Inventory Pledge Risk Prediction for Industrial Enterprises Using Warehouse Knowledge Graph Inference

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Abstract

Inventory pledge financing is widely used by industrial enterprises to obtain short-term liquidity through raw materials, semi-finished goods, finished products, and warehouse receipts. However, this financing mode is exposed to risks from duplicated pledges, false warehouse records, unstable commodity prices, inventory depreciation, abnormal turnover, and weak borrower repayment capacity. This study proposes a warehouse knowledge graph inference model for inventory pledge risk prediction in industrial enterprises. The model links borrowers, pledged inventories, warehouses, warehouse receipts, logistics providers, valuation agencies, insurance records, purchase contracts, sales invoices, commodity prices, and repayment outcomes. A graph neural encoder is used to learn borrower-inventory dependency, while a knowledge reasoning module identifies hidden risk chains involving repeated pledge registration, inventory-location inconsistency, abnormal valuation fluctuation, delayed warehouse inspection, and declining downstream sales. Experiments are conducted on an industrial inventory financing dataset containing 24,800 borrowing enterprises, 680 warehouses, 1.36 million inventory records, 92,000 pledge contracts, 410,000 logistics records, 58,000 insurance entries, and 6,740 confirmed pledge-risk cases over 36 months. The proposed method shortens median warning time before pledge deterioration from 64 days to 21 days compared with a collateral-value scoring baseline. Graph inference identifies 7,860 suspicious inventory-risk chains and 1,690 duplicated pledge structures. The system reduces manual collateral review from 22,400 warehouse batches to 4,960 graph-linked investigation cases. Full monthly assessment is completed in 10.8 minutes, with a median inference latency of 38 ms per pledge node. The results show that warehouse knowledge graph inference can improve inventory pledge risk prediction by connecting collateral authenticity, logistics evidence, price movement, and enterprise repayment behavior.

Keywords: Inventory pledge financing; warehouse knowledge graph; industrial finance; graph neural network; collateral risk; pledge fraud detection; financing risk prediction

1. Introduction

Inventory pledge financing is an important form of supply-chain finance that enables industrial enterprises to obtain short-term working capital by using raw materials, semi-finished goods, finished products, warehouse receipts, and other inventory-related assets as collateral. It can improve asset liquidity and alleviate cash-flow pressure, particularly for manufacturing and trading enterprises with substantial inventories but limited access to unsecured credit. Nevertheless, the effectiveness of this financing mechanism depends heavily on the authenticity, ownership, location, valuation, and controllability of pledged assets. In practice, inventory pledge financing is exposed to risks such as duplicated pledges, falsified warehouse receipts, discrepancies between registered and actual inventory locations, abnormal inventory transfers, commodity price volatility, delayed warehouse inspections, and deterioration in borrower repayment capacity. Traditional risk assessment methods mainly rely on collateral value, borrower credit scores, warehouse inspection reports, historical repayment records, and financial indicators [1,2]. These indicators remain useful for credit evaluation, but they are generally analyzed as independent variables and provide limited support for identifying complex relationships among borrowers, collateral, warehouses, logistics activities, insurance records, sales transactions, and repayment events [3,4]. Recent research on interpretable anomaly detection has also shown that combining machine learning with explainability mechanisms such as SHAP can improve the identification and interpretation of abnormal patterns in complex operational environments [5]. This provides a useful methodological reference for financial risk monitoring, where identifying not only abnormal events but also the factors and relationships responsible for those events is essential for effective risk control [6].

