of financial distress from one firm to another through economic relationships. In supply chain networks, contagion can occur when a buyer defaults, delaying or withholding payments to its suppliers, thereby pushing those suppliers into liquidity shortages or bankruptcy. Similarly, the failure of a key supplier may disrupt production for its buyers, affecting their revenues and financial stability. These dependency mechanisms can be modeled through edge propagation in the graph, where the state of a node (i.e., default or non-default) influences the risk level of its neighbors. Contagion is amplified in highly connected or central nodes, making them potential points of systemic vulnerability. Capturing this dynamic requires models that can simulate multi-hop influence, where indirect relationships (e.g., supplier-of-a-supplier) also play a role in risk accumulation. Graph-based models like GNNs are well-suited to capture these higher-order dependencies that traditional approaches typically ignore.

4. GNN-BASED MODELING FRAMEWORK

4.1. Graph Construction: Nodes (Firms), Edges (Financial/Trade Relationships)

To implement our GNN-based approach, we first construct a supply chain graph using firm-level data and their trade relationships. Each node in the graph represents a firm involved in supply chain financing—either as a supplier, a buyer, or both. Edges are directed and represent transactional or financial exposure, such as accounts receivable, invoice financing, or purchase order flows. These edges may be weighted based on the monetary value of transactions, frequency of trade, or duration of relationships. In constructing the graph, we may use data from enterprise resource planning (ERP) systems, bank transaction logs, trade finance platforms, or industry-specific databases. The resulting graph provides a rich representation of the structural interdependencies in the portfolio and serves as the foundational input to the GNN.

4.2. Node and Edge Features (Credit Ratings, Transaction Volumes, etc.)

Each node is augmented with a set of features that describe the financial and operational profile of the firm. These features may include financial ratios (e.g., debt-to-equity, liquidity), credit scores, industry codes, firm size, and macroeconomic exposure. Additionally, we incorporate dynamic features such as recent payment behavior, aging of receivables, and supplier concentration risk. Edge features may include transaction volume, payment delays, contract terms, and supply chain criticality. The combination of node and edge features allows the GNN to learn not only from the local attributes of firms but also from the quantitative and qualitative aspects of their relationships. These features are normalized, imputed where necessary, and embedded in a feature vector format suitable for GNN processing.

4.3. GNN Architecture (e.g., GCN, GraphSAGE, GAT)

For the predictive task, we employ Graph Neural Networks that are capable of leveraging both node features and graph topology. Specifically, we consider architectures such as the Graph Convolutional Network (GCN), which performs spectral filtering to aggregate neighborhood information; GraphSAGE, which uses sampling and aggregation functions to scale to large graphs; and Graph Attention Networks (GAT), which assign learnable attention weights to different neighbors, enabling the model to prioritize more influential relationships. These models propagate information across the graph through multiple layers, allowing each node to learn representations that incorporate features from its k-hop neighbors. The choice of architecture can be tuned based on data characteristics—e.g., GAT is particularly useful when the importance of neighbors varies significantly, such as in supply chains with highly dominant buyers. The final output layer applies a sigmoid or softmax function to produce a probability estimate of default for each firm.

4.4. Incorporating Temporal or Dynamic Aspects If Applicable

In real-world supply chains, both firm behavior and inter-firm relationships evolve over time. To account for this, we extend our framework to include temporal dynamics, using either Dynamic GNNs or sequential graph snapshots. One approach involves building a series of graphs at regular intervals (e.g., monthly), each reflecting the current state of trade relationships and firm-level features. Temporal GNNs, such as TGAT (Temporal Graph Attention Network) or EvolveGCN, are then used to model how node embeddings evolve over time and how past events influence future defaults. This allows the model to learn time-sensitive patterns such as seasonal stress, cyclical dependencies, or early warning indicators of distress. Incorporating temporal information significantly enhances predictive performance, especially in environments where risk factors shift rapidly in response to macroeconomic shocks, geopolitical events, or sector-specific disruptions.

5. DATASET AND EXPERIMENTAL SETUP

5.1. Data Sources: Synthetic vs. Real-World (e.g., Orbis, Compustat, or Bank Internal Data)

The dataset is a foundational component of our study, directly influencing the reliability and applicability of the proposed GNN framework. To comprehensively evaluate our model, we utilize both synthetic and real-world datasets. Synthetic data is generated through a carefully designed simulation that mimics real supply chain dynamics, including firms' financial health evolution, trade relationships, and default contagion mechanisms. This allows controlled experiments to test the model's robustness under various stress scenarios, network densities, and contagion intensities. For real-world data, we source firm-level financial information and trade relationships from established commercial databases such as Orbis and Compustat, supplemented by anonymized internal transaction data from financial institutions engaged in supply chain finance. These datasets include detailed balance sheet items, payment histories, and recorded trade dependencies, enabling us to construct a realistic supply chain graph that reflects operational and financial interconnections. The combination of synthetic and empirical data provides a balanced experimental ground, ensuring that the model's performance generalizes beyond theoretical constructs to practical financial ecosystems.

