



# Supply Chain Credit Risk Propagation Modeling Through Heterogeneous Graph Learning and Enterprise Relation Inference

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## ABSTRACT

Supply chain finance involves complex credit relationships among core enterprises, upstream suppliers, downstream distributors, logistics providers, and financial institutions. Traditional risk assessment models often rely on isolated financial indicators and fail to capture risk propagation caused by delayed payments, guarantee chains, ownership ties, and transaction dependency. This study proposes a heterogeneous graph learning method for supply chain credit risk propagation modeling. The method constructs an enterprise relation graph using procurement records, invoice flows, payment delays, equity links, guarantee relationships, and litigation events. A graph neural network is used to encode structural dependencies among enterprises, while a knowledge inference module identifies hidden risk paths between financially connected firms. Experiments are conducted on a supply chain finance dataset containing 86,000 enterprises, 1.42 million transaction edges, 318,000 invoice records, 74,000 guarantee links, and 21,600 risk event labels collected over 36 months. The proposed method reduces median early-warning delay from 63 days to 24 days compared with a financial-ratio scoring baseline. The top-decile risk queue captures 3,940 confirmed delayed-payment and credit-deterioration cases during the test period. Graph inference identifies 12,700 indirect risk propagation paths, including supplier concentration risk, cross-guarantee exposure, and delayed receivable chains. The model also reduces manual review volume from 18,400 enterprise alerts to 5,260 relation-level investigation cases through risk-path aggregation. The results show that heterogeneous graph learning and relation inference can improve supply chain credit risk prediction by incorporating both enterprise attributes and network-level risk transmission.

## 1. Introduction

Supply chain finance has become an important mechanism for improving working-capital availability by converting commercial relationships and transaction assets into financing opportunities. Through close interactions among core enterprises, upstream suppliers, downstream distributors, logistics providers, and financial institutions, firms can obtain credit on the basis of accounts receivable, purchase orders, inventories, and other trade-related assets. This structure can reduce financing constraints, particularly for small and medium-sized enterprises that have limited access to traditional bank credit (Msangi & Kasambala, 2025; Zhang, 2026). At the same time, however, the interconnected nature of supply chains creates additional channels through which credit risk may accumulate and propagate. A delayed payment or deterioration in the credit quality

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of a core buyer may directly affect several upstream suppliers, while guarantee relationships, equity links, invoice chains, repeated transactions, and shared counterparties can further expand the range of affected firms (Levänen, 2025; Qi & Qiao, 2026). From a broader data-management perspective, research on large-scale production measurement infrastructure has shown that heterogeneous operational metrics require systematic reconstruction and consistent measurement pipelines when data definitions, indicators, and production environments evolve (Bao & Wang, 2026b). This observation is also relevant to supply chain finance, where risk assessment increasingly depends on the reliable integration of heterogeneous transaction, relationship, and event data rather than on isolated financial indicators (Liang et al., 2026b). Existing studies have therefore introduced financial-ratio models, machine learning algorithms, network analysis, and knowledge-graph techniques to improve supply chain credit risk assessment (Carter & Thompson, 2026; Lin et al., 2020).

