

Receivables Pledge Risk Scoring Through Transaction Knowledge Graph Inference

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Abstract

Receivables pledge financing provides liquidity for industrial enterprises, but it also introduces risks from false trade backgrounds, duplicated pledges, delayed payments, debtor concentration, and weak buyer credit. Traditional risk assessment mainly examines the borrowing enterprise and often ignores the transaction network behind receivables. This study develops a receivables pledge risk scoring method based on transaction knowledge graph inference. The proposed method builds a knowledge graph that links borrowers, debtors, invoices, contracts, logistics records, payment histories, tax declarations, pledge registrations, and guarantee relationships. A relation-aware graph neural network is used to encode transaction credibility and debtor repayment dependency. A rule-guided inference module detects suspicious receivable chains, including repeated invoice pledging, circular trade, abnormal payment delay, and buyer-credit deterioration. The empirical dataset contains 28,600 borrowing enterprises, 96,000 debtor firms, 1.84 million invoices, 420,000 logistics records, 73,000 pledge contracts, and 8,950 confirmed pledge-risk cases collected over 30 months. The model identifies 11,300 suspicious receivable chains and 2,740 duplicated or circular pledge structures. Compared with a borrower-only credit scoring model, the proposed method shortens median warning time before pledge default from 57 days to 19 days. It reduces manual document review from 31,000 invoice batches to 6,480 graph-linked investigation cases. The top-ranked risk explanations mainly involve debtor payment delay, inconsistent logistics evidence, repeated pledge registration, and excessive receivable concentration. These findings suggest that transaction knowledge graph inference can improve receivables pledge risk assessment by connecting financing risk with real trade evidence and inter-enterprise repayment dependency.

Keywords: Receivables pledge financing; transaction knowledge graph; graph neural inference; industrial finance; invoice risk; trade authenticity; credit risk scoring.

1. Introduction

Receivables pledge financing is an important form of supply chain finance that enables industrial firms to obtain short-term liquidity by using accounts receivable as collateral. It is particularly valuable for small and medium-sized enterprises that may have limited access to

traditional unsecured lending or insufficient fixed assets for conventional collateralized loans. By converting future payment claims into current financing capacity, receivables pledging can reduce working-capital pressure and improve the continuity of production and procurement activities [1,2]. However, the credit quality of this financing arrangement depends not only on the borrower but also on the authenticity of the underlying transaction, the repayment capacity of the debtor, the uniqueness of the pledged receivable, and the stability of the associated business relationship. Risks may therefore arise from fabricated trade backgrounds, repeated pledges of the same receivable, delayed payments, debtor concentration, circular transactions, weak buyer credit, and incomplete transaction evidence [3,4]. These risks are often difficult to identify when financing decisions rely mainly on borrower-level financial statements and historical repayment records [5].

The increasing digitalization of industrial transactions has created richer data sources for receivables pledge risk assessment. Contracts, invoices, logistics records, tax declarations, payment histories, pledge registrations, guarantee relationships, and platform settlement records can provide complementary evidence about whether a receivable corresponds to a genuine and enforceable commercial transaction. At the same time, reliable use of such heterogeneous data requires consistent measurement infrastructure and stable data-processing mechanisms [6,7]. Research on large-scale production measurement systems has shown that systematic metric migration and reconstruction are important for maintaining the consistency, scalability, and reliability of operational measurements across complex data environments [8]. This issue is also relevant to receivables pledge financing, where risk assessment may depend on the alignment of multiple records generated by different business systems [9]. If invoice amounts, contract values, logistics information, tax declarations, and pledge registrations cannot be accurately matched, hidden inconsistencies may remain undetected [10,11]. Recent studies further indicate that transaction records, supply-chain relationships, knowledge graphs, and graph-based learning methods can improve credit and fraud risk prediction by incorporating information beyond conventional financial variables [12,13]. Despite these advances, important limitations remain in current receivables financing research. Many existing studies focus primarily on the creditworthiness of the borrowing enterprise, while the repayment behavior of the underlying debtor and the evidentiary strength of the trade transaction receive less systematic attention [14,15]. However, the actual value of a pledged receivable depends directly on whether the debtor is capable of and willing to make payment under the corresponding contract. A financially stable borrower may still create significant pledge risk when the associated receivables are concentrated in a small number of weak debtors or when payment delays increase continuously [16,17]. In addition, invoices, contracts, logistics records, tax declarations, pledge registrations, guarantees, and historical payments are often modeled separately rather than as interconnected evidence [18,19]. This separation can make it difficult to identify repeated invoice pledging, circular trade structures, abnormal transaction chains, or inconsistencies between commercial documents and actual goods movement [20,21]. Graph-based methods provide a possible solution because

