Export Order Financing Risk Prediction Using Cross-Border Trade Knowledge Graphs

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Abstract

Export order financing provides working capital for industrial enterprises before goods are delivered and payments are received. However, this financing mode is exposed to risks from unstable overseas buyers, delayed customs clearance, abnormal logistics records, exchange-rate fluctuation, export-document inconsistency, and weak supplier fulfillment capacity. Traditional credit assessment models mainly focus on the exporter's financial statements and often fail to verify the reliability of cross-border trade relationships. This study proposes a cross-border trade knowledge graph model for export order financing risk prediction. The model links exporters, overseas buyers, purchase orders, customs declarations, shipping records, logistics providers, letters of credit, exchange-rate movements, tax rebate records, and repayment outcomes. A graph neural encoder learns exporter-buyer dependency, while a knowledge inference module identifies risk chains involving repeated order cancellation, delayed shipment, abnormal customs declaration, buyer credit deterioration, and foreign-exchange exposure. Experiments are conducted on an export finance dataset containing 26,400 industrial exporters, 91,000 overseas buyers, 1.72 million export orders, 640,000 customs declarations, 480,000 shipping records, and 6,920 confirmed financing-risk cases over 38 months. The proposed method shortens median warning time before repayment deterioration from 66 days to 23 days compared with an exporter-level credit scoring baseline. Graph reasoning identifies 8,760 cross-border trade risk paths and 2,180 buyer-concentration risk chains. The system reduces manual document review from 24,300 order batches to 5,120 graph-linked investigation cases. Full monthly assessment is completed in 12.1 minutes, with a median inference latency of 44 ms per exporter node. These results indicate that cross-border trade knowledge graphs can improve export order financing risk prediction by connecting credit risk with order authenticity, logistics evidence, and buyer-side repayment uncertainty.

Keywords: Export order financing; cross-border trade knowledge graph; industrial finance; graph neural network; buyer credit risk; logistics verification; financing risk prediction.

1. Introduction

Export order financing is an important source of working capital for industrial exporters, particularly during the period between production, shipment, and final payment collection. It enables firms to maintain production schedules, purchase raw materials, arrange logistics, and fulfill overseas contracts without waiting for receivables to be settled. However, the risk structure of export order financing is more complex than conventional firm-level credit assessment. Financing outcomes are affected not only by the exporter's financial condition and repayment capacity, but also by the stability of overseas buyers, supplier fulfillment capacity, customs clearance, logistics performance, trade-document consistency, exchange-rate fluctuations, and the enforceability of payment arrangements. Traditional credit models mainly rely on financial ratios, repayment histories, and borrower-level credit scores, while recent machine learning methods based on random forests, gradient boosting, and neural networks have improved predictive performance by capturing nonlinear relationships among financial and behavioral variables [1,2]. At the same time, the increasing digitalization of cross-border trade has made secure and auditable information infrastructure increasingly important for integrating transaction, logistics, customs, and financing records. Recent research on open-source cloud security frameworks has emphasized the need for reliable security mechanisms, transparent system control, and auditable data environments in cloud-based infrastructures [3]. These requirements are directly relevant to export finance systems, where risk assessment increasingly depends on the integrity and traceability of distributed trade data [4,5].

Despite the progress of machine learning in financial risk prediction, most existing models continue to treat exporters as independent borrowers and evaluate financing decisions mainly from firm-level or contract-level features [6,7]. This assumption is restrictive in export order financing because repayment performance is closely linked to the underlying trade relationship and the execution status of the export transaction [8]. An exporter with acceptable financial indicators may still face substantial repayment pressure when major buyers cancel orders, shipments are delayed, customs declarations are inconsistent, logistics records are abnormal, or exchange-rate movements sharply reduce expected cash inflows. Similarly, a deterioration in overseas buyer credit may affect multiple exporters simultaneously when they share concentrated exposure to the same buyer or market [9,10]. These risks are difficult to identify from balance sheets or isolated credit scores alone because they emerge from interactions among firms, buyers, contracts, documents, logistics activities, and external market conditions. Recent studies on supply chain finance have therefore increasingly introduced network analysis, knowledge graphs, and graph neural networks to represent enterprise relationships and model the transmission of financial risk across connected entities [11,12]. Knowledge graph-based approaches have also been applied to credit risk assessment, fraud detection, transaction monitoring, and financial relationship mining, demonstrating that relational information can reveal hidden dependencies that are not visible in conventional tabular datasets [13,14]. These approaches are particularly suitable for industrial finance because financing risk is often embedded in repeated business relationships, shared counterparties, common guarantors, overlapping transactions, and interconnected operational activities [15,16]. Nevertheless, most existing graph-based models remain focused on static enterprise attributes, domestic supply chain links, or generalized transaction networks. They rarely describe the complete execution process of cross-border trade, where risk may develop progressively through purchase orders, customs declarations, shipping records, logistics providers, letters of credit, tax rebate records, foreign-exchange movements, and repayment outcomes. The dynamic nature of export trade further increases the need for an integrated relational representation [17,18]. A single export order may involve an exporter, one or more suppliers, an overseas buyer, customs authorities, shipping companies, logistics providers, banks, and settlement institutions [19,20]. The same buyer may be connected to multiple exporters, while one exporter may simultaneously depend on several buyers, shipping channels, and payment arrangements. Delayed shipment may indicate production or logistics difficulties, repeated order cancellation may signal weakening demand, and abnormal customs declarations may suggest inconsistency between the reported transaction and actual trade activity [21,22]. Concentrated exposure to a small number of overseas buyers can amplify default risk, while foreign-exchange volatility can reduce expected repayment capacity even when the underlying goods are delivered successfully [23,24]. These heterogeneous signals are generated at different stages of the trade process and are usually stored in separate operational systems. As a result, conventional risk models often fail to connect related events across entities and time, limiting their ability to detect emerging risk chains before repayment deterioration becomes visible.

