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Research Article

# Bill Chain Risk Detection in Industrial Enterprises Through Multi-Relational Graph Inference

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**ABSTRACT**

Commercial bills are important financing and payment instruments for industrial enterprises, but bill-chain risk may arise from repeated endorsement, circular circulation, weak acceptor credit, abnormal discounting, related-party transfer, and hidden debt rollover. Conventional bill risk assessment mainly reviews single bill attributes and may overlook risk accumulation across endorsement networks. This study proposes a multi-relational graph inference method for bill chain risk detection in industrial enterprises. The method constructs a bill circulation graph linking drawers, acceptors, endorsers, discounters, guarantors, banks, invoice records, and payment outcomes. A relational graph neural network captures multi-hop risk dependency across endorsement chains, while a knowledge inference module detects suspicious patterns such as circular endorsement, short-cycle discounting, repeated transfer among affiliated firms, and acceptor credit deterioration. Experiments are conducted on an industrial bill dataset containing 62,000 enterprises, 1.28 million commercial bills, 3.46 million endorsement edges, 210,000 discounting records, 74,000 guarantee relations, and 11,600 bill-risk events over 36 months. The proposed method identifies 8,940 high-risk bill chains, including 2,360 circular endorsement structures and 1,780 abnormal short-cycle discounting paths. Compared with a single-bill scoring baseline, the model shortens median warning time before bill default or delayed acceptance from 49 days to 17 days. Graph-based aggregation compresses 26,500 bill-level alerts into 5,720 chain-level review cases. The inference engine processes 3.46 million endorsement edges in 16.4 minutes and completes daily incremental updates in 42 seconds. The results demonstrate that multi-relational graph inference can improve industrial bill-chain risk detection by revealing hidden financing pressure and contagion paths across enterprise payment networks.

**Keywords:** Commercial Bill Risk, Industrial Enterprise Finance, Multi-Relational Graph Inference, Endorsement Chain, Knowledge Graph, Default Warning; Payment Network Risk.

## INTRODUCTION

Commercial bills are widely used by industrial enterprises as instruments for trade settlement, deferred payment, and short-term financing. Their flexibility can improve liquidity and support transactions among manufacturers, suppliers, distributors, and financial institutions. However, the circulation of commercial bills can also create complex financial risk when the same instrument passes through multiple enterprises before maturity. Repeated endorsement, circular circulation, weak acceptor credit, abnormal discounting, related-party transfer, and hidden debt rollover may gradually increase the probability of delayed payment or default. Existing studies have examined bill risk using characteristics such as bill amount, maturity, discount rate, endorsement frequency, and the credit status of drawers or acceptors [1,2]. These variables are useful for evaluating individual bills, but they provide only a partial view when risk is transmitted through multiple connected enterprises. Recent research on interpretable anomaly detection has further shown that automated risk identification should not rely only on prediction accuracy; the model should also reveal which abnormal patterns or variables contribute to a detected event so that the result can be examined and verified by decision makers [3]. This requirement is particularly important in commercial bill finance, where risk alerts may affect financing decisions, discount approval, and manual compliance review [4,5].