Recent advances in machine learning and supply-chain finance have further improved credit and default risk prediction through the incorporation of transaction records, enterprise relationships, market information, behavioral variables, and operational indicators [7,8]. Compared with conventional statistical scoring models, these approaches can capture nonlinear patterns and interactions among multiple risk factors [9,10]. However, most existing methods still represent financing activities through tabular features, aggregated enterprise indicators, or relatively simple pairwise relationships. Such representations are insufficient for inventory pledge financing because risk is often generated through interconnected entities and multi-stage business processes [11,12]. For example, the same inventory may be associated with multiple pledge contracts or warehouse receipts; a warehouse receipt may be inconsistent with logistics records; a valuation change may not correspond to market price movements; and declining downstream sales may gradually weaken the borrower's repayment capacity. These risks are difficult to identify through isolated borrower-level or collateral-level variables. Moreover, existing models generally emphasize prediction accuracy while providing limited support for tracing how a suspicious relationship develops into a specific pledge-risk event. This limitation is particularly important in industrial financing, where financial institutions need to determine whether a warning originates from the borrower, the warehouse, the pledged inventory, the logistics process, the valuation procedure, or the downstream transaction network [13,14]. Knowledge graphs provide a suitable representation framework for addressing these limitations because they can organize heterogeneous business information as interconnected entities, relationships, and events [15,16]. In inventory pledge financing, borrowers, inventories, warehouses, warehouse receipts, logistics providers, valuation agencies, insurers, purchase contracts, sales invoices, commodity prices, and repayment outcomes can be represented within a unified relational structure. Such a representation makes it possible to examine not only the attributes of individual entities but also the structural relationships among them [17,18]. Graph neural networks can further learn latent dependency patterns from these relationships and propagate risk information across connected entities [19,20]. When combined with knowledge reasoning, graph-based models can support the identification of multi-hop risk chains, such as repeated pledge registration involving the same inventory, inconsistency between inventory location and logistics records, abnormal collateral valuation changes, delayed warehouse inspection, insufficient insurance coverage, and declining downstream sales associated with deteriorating repayment performance. This relational perspective is therefore more suitable for inventory pledge risk than conventional collateral-value scoring methods that evaluate individual borrowers or assets in isolation [21,22].

Based on this perspective, this study develops a warehouse knowledge graph inference model for inventory pledge risk prediction in industrial enterprises. The proposed framework integrates borrower information, pledged inventory records, warehouse information, warehouse receipts, logistics records, valuation results, insurance entries, purchase contracts, sales invoices, commodity prices, and repayment outcomes into a unified knowledge graph. A graph neural encoder is used to learn borrower–inventory dependencies and other latent relational characteristics, while a knowledge reasoning module is introduced to identify suspicious structural patterns and risk propagation paths associated with pledge activities. The empirical analysis is conducted on a dataset covering 24,800 borrowing enterprises, 680 warehouses, 1.36 million inventory records, 92,000 pledge contracts, 410,000 logistics records, 58,000 insurance entries, and 6,740 confirmed pledge-risk cases over a 36-month period. The study aims to improve the early identification of inventory pledge risk by moving from isolated collateral assessment toward relationship-based and process-oriented risk analysis. It also seeks to identify duplicated pledge structures, reveal inconsistencies among inventory, warehouse, logistics, and transaction records, and provide more traceable evidence for risk warnings. From a practical perspective, the proposed approach can reduce dependence on repetitive manual collateral reviews, strengthen continuous monitoring of pledged assets, and help financial institutions detect abnormal financing structures before repayment problems become fully observable. More broadly, the study provides a graph-based framework for integrating heterogeneous operational and financial information in industrial supply-chain finance and offers a practical basis for improving the transparency, efficiency, and interpretability of inventory pledge risk management.

2. Materials and Methods

2.1 Sample and Study Area Description

This study used an industrial inventory financing dataset including 24,800 borrowing enterprises, 680 warehouses, 1.36 million inventory records, 92,000 pledge contracts, 410,000 logistics entries, 58,000 insurance records, and 6,740 confirmed pledge-risk cases over 36 months. The sample included manufacturers in heavy machinery, transport equipment, electronics, and industrial components. Enterprises were selected when they had complete registration records, traceable warehouse and logistics information, verified inventory pledges, and confirmed repayment outcomes. Enterprises were excluded if inventory records were missing for more than six months, warehouse or logistics data were incomplete, or financial-risk status could not be confirmed. The final dataset included only enterprises with complete inventory, warehouse receipt, logistics, and repayment records.

2.2 Experimental Design and Control Settings

The experiment tested whether using warehouse knowledge graph inference improves inventory pledge risk prediction. The proposed model was the experimental group, integrating borrower attributes, inventory batches, warehouses, warehouse receipts, logistics providers, valuation agencies, insurance records, purchase contracts, sales invoices, commodity prices, and repayment records into a heterogeneous graph. Three control models were used for comparison: (1) a collateral-value model using only borrower financials and inventory value, (2) a service-feature model including warehouse and logistics data but excluding valuation and insurance records, and (3) a simplified graph model linking borrowers only to warehouse receipts. This design allowed evaluation of the contribution of warehouse, logistics, valuation, and insurance data. Data were split by time: the first 24 months for training, the next 6 months for validation, and the final 6 months for testing.