The growing availability of enterprise relational data has further shifted credit risk modeling from individual-firm analysis toward network-based risk representation. Recent graph-based studies indicate that transaction relationships, ownership connections, guarantee links, and other interfirm associations can provide predictive information that is difficult to capture using conventional firm-level variables alone (Hong et al., 2026; Xiong et al., 2026). Graph neural networks have consequently been applied to financial fraud detection, corporate default prediction, credit evaluation, and financial risk warning because they can jointly learn from node attributes and graph structures while aggregating information from connected entities (Huang et al., 2026; Khoozani et al., 2026). These models are particularly suitable for supply chain finance because the credit condition of one enterprise is often influenced not only by its own balance-sheet characteristics but also by the behavior and financial condition of its trading partners (Gu, 2026; Zheng & Makar, 2022). Nevertheless, current approaches still have difficulty representing the full complexity of real supply chain finance networks. Many models depend primarily on static enterprise attributes, aggregated financial ratios, or limited transaction records, which makes it difficult to describe how risk develops through payment delays, repeated invoice transfers, guarantee chains, equity control, litigation events, and changes in trading intensity (Collins et al., 2026; Jiao et al., 2026b). When these heterogeneous signals are treated separately, potentially important interactions among transaction behavior, legal events, and enterprise relations may be lost (Bao & Wang, 2026c; Liang et al., 2026a). Another limitation concerns the representation of indirect risk transmission. Existing graph models often emphasize observed direct links, such as a buyer–supplier relationship or a direct guarantee relationship, while hidden transmission paths among indirectly connected enterprises receive less attention. In practice, however, supply chain risk may propagate through multi-hop structures (Hara & Sasabe, 2026; Wang et al., 2026). A financially distressed enterprise may delay payments to several suppliers, one of these suppliers may have guarantee obligations with another firm, and the resulting liquidity pressure may subsequently affect additional firms outside the original transaction chain. Similar propagation may occur through common shareholders, repeated invoice counterparties, shared guarantors, or clusters of enterprises connected by multiple types of relationships (Yang & Du, 2026; Zhao et al., 2026). Simple pairwise links may therefore underestimate the actual scope of risk exposure. In addition, many existing experiments have been conducted on relatively small samples, simplified enterprise networks, or datasets containing only a limited number of relation types (Ozdem, 2025; You, 2026). Such settings are useful for methodological validation but may not fully reflect the scale, heterogeneity, sparsity, and dynamic interaction patterns encountered in operational supply chain finance systems. These limitations reduce the ability of existing models to identify early-stage risk

diffusion and may lead either to missed high-risk enterprises or to excessive manual review of firms whose observed risk signals are weak or indirect.

This study develops a heterogeneous graph learning framework for modeling and predicting credit risk propagation in large-scale supply chain finance networks. The proposed framework constructs an enterprise relation graph by integrating procurement records, invoice flows, payment delays, equity relationships, guarantee connections, and litigation events into a unified relational structure. Enterprise attributes and relation-specific information are jointly represented so that the model can distinguish different economic meanings of transaction, ownership, guarantee, and legal links rather than treating all enterprise connections as homogeneous edges. A graph neural network is then employed to learn enterprise-level and relation-level risk representations by aggregating information from connected firms, while a relation inference module is introduced to identify latent and indirect risk paths that may not be visible from direct transaction links alone. Through this design, the study aims to capture both observable credit deterioration and the network mechanisms through which such deterioration may spread across interconnected enterprises. The resulting framework is intended to improve early-warning accuracy, identify firms exposed to hidden multi-hop risk, and provide interpretable evidence on the main channels of risk transmission. From a practical perspective, a more complete representation of enterprise relationships can help financial institutions prioritize high-risk cases, reduce unnecessary manual investigation, and allocate risk-management resources more efficiently. From a methodological perspective, the study extends conventional firm-level credit assessment toward heterogeneous relational learning and provides a scalable approach for integrating multi-source enterprise data into supply chain finance risk analysis. The proposed framework therefore seeks not only to improve predictive performance but also to strengthen the ability of financial institutions to understand where credit risk originates, how it propagates through complex enterprise networks, and which connected firms should receive earlier attention.

## **2. Materials and Methods**

### **2.1 Samples and Study Area**

The dataset includes 86,000 enterprises, covering core firms, upstream suppliers, downstream distributors, logistics providers, and financial institutions. Enterprises were selected if they had active procurement and invoice records over a 36-month period. The dataset contains firms of different sizes and industries. Each firm is described by financial attributes, transaction volume, ownership structure, guarantee links, and payment delay records. This study focuses on the transmission of credit risk through these enterprise connections, including both direct and indirect financial links.

### **2.2 Experimental Design and Control Setup**

Two experimental settings were used to assess the proposed method. The experimental group applied a graph-based model with a module for inferring hidden risk paths. The control group used a standard financial-ratio scoring model without network information. This design allows comparison of early-warning performance, detection of risk paths, and the reduction of manual reviews. The setup ensures that observed differences are due to the inclusion of network and relational information.

### **2.3 Measurement Methods and Quality Control**

Enterprise and transaction data were collected from official procurement records, invoices,

and financial statements. Records were checked for completeness and consistency. Missing numerical values were replaced with medians, and missing categorical values were replaced with the mode. Duplicates, inconsistent dates, and abnormal transaction amounts were removed. Invoice and guarantee links were cross-checked. All data processing and feature extraction steps were documented to ensure reproducibility.