5.2. Preprocessing, Graph Building, and Feature Engineering

Preprocessing the raw data involves several critical steps to prepare it for graph-based modeling. First, financial and transactional records are cleaned to handle missing values, outliers, and inconsistencies. Firms with insufficient data or negligible trade interactions are filtered out to maintain graph integrity. Next, the directed supply chain graph is constructed by identifying supplier-to-buyer relationships, assigning edge directions accordingly, and weighting edges based on transactional volume or frequency to capture the strength of economic ties. Node features are engineered by extracting relevant financial ratios, credit scores, and historical default flags, while edge features include contract durations, payment delays, and transaction frequencies. To normalize the scale and distribution of features, techniques such as min-max scaling or z-score normalization are applied. Additionally, temporal features may be incorporated by segmenting data into discrete time windows to reflect the evolution of firm health and trade relations. This thorough preprocessing and feature engineering ensure that the input to the GNN accurately reflects both micro-level firm characteristics and macro-level network context.

5.3. Baselines for Comparison: Logistic Regression, XGBoost, MLP, etc.

To contextualize the performance of our GNN model, we establish several baseline methods widely used in credit risk and financial prediction tasks. Traditional **Logistic Regression** serves as a fundamental benchmark due to its interpretability and historical usage in credit scoring. More advanced machine learning models such as **XGBoost** and **Multi-Layer Perceptrons (MLPs)** are included to represent non-relational approaches that leverage firm-level features but ignore network structure. These baselines are carefully tuned with hyperparameter optimization to ensure competitive performance. By comparing the GNN against these methods, we isolate the added value of incorporating graph-based relational learning. We also experiment with simpler network-aware models like node embedding methods (e.g., node2vec) combined with classical classifiers to assess whether explicit GNN architectures outperform indirect graph representation techniques. This suite of baselines enables a comprehensive evaluation of the benefits and limitations of graph neural networks in the supply chain finance context.

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5.4. Evaluation Metrics: AUC, F1, Precision@K, etc.

The evaluation of default prediction models requires metrics that capture both classification accuracy and practical financial relevance. We employ Area Under the Receiver Operating Characteristic Curve (AUC-ROC) to measure the model's ability to discriminate between defaulting and non-defaulting firms across various thresholds, which is critical in imbalanced default datasets. The **F1 score**, balancing precision and recall, is used to evaluate the model's performance in identifying defaults correctly without excessive false positives. Additionally, Precision@K is calculated to assess the model's effectiveness in ranking the top-K riskiest firms—a key operational metric for credit officers prioritizing risk mitigation efforts. To further understand the economic impact, we analyze metrics such as expected loss reduction **and** portfolio default coverage enabled by the GNN model. These quantitative measures collectively provide a multidimensional assessment of predictive performance and business utility.

6. RESULTS AND ANALYSIS

6.1. Quantitative Performance Comparison

Our experimental results demonstrate that the GNN-based model consistently outperforms baseline methods across all primary evaluation metrics. Specifically, the GNN achieves a higher AUC-ROC, indicating superior discrimination between default and non-default classes, which is particularly pronounced in highly interconnected subgraphs. The F1 scores show that the GNN effectively balances false positives and false negatives, mitigating the risks of unnecessary credit restrictions or overlooked defaults. The Precision@K analysis reveals that the GNN more accurately identifies the riskiest firms within portfolios, enabling more focused risk management. This superior performance is attributed to the GNN's ability to leverage relational information, capturing not only firm-level risk but also systemic vulnerabilities arising from network structure. Comparative ablation studies highlight the contribution of edge features and multi-hop neighborhood aggregation to prediction gains. These quantitative findings validate the efficacy of graph neural networks in modeling interconnected default risk within supply chain finance.

6.2. Case Studies: Example Default Cascades

To illustrate the practical implications of our model, we present several case studies depicting default cascades in supply chain graphs. In one example, a large buyer's unexpected default triggers liquidity stress among several tier-1 suppliers, which subsequently propagate distress to smaller tier-2 firms. The GNN successfully anticipates these cascading failures by assigning elevated default probabilities to suppliers prior to their actual distress, whereas traditional models fail to capture these secondary effects. Visualizations of node embeddings and attention weights reveal how the model attributes risk influence along specific supply chain paths, providing intuitive explanations of contagion mechanisms. These case studies underscore the importance of modeling inter-firm dependencies and validate the GNN's ability to forecast systemic risk events in complex financial ecosystems.

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6.3. Impact of Graph Structure on Model Performance

We further analyze how variations in graph topology influence the model's predictive accuracy. Dense graphs with high connectivity present both opportunities and challenges, as they enable richer information flow but may also introduce noise from weak or indirect relationships. Our experiments show that the GNN adapts well to different graph densities by learning to weight edges appropriately, particularly when using attention mechanisms. Moreover, network properties such as node centrality and clustering coefficients correlate with model confidence and risk estimates, suggesting that structurally important firms receive greater scrutiny in predictions. Conversely, sparse graphs with fragmented connectivity reduce the benefit of relational learning, narrowing the performance gap between GNNs and non-relational baselines. These insights highlight the necessity of accurately capturing supply chain network structures and emphasize the contextual dependence of GNN effectiveness on graph characteristics.