2.3 Measurement Methods and Quality Control

Service and inventory variables included warehouse receipt counts, inventory quantity, repeated pledges, logistics verification, warranty coverage, and insurance status. Financial-risk variables included delayed payments, contract breaches, and confirmed pledge-risk events. Data cleaning removed duplicate enterprise IDs, repeated warehouse receipts, inconsistent pledge records, and incorrect logistics entries. Missing monthly values shorter than two months were linearly interpolated; longer gaps were treated as missing. Extreme values from one-time settlements, corrections, or shipment errors were checked against warehouse and logistics records. All quantitative variables were normalized by enterprise size and product category to reduce scale bias.

2.4 Data Processing and Model Formulation

A heterogeneous warehouse knowledge graph was constructed as $G=(V,E)$, where V denotes nodes and E denotes edges. The nodes included borrowing enterprises, pledged inventory batches, warehouses, warehouse receipts, logistics providers, valuation agencies, insurance records, purchase contracts, sales invoices, commodity prices, and repayment records. The edges represented ownership, storage, pledge, logistics verification, valuation, insurance, sales, and repayment relations. Each node contained features such as inventory value, pledge frequency, warehouse location, logistics verification count, insurance coverage, commodity price change, downstream sales, and repayment status. To better capture inventory pledge risk, the pledge anomaly score of enterprise i was calculated as:

$$A_i=\lambda_1 D_i+\lambda_2 L_i+\lambda_3 V_i+\lambda_4 I_i+\lambda_5 S_i$$

where A_i is the pledge anomaly score of enterprise i, D_i denotes the repeated pledge indicator, L_i denotes the inventory-location inconsistency indicator, V_i denotes the abnormal valuation fluctuation indicator, I_i denotes the delayed warehouse inspection indicator, and S_i denotes the downstream sales decline indicator. The coefficients λ_1 to λ_5 represent the weights of different pledge-risk factors. Based on this anomaly score and repayment behavior, the final pledge-risk probability was estimated as:

$$P_i=\frac{1}{1+\exp\left[-(\beta_0+\beta_1 A_i+\beta_2 C_i+\beta_3 M_i+\beta_4 R_i)\right]}$$

where P_i is the predicted pledge-risk probability of enterprise i, A_i is the pledge anomaly score, C_i is the commodity price change variable, M_i is the mismatch between logistics evidence and warehouse records, and R_i is the repayment delay variable. This formulation links collateral authenticity, warehouse consistency, valuation change, logistics evidence, and repayment behavior. It is more suitable for inventory pledge financing because it directly measures the main causes of pledge deterioration.

2.5 Model Evaluation and Robustness Analysis

Model performance was evaluated using AUC, F1-score, precision, recall, early-warning lead time, alert reduction, and inference latency. AUC and F1-score measured overall prediction accuracy, while precision and recall measured correct identification of confirmed pledge-risk cases. Lead time was defined as the days between first warning and confirmed pledge deterioration. Alert reduction measured the decrease in manual warehouse review after graph aggregation. Robustness tests were performed across industries, enterprise sizes, warehouse scales, and time periods. Ablation tests removed warranty claims, logistics, valuation, or insurance features to assess their contribution. These tests confirmed that each feature improved prediction and that the model remained stable under different inventory pledge conditions.

3. Results and Discussion

3.1 Prediction Performance of the Warehouse Knowledge Graph Model

The warehouse knowledge graph inference model performed better than the collateral-value scoring baseline, the warehouse-logistics feature model, and the borrower-only credit model. AUC, F1-score, precision, and recall all improved. This result shows that inventory pledge risk cannot be assessed by collateral value or borrower financial status alone. Repeated pledge records, warehouse receipt consistency, logistics verification, insurance coverage, valuation changes, commodity price movement, and repayment behavior all provide useful risk signals [23,24]. As shown in Fig.1, the graph structure links borrowers, inventories, warehouses, warehouse receipts, logistics providers, valuation agencies, insurers, contracts, invoices, prices, and repayment outcomes. This structure helps detect hidden pledge risk that is difficult to identify from separate data tables. Compared with earlier credit risk models based mainly on borrower attributes or transaction variables, the proposed model captures the link between collateral authenticity and repayment risk. This is important because inventory pledge risk often begins with ownership, storage location, or pledge registration before repayment problems appear.