## 2.4 Data Processing and Model Formulation

The enterprise network was represented as a heterogeneous graph  $G=(V,E)$ , where nodes  $V$  represent enterprises and edges  $E$  represent procurement, payment delays, equity links, or guarantees. Node features  $x_i$  include financial indicators, size, and transaction statistics. Node embeddings were updated layer by layer as:

$$h_i^{(l+1)} = \sigma \left( \sum_{j \in N(i)} \frac{1}{|N(i)|} W^{(l)} h_j^{(l)} + W_0^{(l)} h_i^{(l)} \right)$$

where  $h_i^{(l)}$  is the embedding of node  $i$  at layer  $l$ ,  $N(i)$  are its neighbors, and  $\sigma$  is the activation function. The risk score of an enterprise  $R_i$  is calculated as:

$$R_i = \sum_{p \in P_i} \prod_{(u,v) \in p} w_{uv}$$

Here,  $P_i$  is the set of risk paths ending at node  $i$ , and  $w_{uv}$  is the weight of each edge, indicating the strength of risk transmission. This allows evaluation of both direct and indirect risk in the network.

## 2.5 Statistical Analysis

All computations were carried out using Python and standard network libraries. Model performance was measured by early-warning delay, detection precision for delayed payments, and reduction in manual review effort. Differences between experimental and control groups were assessed using t-tests or non-parametric tests. Sensitivity analysis was conducted by varying edge types and checking the stability of inferred risk paths. Results are reported with 95% confidence intervals, and a p-value of less than 0.05 was considered significant.

# 3. Results and Discussion

## 3.1 Model Performance and Early Warning Accuracy

The proposed model showed better early-warning performance than the financial-ratio scoring model. The median warning delay was reduced from 63 days to 24 days, indicating that risk signals were detected earlier when enterprise links were included. The top-decile risk queue captured 3,940 confirmed delayed-payment and credit-deterioration cases during the test period. This result suggests that transaction links, guarantee relations, payment delays, and ownership ties provide useful risk information that cannot be fully reflected by firm-level financial ratios alone. Similar findings have been reported in graph-based supply chain finance research, where enterprise relations improved the detection of abnormal financial behavior (Bao & Wang, 2026a; Wu & Su, 2026). As shown in Fig. 1, graph-based models usually perform better than models based only on isolated firm attributes.

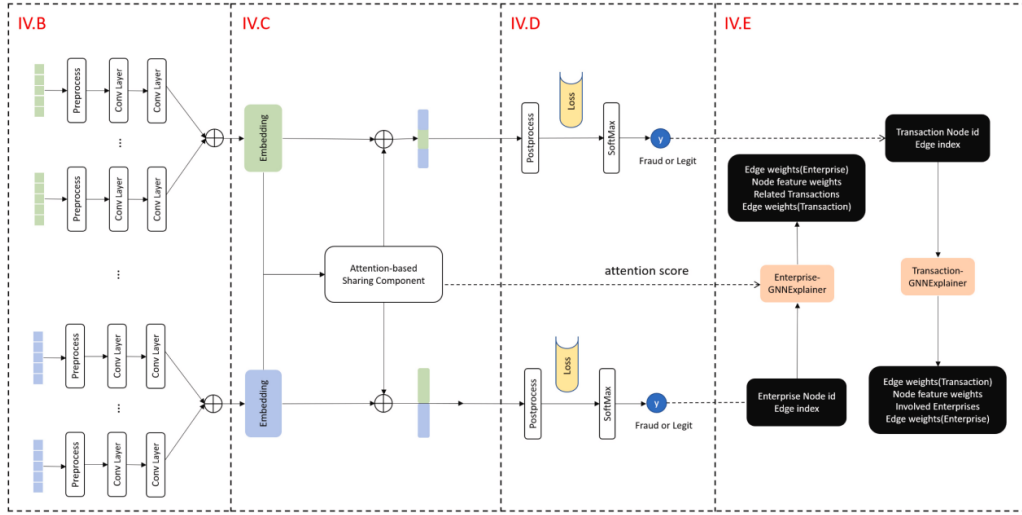


Fig. 1. Early-warning performance of the proposed model compared with the baseline.

### 3.2 Identification of Risk Propagation Paths

The relation inference module identified 12,700 indirect risk propagation paths in the enterprise network. These paths mainly involved supplier concentration risk, cross-guarantee exposure, and delayed receivable chains. This finding shows that credit risk does not only move through direct transaction links. It may also spread through hidden business ties and repeated financial dependence. Compared with earlier network-based studies, the proposed method provides a more detailed description of firm-level risk transmission because it uses real procurement records, invoice flows, guarantee links, and litigation events (Akarsu et al., 2026; Xu et al., 2026). Fig. 2 presents a typical network-based view of credit risk diffusion, which supports the need to study supply chain finance from a relational perspective.