To address these limitations, this study proposes a cross-border trade knowledge graph framework for export order financing risk prediction. The proposed framework integrates exporters, overseas buyers, export orders, customs declarations, shipping records, logistics providers, letters of credit, exchange-rate movements, tax rebate records, and repayment outcomes into a unified relational structure. A graph neural encoder is employed to learn dependencies between exporters and overseas buyers, including buyer concentration, repeated transaction exposure, and interconnected trade relationships. A knowledge inference module is further introduced to identify hidden risk paths associated with delayed shipment, abnormal customs declarations, repeated order cancellation, buyer credit deterioration, and foreign-exchange exposure. Unlike traditional exporter-level credit scoring, the proposed method evaluates financing risk as the outcome of interactions among the borrower, overseas counterparties, and the trade execution process rather than as an isolated borrower characteristic. The reasoning results are also transformed into interpretable investigation cases that can support manual review and post-financing monitoring. The empirical analysis is conducted on a large-scale export finance dataset containing 26,400 industrial exporters, 91,000 overseas buyers, 1.72 million export orders, 640,000 customs declarations, 480,000 shipping records, and 6,920 confirmed financing-risk cases collected over a 38-month period. By combining large-scale transaction information with cross-border relational structures, this study aims to determine whether trade knowledge graphs can improve the timeliness and accuracy of financing-risk identification, reveal interpretable risk propagation chains, and support scalable monthly assessment of industrial export portfolios. The proposed framework is expected to extend conventional credit assessment from borrower-centered prediction toward process-aware and relationship-aware risk analysis. In practical terms, it can help financial institutions identify suspicious trade patterns earlier, prioritize high-risk cases for manual investigation, reduce repetitive review of low-risk transactions, and strengthen portfolio-level monitoring of exporters, overseas buyers, and trade channels. The study therefore provides both a methodological contribution to graph-based financial risk modeling and a practical framework for improving the transparency, efficiency, and robustness of export order financing decisions.

2. Materials and Methods

2.1 Sample and Study Setting

This study used a transaction-level export finance dataset covering 38 months. The sample included 26,400 exporters, 91,000 overseas buyers, 1.72 million export orders, 640,000 customs declarations, 480,000 shipping records, and 6,920 confirmed financing-risk cases. The research subjects were industrial exporters applying for short-term working-capital financing before delivery and payment. Each financing case was linked with purchase orders, customs records, shipping events, letters of credit, exchange rates, tax rebates, and repayment results. Records with missing exporter identity, invalid order numbers, duplicate customs declarations, or incomplete repayment labels were removed. The final dataset included exporters of various sizes, buyer compositions, shipment frequency, and repayment patterns, allowing the model to capture both firm-level credit and trade-process risk.

2.2 Experimental Design and Control Setting

The experiment compared the proposed cross-border trade knowledge graph model with traditional exporter-level credit assessment. The experimental group used the full graph dataset, including exporter–buyer links, order records, customs declarations, shipments, logistics providers, letters of credit, exchange rates, tax rebates, and repayment outcomes. The control group used only exporter-level variables, such as firm age, financing frequency, average order value, past overdue records, repayment ratio, and recent transaction volume. The training, validation, and testing periods were the same for all models: the first 26 months for training, the next 6 months for validation, and the final 6 months for testing. Baseline models included logistic regression, random forest, XGBoost, and a multilayer perceptron using exporter-level features.