borrowers, debtors, transactions, invoices, guarantees, and pledge records can be represented as linked entities within a unified relational structure [23]. Nevertheless, many existing graph models are developed and evaluated using general corporate credit, fraud, or transaction datasets, and their predictive mechanisms may not fully reflect the specific structure of receivables pledge financing [24]. They may also provide insufficient explanation of how a particular pledged receivable becomes risky and which transaction path contributes most strongly to the resulting risk score.

This study proposes a transaction knowledge graph inference method for receivables pledge risk scoring. The proposed framework integrates borrowers, debtors, invoices, contracts, logistics records, payment histories, tax declarations, pledge registrations, and guarantee relationships into a unified transaction knowledge graph. By linking commercial evidence with enterprise relationships, the method is designed to evaluate not only the financial condition of the borrowing firm but also the authenticity, uniqueness, enforceability, and repayment quality of the pledged receivable itself. Knowledge-based inference is used to identify abnormal patterns associated with repeated pledging, debtor concentration, circular trade, delayed repayment, inconsistent transaction evidence, and risk propagation through guarantee or affiliated-enterprise relationships. The objective of this study is therefore not limited to improving predictive accuracy. It also seeks to provide interpretable evidence showing why a particular receivable presents elevated financing risk and which transaction or relationship chain generates that risk. By shifting the assessment focus from isolated borrower indicators to transaction-level evidence and interconnected enterprise relationships, the proposed method offers a more comprehensive framework for receivables pledge financing. The resulting approach can support banks and supply chain finance platforms in early risk detection, reduce dependence on repetitive manual document verification, strengthen identification of fraudulent or duplicated pledges, and provide clearer decision evidence for collateral evaluation, credit approval, post-loan monitoring, and industrial supply-chain risk management.

2. Materials and Methods

2.1 Samples and Study Area

This study used a receivables pledge financing dataset collected over 30 months. The sample included 28,600 borrowing firms, 96,000 debtor firms, 1.84 million invoices, 420,000 logistics records, 73,000 pledge contracts, and 8,950 confirmed pledge-risk cases. Firms were included when borrower information, invoice records, contract data, payment history, and pledge registration data were available. The study objects were industrial firms involved in receivables pledge financing, including manufacturers, suppliers, buyers, and guarantee parties. The dataset covered firms with different sizes, transaction volumes, debtor concentrations, and repayment records.

2.2 Experimental Design and Control Setup

Two model settings were used in this study. The experimental group used the transaction knowledge graph model. This model included borrowers, debtors, invoices, contracts, logistics records, tax records, payment records, pledge registrations, and guarantee links. The control group used a borrower-only credit scoring model. It was based on financial indicators, firm age, registered capital, repayment history, and credit events. This design was used because receivables pledge risk is closely related to trade truth and debtor payment ability. The comparison was used to test whether transaction records and enterprise links can improve risk scoring.

2.3 Measurement Methods and Quality Control

Data were collected from pledge contracts, invoice systems, logistics records, tax records, payment records, guarantee documents, and pledge registration files. Each invoice was matched with its contract, debtor, logistics record, tax record, and payment status. Records with missing key identifiers, repeated invoice numbers, abnormal dates, or inconsistent contract amounts were checked before model training. Invoice amount, payment delay, debtor concentration, pledge frequency, and logistics consistency were used as risk variables. Quality control was conducted in three steps. First, repeated invoices and repeated pledge registrations were removed or marked. Second, contract amounts were compared with invoice and tax records. Third, logistics records were checked against delivery dates and buyer information. These steps improved the accuracy of graph links.