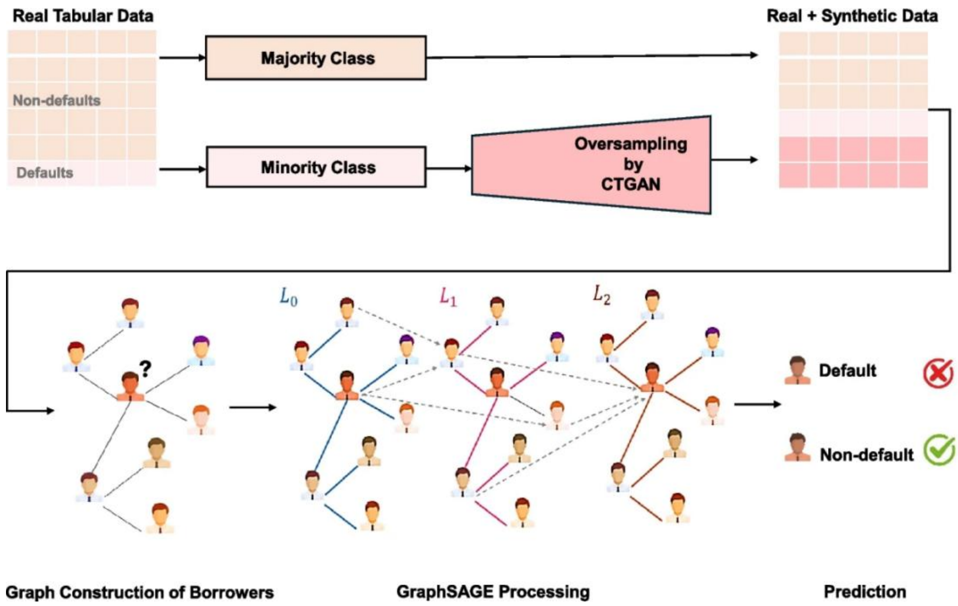

Fig. 1. Warehouse knowledge graph linking borrowers, inventories, logistics, and repayment risk.

3.2 Early Warning Effect of Inventory and Warehouse Signals

The proposed model shortened the median warning time before pledge deterioration from 64 days to 21 days. This result indicates that inventory and warehouse signals appear earlier than repayment indicators [25,26]. In many confirmed risk cases, abnormal pledge registration or inventory-location inconsistency appeared first. Delayed warehouse inspection, abnormal valuation change, weaker downstream sales, and repayment pressure then followed. This pattern is consistent with inventory pledge financing practice. When the same inventory is pledged more than once, or when warehouse records do not match logistics evidence, collateral control risk increases before formal default. Commodity price decline may further weaken collateral coverage and increase lender exposure. Traditional collateral-value scoring models often lag because they depend on periodic valuation reports and post-loan inspection. In contrast, the proposed model uses graph-linked warehouse, logistics, valuation, and repayment data. This supports earlier detection of pledge deterioration.

3.3 Identification of Suspicious Risk Chains and Review Reduction

The graph inference module identified 7,860 suspicious inventory-risk chains and 1,690 duplicated pledge structures. These results show that inventory pledge risk often develops through linked events rather than one isolated abnormal record. A typical risk path was observed: repeated pledge registration occurred, inventory location became inconsistent, logistics evidence weakened, valuation fluctuated abnormally, and borrower repayment deteriorated [27,28]. Such paths are more useful for collateral review than a single risk score because they show how risk is formed. As shown in Fig.2, the system reduced manual collateral review from 22,400 warehouse batches to 4,960 graph-linked investigation cases. This reduction is important for banks and warehouse supervisors because repeated alerts from the same borrower, inventory batch, or warehouse receipt can be merged into one review case. Compared with feature-importance methods, path-based inference provides clearer evidence for investigation. It shows whether the warning comes from duplicated pledge, false storage information, weak logistics proof, price decline, or delayed repayment.