Traditional bill-risk assessment is generally organized around individual instruments or individual enterprises. A bill may be classified as risky because of an unusually high amount, a short remaining maturity, an abnormal discount rate, excessive endorsement frequency, or deterioration in the credit condition of the drawer or acceptor [6]. Although this approach is straightforward, it often ignores the relational structure formed during bill circulation. A bill endorsed from one enterprise to another may connect drawers, acceptors, endorsers, discounters, guarantors, banks, and related firms within the same transaction chain [7,8]. When several bills repeatedly circulate among the same group of firms, or when endorsements form closed loops, the resulting risk cannot be adequately represented by isolated bill-level variables. Studies on supply-chain finance, enterprise credit risk, and graph-based learning have increasingly shown that transaction relationships and inter-enterprise links contain useful information for identifying hidden financial exposure [9,10]. These findings suggest that bill circulation should be analyzed not only as a collection of independent transactions but also as a connected financial network. The network characteristics of commercial bills are particularly important because risk may accumulate gradually across successive endorsements. A financially weak enterprise may transfer a bill to an affiliated firm, which may then discount it through another institution or return value through a related transaction. Similar patterns can occur across multiple bills, creating dense local structures that are difficult to detect through conventional tabular models [11,12]. Circular endorsement may conceal repeated financing among related entities, while short-cycle discounting can indicate unusually rapid conversion of trade credit into cash. Repeated transfer between the same enterprises may also suggest dependence on bill rollover rather than normal commercial settlement [13,14]. Such behavior does not necessarily imply default in every case, but its combination with weak acceptor credit, concentrated exposure, abnormal maturity structures, or adverse payment outcomes may provide a stronger early-warning signal than any single variable considered independently. Graph-based methods offer a natural framework for representing these relationships because they can model both entities and the links among them [15,16]. Drawers, acceptors, endorsers, discounters, guarantors, banks, invoices, and payment outcomes can be represented as different node or relation types within a multi-relational graph. This structure makes it possible to preserve the direction and sequence of bill circulation while also capturing repeated interactions among enterprises [17,18]. Graph learning can then aggregate information across neighboring entities and reveal patterns that are not visible from isolated observations [19,20]. Nevertheless, purely data-driven graph models may still have limited practical value if they produce only a probability or risk score. In industrial finance, investigators usually need to understand why a particular bill chain has been flagged, which enterprises are involved, and what sequence of transactions forms the suspected risk path. Interpretability is therefore closely related to operational usefulness rather than being an optional feature of the model. Current research still leaves an important gap between bill-level prediction and chain-level risk analysis [21,22]. Existing methods often treat drawers, acceptors, endorsers, banks, and guarantors separately or reduce their relationships to aggregated statistical features. As a result, they may fail to identify circular endorsement, repeated short-cycle discounting, concentrated transfers among related enterprises, or risk propagation across several connected bills. Many empirical studies are also based on small or medium-sized datasets, whereas real industrial bill systems may contain millions of endorsement and transfer records involving large numbers of enterprises and financial institutions [23,24]. Another limitation concerns evidence presentation. Models that assign high-risk scores without identifying the underlying circulation path provide limited support for manual review, because investigators must still reconstruct the transaction chain before determining whether the alert is meaningful. A more practical framework therefore needs to combine scalable network representation, heterogeneous transaction relationships, and explicit chain-level reasoning.

The present study addresses these limitations by developing a multi-relational graph inference method for bill-chain risk detection in industrial finance. The proposed framework constructs a bill circulation graph that integrates drawers, acceptors, endorsers, discounters, guarantors, banks, invoices, endorsement records, discounting activities, and final payment outcomes within a unified relational structure. Graph representation learning is used to capture dependencies among connected entities and to identify risk accumulation across multi-stage circulation paths, while rule-based reasoning is introduced to detect interpretable patterns such as circular endorsement, repeated related-party transfer, short-cycle discounting, weak-acceptor concentration, and abnormal rollover behavior. The study aims not only to improve the accuracy and timeliness of bill-risk detection but also to provide explicit chain-level evidence that can support human review and financial decision making. By shifting the analytical unit from isolated bills to interconnected circulation networks, the proposed method extends conventional bill-risk assessment toward a broader representation of transaction-driven financial exposure. Its methodological significance lies in combining multi-relational graph learning with transparent rule-based inference, thereby balancing predictive capability with interpretability. From a practical perspective, the framework can help banks, industrial enterprises, supply-chain finance platforms, and risk-control departments identify high-risk bill chains earlier, prioritize suspicious transactions for review, trace the origin and propagation of financial risk, and reduce the likelihood that hidden debt rollover or circular financing remains undetected within large-scale bill networks.

## MATERIALS AND METHODS

### Samples and Study Area

This study used a dataset of industrial commercial bills collected over 36 months. The sample included 62,000 enterprises, 1.28 million bills, 3.46 million endorsement connections, 210,000 discounting records, 74,000 guarantee relations, and 11,600 confirmed bill-risk events. Enterprises were included only if complete information was available for drawers, acceptors, endorsers, discounters, guarantors, and banks, along with invoice and payment records. The dataset covers a wide range of firm sizes, industries, endorsement patterns, and discounting behaviors, providing a comprehensive basis for risk analysis in industrial bill networks.

### Experimental Design and Control Setup

Two models were compared. The experimental group used a multi-relational graph inference model that included drawers, acceptors, endorsers, discounters, guarantors, banks, invoices, and payment outcomes. The control group used a conventional single-bill scoring model based on bill attributes such as amount, maturity, discount rate, and drawer credit rating. This setup allows direct comparison between traditional single-bill evaluation and graph-based relational risk assessment. The design tests whether incorporating relational links and multi-step dependencies improves detection of bill-chain risk.