2.4 Data Processing and Model Formulation

The transaction data were built as a knowledge graph $G=(V,E)$. In this graph, V represents borrowers, debtors, invoices, contracts, logistics records, tax records, pledge contracts, and guarantee parties. E represents transaction, payment, pledge, guarantee, and registration relations. Numerical variables were standardized. Categorical variables were encoded before model training. Missing numerical values were replaced by medians, and missing categorical values were replaced by the most frequent value. The node features were updated as follows:

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

where $h_i^{(l)}$ is the feature vector of node i at layer l , $N_r(i)$ is the neighbor set under relation type r , $W_r^{(l)}$ is the weight matrix for relation r , and σ is the activation function. The pledge risk score was calculated as follows:

$$S_i = \alpha C_i + (1 - \alpha) D_i$$

where S_i is the final pledge risk score, C_i is the transaction credibility risk, D_i is the debtor repayment risk, and α is the weight parameter. A higher score means a higher risk of pledge default or suspicious receivable chains.

2.5 Statistical Analysis

Model performance was measured by warning time, precision, recall, F1-score, and reduction in manual review volume. The proposed model and the borrower-only scoring model used the same training and test split. Median warning time before pledge default was used to assess early-warning ability. Manual review reduction was measured by comparing invoice batches with graph-linked investigation cases. Group differences were tested with paired tests when applicable. Sensitivity analysis was conducted by removing logistics records, guarantee links, and pledge registration data separately. Statistical significance was set at $p < 0.05$.

3. Results and Discussion

3.1 Risk Scoring Performance

The transaction knowledge graph model performed better than the borrower-only credit scoring model. The median warning time before pledge default was reduced from 57 days to 19 days. This shows that receivables pledge risk cannot be fully assessed using borrower-level financial indicators alone. Early warning signals often came from delayed debtor payment, repeated invoices, abnormal pledge registration, or inconsistent logistics records. Similar studies have found that including supply chain links improves financial fraud detection compared with models using only financial data [25,26]. As shown in Fig. 1, a graph-based approach can combine financial records and trade links to support risk identification.

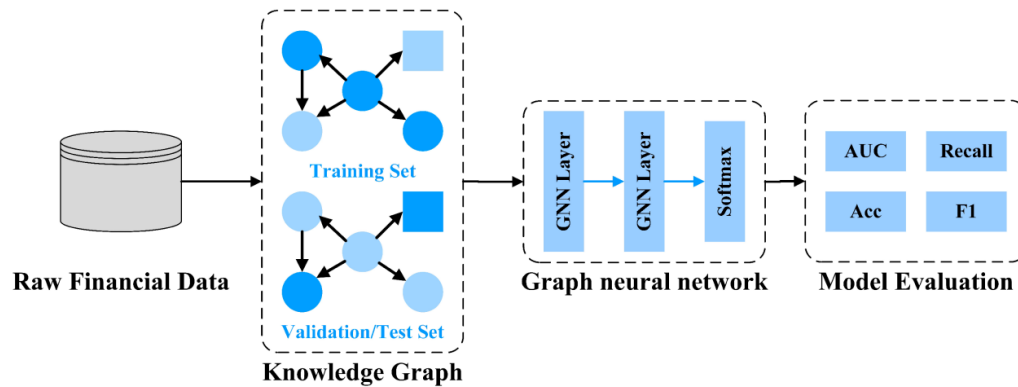


Fig. 1. Architecture of the transaction knowledge graph-based risk scoring model.

3.2 Suspicious Receivable Chain Detection

The model detected 11,300 suspicious receivable chains and 2,740 duplicated or circular pledge structures. These results indicate that pledge risk often occurs along chains of transactions rather than in single documents. Repeated invoice pledging was mainly linked to the same debtor, similar contract amounts, or overlapping pledge periods [27,28]. Circular trade was mostly observed in closed transaction loops among related firms. Compared with rule-based document checks, the graph approach provides clearer evidence by connecting invoices, contracts, logistics records, tax declarations, and pledge registrations. Fig. 2 illustrates how a continuous supply chain

knowledge graph can describe links across firms and over time, helping to identify hidden risk paths.