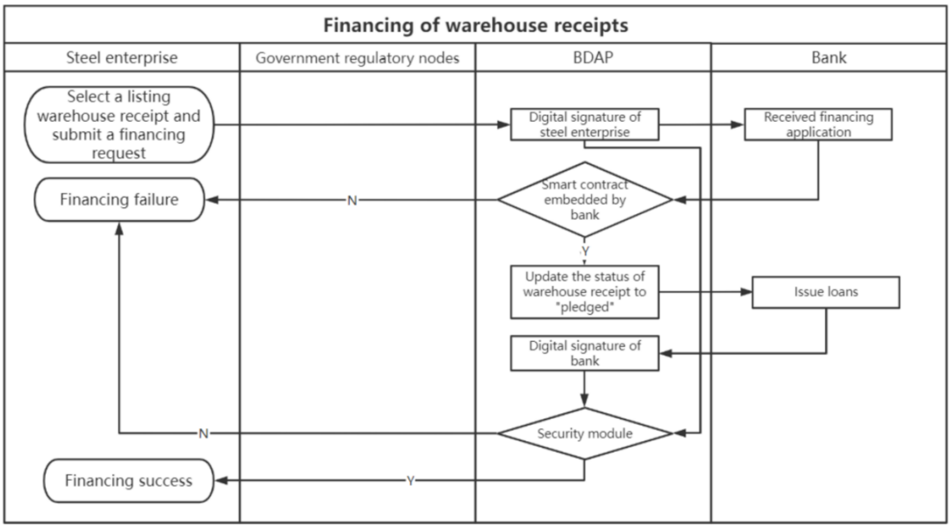

Fig. 2. Workflow for inventory pledge risk monitoring using warehouse receipts.

3.4 Comparison with Existing Studies and Practical Implications

The findings extend existing inventory pledge and supply-chain finance studies in several ways. First, prior models often focus on borrower credit, collateral value, or warehouse supervision rules. This study combines collateral authenticity, warehouse consistency, logistics evidence, insurance records, commodity prices, sales invoices, and repayment outcomes in one graph. Second, many machine learning models treat each borrower as an independent sample. The proposed method models inventory pledge risk as a linked process among borrowers, warehouses, receipts, logistics providers, valuation agencies, insurers, buyers, and financial institutions [29,30].

Third, this study evaluates not only prediction accuracy but also warning time, duplicated pledge detection, review reduction, and inference speed. Full monthly assessment was completed in 10.8 minutes, and the median inference latency was 38 ms per pledge node. These results suggest that the model can support large-scale post-loan monitoring. In practice, it can help banks, warehouse operators, logistics providers, and financing platforms detect suspicious pledge structures earlier. However, the model depends on complete warehouse, logistics, valuation, and insurance records. Missing warehouse receipts, delayed logistics updates, and fragmented price data may reduce prediction stability. Future studies should test the model across more commodity types, warehouse systems, and real-time inventory monitoring settings.

4. Conclusion

This study developed a warehouse knowledge graph model to predict inventory pledge risk in industrial enterprises. The results show that repeated pledge records, warehouse receipt consistency, logistics verification, insurance coverage, valuation changes, commodity price fluctuations, and repayment behavior can provide early signals of risk. Compared with a collateral-value scoring model, the proposed method reduced the median warning time from 64 days to 21 days. It also identified 7,860 suspicious inventory-risk chains and 1,690 duplicated pledge cases. Graph aggregation reduced manual collateral review from 22,400 warehouse batches to 4,960 investigation cases, improving operational efficiency. The main contribution is the construction of a warehouse-centered knowledge graph that links borrowers, inventories, warehouses, warehouse receipts, logistics providers, valuation agencies, insurers, contracts, invoices, prices, and repayment outcomes. This framework captures how collateral authenticity, warehouse control, logistics evidence, market prices, and repayment behavior jointly affect risk. The findings indicate that warehouse graph inference can provide earlier and more interpretable risk assessment in inventory pledge financing. In practice, the model can help banks, warehouse operators, logistics providers, and financing platforms conduct post-loan monitoring and collateral review. Limitations include dependence on complete warehouse, logistics, valuation, and insurance data; missing or delayed records may reduce prediction reliability. Future research should test the model across more commodity types, warehouse systems, and real-time inventory monitoring scenarios.

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