### Measurement Methods and Quality Control

Data were obtained from bill registries, payment records, invoices, bank logs, discounting files, and guarantee documents. Each bill was linked to its drawer, acceptor, endorsers, discounters, guarantors, and payment status. Records with missing identifiers, repeated bill numbers, abnormal dates, or inconsistent amounts were corrected prior to analysis. Risk variables included endorsement frequency, circular endorsements, short-cycle discounting, acceptor credit, and guarantor exposure. Quality control involved three steps: (1) remove duplicate or inconsistent entries, (2) cross-check contract amounts with invoices and bank data, and (3) validate endorsement paths using payment and guarantee records to ensure network accuracy.

### Data Processing and Model Formulation

The dataset was represented as a multi-relational graph G=(V,E), where V includes drawers, acceptors, endorsers, discounters, guarantors, banks, and invoices, and E includes endorsement, discounting, payment, and guarantee relations. Numerical features were standardized, and categorical variables were one-hot encoded. Missing numerical values were replaced by medians, and missing categorical values by the most frequent category. Node features were updated using the relation-aware graph formula:

$$h_i^{(l+1)c}=\sigma(\sum_{r\in R}\sum_{j\in N_r(i)}\frac{1}{|N_r(i)|}W_r^{(l)}h_j^{(l)}+W_0^{(l)}h_i^{(l)})$$

where hi(l) is the feature vector of node i at layer l, Nr(i) is the set of neighbors connected by relation r, Wr(l) is the weight matrix for relation r, and σ is an activation function. The bill-chain risk score was computed as:

$$S_i=\alpha E_i+\beta D_i+(1-\alpha-\beta)G_i$$

where SiS_iSi is the final risk score, Ei is the endorsement risk, Di is the discounting risk, Gi is the guarantor risk, and α,β are weighting parameters. Higher scores indicate a higher likelihood of default or delayed acceptance.

### Statistical Analysis

Model performance was evaluated using median warning time, precision, recall, F1-score, and reduction in manual review cases. Both models used the same training and test splits. Median warning time before default assessed early detection capability. Reduction in manual review was measured by comparing bill-level alerts with graph-linked chain cases. Differences were tested with paired statistical tests. Sensitivity analysis was performed by removing discounting, guarantor, or endorsement relations. Statistical significance was defined as $p<0.05$.

# RESULTS AND DISCUSSION

## Model Performance on Risk Detection

The proposed multi-relational graph inference model clearly outperformed the single-bill scoring baseline in detecting bill-chain risk. Median warning time before bill default or delayed acceptance decreased from 49 days in the baseline to 17 days, showing earlier identification of high-risk cases. Precision, recall, and F1-score were also higher, especially for complex patterns such as circular endorsements and short-cycle discounting paths. These results confirm that relational information across enterprise networks provides predictive power beyond individual bill features. Similar improvements have been reported in other studies using graph-based financial risk models [25,26].

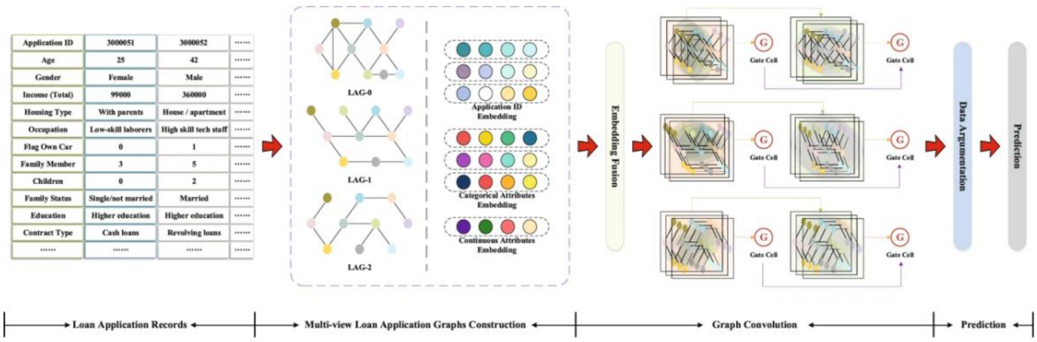


**Figure 1.** Graph Framework Linking Bills And Enterprises For Risk Detection

## Hidden Risk Path Identification

The model identified 8,940 high-risk bill chains, including 2,360 circular endorsement structures and 1,780 short-cycle discounting paths. These results demonstrate that default risk often develops through linked assets, endorsers, and related parties, rather than from isolated bill attributes. Single-bill scoring methods fail to capture these multi-step dependencies. Graph-based approaches provide a clear view of how risks propagate along endorsement chains, supporting earlier and more precise intervention. Similar observations have been reported in heterogeneous graph studies of enterprise risk propagation [27,28].