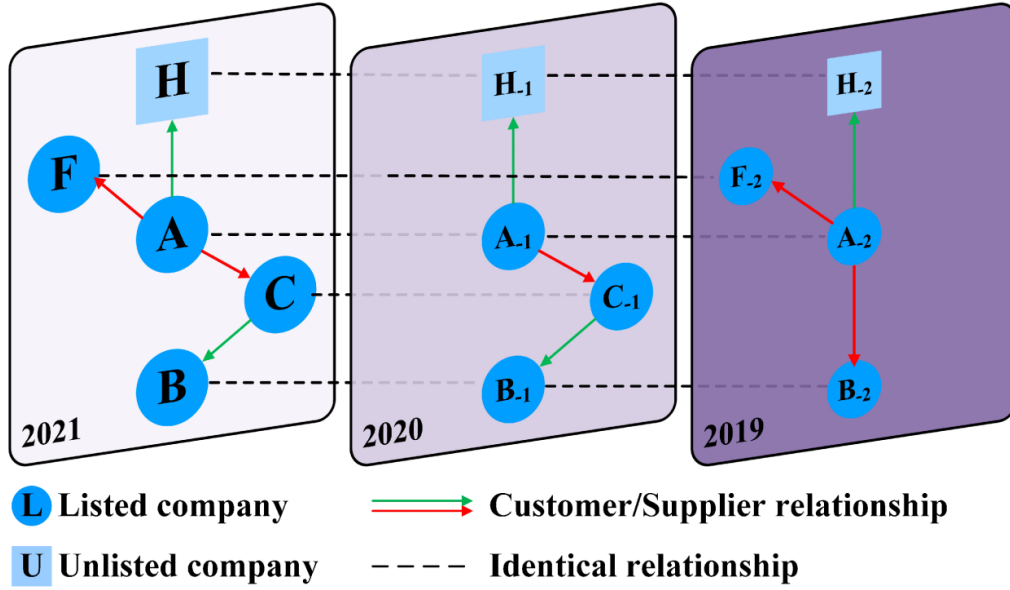


Fig. 2. Illustration of suspicious receivable chain detection based on the supply chain knowledge graph.

3.3 Reduction in Manual Review Workload

Using the graph-based method, manual document review decreased from 31,000 invoice batches to 6,480 graph-linked investigation cases. This reduction is important because reviewing receivables pledges usually involves many repetitive documents. Batch-level review may overlook hidden links among invoices, contracts, debtors, and pledge registrations. Grouping related records into graph-linked cases allowed reviewers to focus on high-risk transaction chains. The top-ranked risk explanations included delayed debtor payments, inconsistent logistics evidence, repeated pledge registration, and high receivable concentration [29,30]. These results suggest that the graph-based review can improve efficiency and provide clearer risk explanations.

3.4 Comparison with Existing Methods and Limitations

Compared with borrower-only scoring models, the proposed method uses both credit information and transaction evidence. Compared with common fraud detection models, it links invoices, debtors, logistics records, tax data, pledge registrations, and guarantee relations in a single graph. This structure is effective because the value of pledged receivables depends on trade authenticity and debtor repayment ability. However, the method has limitations. First, it depends on the completeness and accuracy of invoices, logistics, tax records, and pledge registrations. Missing or incorrect data can reduce the quality of graph links and risk scores. Second, the dataset covers 30 months; longer periods may provide stronger evidence of delayed payments. Third,

industry-specific effects were not fully separated. Future studies should test the method in other sectors and under partial data conditions.

4. Conclusion

This study demonstrates that transaction knowledge graph inference can improve risk assessment in receivables pledge financing. By connecting borrowers, debtors, invoices, contracts, logistics records, tax records, payment histories, pledge registrations, and guarantee relations, the method links credit risk to actual trade evidence. The model reduced the median warning time before pledge default from 57 days to 19 days and decreased manual review from 31,000 invoice batches to 6,480 graph-linked investigation cases. It also detected suspicious receivable chains, repeated pledges, circular trade, delayed debtor payments, and weak buyer credit. These findings show that pledge risk should be evaluated not only from borrower information but also from transaction chains and debtor repayment patterns. The method offers a practical tool for financial institutions to improve early warning, reduce review workload, and support risk-based decisions. However, the approach relies on the completeness and accuracy of invoice, logistics, tax, and pledge registration data. Missing or incorrect records may lower graph reliability and risk scores. Future work should test the method in other sectors, over longer periods, and under incomplete data conditions. Overall, this study provides a clear and practical framework for receivables pledge risk control and trade-based credit evaluation.

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