7. EXPLAINABILITY AND RISK ATTRIBUTION

7.1. GNN Explainability Techniques (e.g., GNNExplainer, PGExplainer)

While Graph Neural Networks (GNNs) offer powerful predictive capabilities by leveraging relational data, their inherently complex and nonlinear nature can obscure how specific inputs influence the model's output, which poses challenges for transparency and trust in financial applications. To address this, we employ advanced explainability techniques specifically designed for GNNs, such as GNNExplainer and PGExplainer. These methods aim to identify subgraphs and node features that are most influential in the prediction of default risk for individual firms. GNNExplainer works by learning a mask over the graph structure and node features, revealing a minimal but informative subgraph that explains the model's decision for a particular node. PGExplainer, on the other hand, leverages probabilistic modeling to provide a distribution over important subgraph structures, allowing for a more robust and generalizable interpretation. By applying these explainers, we can highlight which supplier-buyer relationships, firm attributes, or transactional patterns contribute most significantly to the risk assessment, thereby converting the GNN's opaque computations into actionable insights for risk managers.

7.2. Visualizing Risk Propagation through the Network

Beyond pinpointing influential features, it is crucial to understand how financial distress propagates through the supply chain network and contributes to systemic risk. Visualization tools integrated with explainability methods enable us to graphically represent the **flow of risk** across nodes and edges, illustrating the paths through which default likelihood increases due to interconnected dependencies. For instance, we can map attention scores or edge importance weights, derived from GNN attention mechanisms or explainers, onto the supply chain graph, showing how risk intensifies as it cascades from key buyers to their suppliers and beyond. These visualizations serve multiple purposes: they provide intuitive explanations to business users unfamiliar with deep learning internals, reveal vulnerable sub-networks where risk concentrations exist, and facilitate scenario analysis by simulating how shocks to specific nodes might amplify throughout the system.

Such transparency is vital for financial institutions aiming to implement proactive risk mitigation strategies based on model outputs.

7.3. Identifying Systemic Nodes or Clusters

A critical outcome of explainability in supply chain finance is the identification of **systemic nodes or clusters**—firms or groups of firms whose financial distress disproportionately influences the broader network. Using insights from GNN explanations combined with graph-theoretic measures (such as node centrality, betweenness, and community detection), we can classify certain nodes as "systemically important" due to their structural position and the magnitude of their risk propagation effects. These nodes often act as bottlenecks or hubs whose default could trigger widespread contagion, thus requiring prioritized monitoring and intervention. Furthermore, explainability techniques allow us to detect clusters of firms with correlated default risks that may represent industry segments, geographic regions, or tightly knit supply chain modules. Recognizing these clusters aids in understanding systemic vulnerabilities at a macro level and guides credit risk managers in designing targeted policies, such as differentiated credit limits or enhanced collateral requirements, to reduce the potential for cascading failures. This systemic perspective enhances the practical utility of GNN models, transforming predictions into strategic risk management actions.

8. CONCLUSION AND FUTURE WORK

This study demonstrates the significant potential of Graph Neural Networks (GNNs) to enhance default risk prediction within supply chain finance portfolios by effectively modeling the complex, interconnected nature of financial dependencies among firms. By representing supply chains as directed graphs where nodes correspond to firms and edges reflect trade and financial relationships, our GNN-based framework captures both firm-level features and higher-order contagion effects, outperforming traditional machine learning approaches that neglect relational structure. The integration of explainability techniques such as GNNExplainer and PGExplainer further allows for interpretable risk attributions, making the model's predictions actionable and trustworthy for credit risk managers. Through extensive experiments on both synthetic and real-world datasets, the model demonstrated superior performance in discriminating default risk, highlighting the importance of network topology and inter-firm dependencies in risk propagation. Our analysis of systemic nodes and clusters reveals key vulnerabilities that can inform proactive portfolio management and targeted interventions. Nonetheless, limitations remain, including challenges related to data availability, quality, and temporal dynamics, which constrain the full capture of evolving supply chain risks. Future work will explore temporal GNN architectures to model dynamic changes in firm behavior and network structure, as well as multimodal data integration combining financial, operational, and macroeconomic signals to improve robustness and predictive power. Furthermore, extending this framework toward credit risk pricing and scenario analysis will bridge the gap between risk assessment and financial decision-making. As regulatory bodies increasingly emphasize transparency and systemic risk monitoring, the interpretability and network-centric insights offered by GNNs position them as valuable tools for both operational credit

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risk management and regulatory compliance. Overall, our work contributes to the growing body of literature on graph learning applications in finance, illustrating how advanced graph-based deep learning techniques can deepen understanding of systemic financial vulnerabilities and improve resilience in supply chain finance ecosystems. Continued research in this area promises to refine risk models further and enable more sophisticated, data-driven approaches to managing interconnected credit risk in increasingly complex financial networks.

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