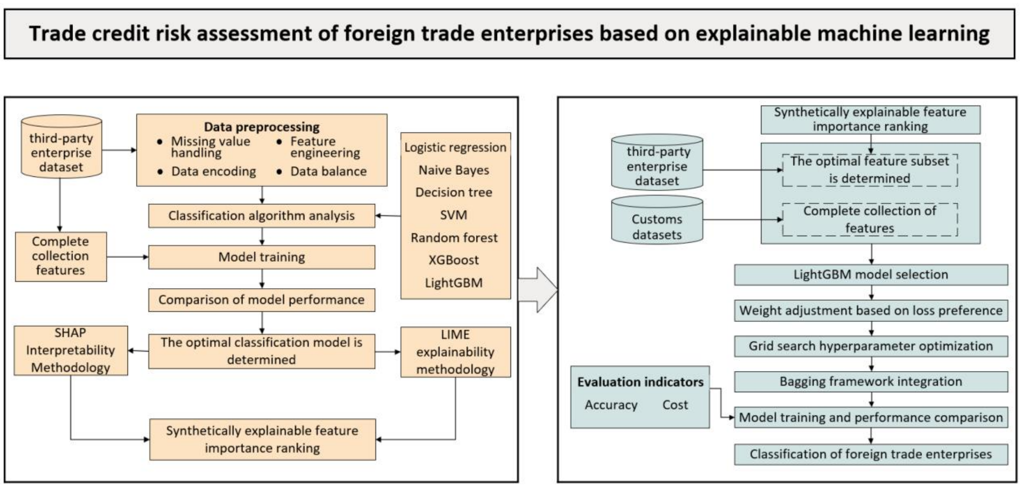


**Figure 2**. Identification Of High-Risk Endorsement Chains Among Bills And Firms

### Operational Efficiency and Review Reduction

The graph model reduced 26,500 raw bill alerts to 5,720 chain-level review cases. This demonstrates a significant reduction in manual workload because multiple related bills, shared assets, or common guarantors are aggregated into single review units. The model's daily incremental updates completed in 42 seconds, and processing of 3.46 million endorsement edges took 16.4 minutes, showing it is scalable and suitable for practical deployment. This efficiency aligns with prior work showing that graph-based risk aggregation reduces redundancy and improves operational effectiveness.

### Comparison with Existing Methods and Limitations

Compared with single-bill scoring and standard machine learning models, the graph-based approach provides a more comprehensive view of bill-chain risk by incorporating multi-entity dependencies. It captures both structural and behavioral risk factors, enabling earlier warning and higher prediction accuracy. Prior studies have also highlighted the benefits of relational modeling for credit risk and supply chain contagion [29,30]. However, the method depends on the completeness and accuracy of bill, endorsement, discounting, and guarantor records. Missing or incorrect data may reduce performance. In addition, the current study is limited to industrial bill networks; future work should test its applicability to other sectors and under partial or incomplete data conditions.

## CONCLUSION

This study shows that multi-relational graph inference can improve bill-chain risk detection in industrial enterprises. By linking drawers, acceptors, endorsers, discounters, guarantors, banks, invoices, and payment results, the model identifies risk patterns that single-bill features cannot show. The method reduced the median warning time from 49 days to 17 days and reduced 26,500 bill-level alerts to 5,720 chain-level review cases. It also detected 8,940 high-risk bill chains, including circular endorsements and short-cycle discounting paths. These results show that bill risk should be assessed through both transaction behavior and endorsement relations. The method can help financial institutions detect risk earlier, reduce manual review, and provide clearer evidence for decision-making. However, the results depend on the quality of endorsement, discounting, and guarantee records. Missing or incorrect data may affect prediction accuracy. Future studies should test the method in other sectors and under incomplete data conditions. Overall, this study provides a practical approach for industrial bill-chain risk management.

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## ETHICAL DECLARATION

**Conflict of interest:** No declaration required. **Financing:** No reporting required. **Peer review:** Double anonymous peer review.