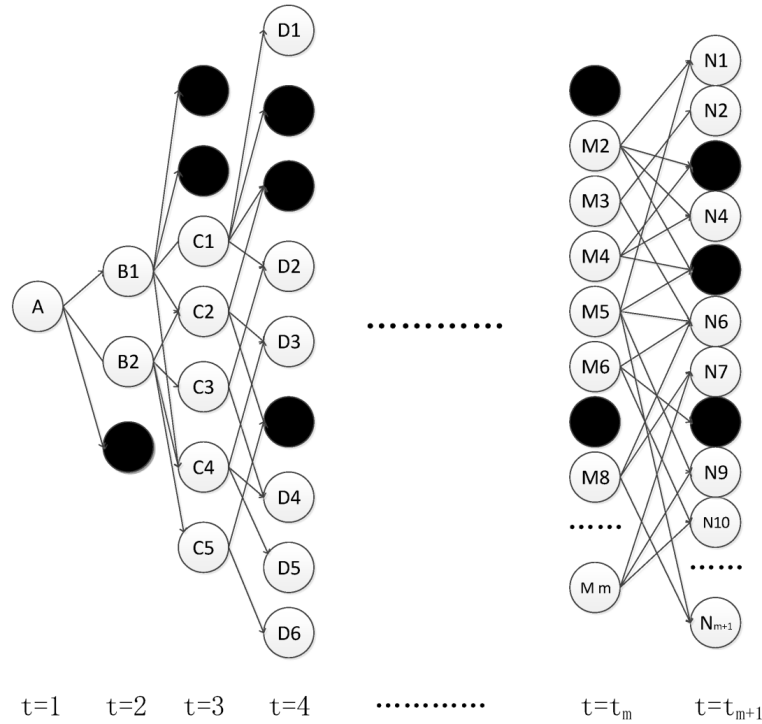


Fig. 2. Inferred credit risk paths across connected enterprises in the supply chain network.

### 3.3 Manual Review Reduction and Practical Value

The proposed method also reduced the manual review workload. The number of enterprise alerts decreased from 18,400 to 5,260 relation-level investigation cases after risk-path aggregation. This reduction is important for practical risk management because financial institutions usually face a large number of daily warning signals. Isolated alerts often require repeated manual checks and may increase review costs. By grouping related firms and risk paths, the model helps reviewers focus on key chains of risk transmission. This result indicates that the proposed method can improve not only prediction accuracy but also the efficiency of post-warning investigation (Jiao et al., 2026a; Omer et al., 2026).

### 3.4 Comparison with Existing Methods and Limitations

Compared with traditional credit scoring models, the proposed method makes better use of network information. Compared with common machine learning models, it can further describe how risk moves among connected firms. This advantage is useful in supply chain finance, where one firm's payment delay may affect several partners through invoices, guarantees, or ownership relations. However, the method still has some limitations. First, the model depends on the quality of transaction, invoice, legal, and guarantee records. Missing or incorrect links may affect the accuracy of risk-path inference. Second, the current experiment is based on a 36-month dataset, and longer observation periods may provide stronger evidence on delayed risk transmission. Third, industry-specific differences were not fully separated in this study. Future work should test the model across different industries and improve its ability to handle incomplete enterprise relation data.

## 4. Conclusion

This study shows that combining graph-based learning with relation inference can effectively capture credit risk propagation in supply chain finance. By using procurement records, invoice flows, payment delays, equity ties, guarantee links, and litigation events, the method constructs a complete enterprise network. The approach improves early-warning accuracy, reveals indirect risk paths, and reduces the number of manual reviews compared with traditional financial-ratio models. The results highlight key risk patterns, such as supplier concentration and cross-guarantee exposure, which are often missed by conventional approaches. The method provides a practical framework for large-scale enterprise networks and offers clear guidance for risk managers. Limitations include reliance on the completeness and quality of transaction and legal data, as well as potential differences across industries. Future work should test the approach under incomplete data and across multiple sectors. Overall, this study advances understanding of how credit risk spreads in supply chains and offers a scalable tool for managing systemic risk.

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