2.3 Measurement Methods and Quality Control

Risk labels were based on confirmed repayment failure, including overdue repayment, forced extension, post-financing order cancellation, buyer-side payment failure, and document checks by credit officers. Order authenticity was measured by matching purchase orders with customs and shipping records. Logistics reliability was measured by shipment delays, carrier changes, route interruptions, and missing tracking events. Buyer stability was measured by repeated cancellations, buyer concentration ratio, payment delay history, and transaction volume changes. Exchange-rate exposure was measured as the difference between financing approval and expected repayment rates. Quality control was conducted at three levels. First, entity names, tax numbers, buyer codes, order IDs, and shipment numbers were standardized. Second, duplicate declarations, reversed invoices, invalid timestamps, or inconsistent currency units were checked and corrected. Third, 10% of high-risk samples and 5% of low-risk samples were manually verified against the original documents.

2.4 Data Processing and Model Formulation

After cleaning, all entities and relations were converted into a mixed-type trade graph. Exporters, buyers, orders, customs declarations, shipping records, logistics providers, letters of credit, exchange rates, tax rebates, and repayment outcomes were graph nodes. Relations included “places order,” “exports to,” “declares through customs,” “ships by,” “financed by,” “repaid after,” and “linked to tax rebate.” Numerical variables were normalized using z-scores; categorical variables were encoded by entity and relation type. The exporter risk probability was estimated as:

$$P(y_i=1)=\sigma(\beta_0+\beta_1 C_i+\beta_2 B_i+\beta_3 L_i+\beta_4 D_i+\beta_5 F_i+\varepsilon_i),$$

where C_i is exporter credit condition, BiB_iBi is buyer stability, L_i is logistics reliability, D_i is document consistency, and F_i is exchange-rate exposure. Node representations were updated by aggregating neighboring trade evidence:

$$h_i^{(k+1)}=\sigma(W^{(k)}h_i^{(k)}+\sum_{j\in N(i)}\alpha_{ij}^{(k)}W_r^{(k)}h_j^{(k)})$$

where $h_i^{(k)}$ is the node representation at layer k, $N(i)$ is the neighboring node set, $\alpha_{ij}^{(k)}$ is the relation weight, and $W_r^{(k)}$ is the relation-specific transformation. Model performance was evaluated using AUC, precision, recall, F1-score, early-warning lead time, and reduction in manual review cases.

2.5 Model Training and Evaluation Procedure

The model was trained using confirmed financing-risk cases as positive samples and normally repaid cases as negative samples. Since risk cases were relatively few, class weights and stratified sampling were applied. Hyperparameters such as layer number, hidden dimension, learning rate, dropout rate, and batch size were selected based on the validation set. Early stopping was applied when validation AUC did not improve for five epochs. In testing, each exporter received a monthly risk score, and high-risk paths were generated to guide credit review. A warning was correct if issued before confirmed repayment failure. The proposed method was compared with baseline models over the same test period. Operational evaluation included median warning lead time, number of investigation cases, and reduction in manual review workload.

3. Results and Discussion

3.1 Predictive Performance of the Proposed Model

The proposed cross-border trade knowledge graph model showed better prediction results than the exporter-level baseline models. As shown in Fig.1, the proposed model achieved higher AUC, precision, recall, and F1-score than logistic regression, random forest, XGBoost, and the multilayer perceptron. This result suggests that trade-chain information can provide useful signals for financing risk assessment [25,26]. Traditional models mainly use firm-level variables, such as financing frequency, past overdue records, average order value, and repayment ratio. These variables reflect the general credit status of exporters, but they cannot fully describe whether the export transaction is reliable. In contrast, the proposed model includes buyer relationships, customs declarations, shipping records, logistics events, exchange-rate changes, and tax rebate information. These data help the model detect risk before it is reflected in financial indicators. This finding is consistent with Gu et al. (2026), who reported that graph-based learning improves loan default prediction by using relationships among samples. However, this study applies this idea to export order financing, where risk is related not only to exporters but also to overseas buyers, logistics providers, customs records, and trade documents.

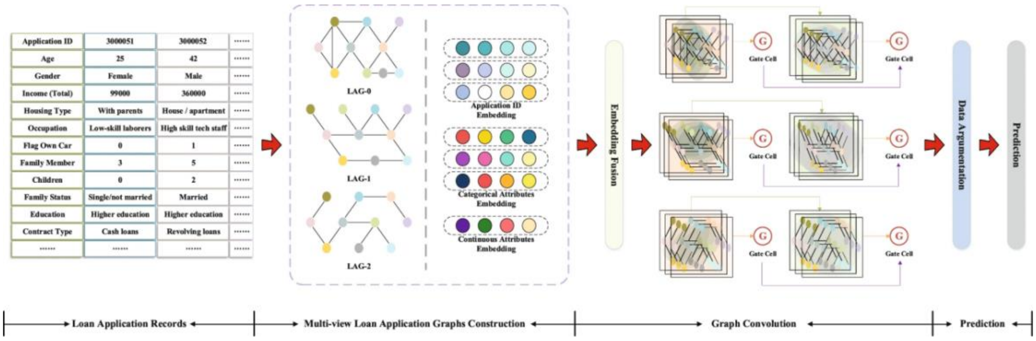

Fig. 1. Prediction results of the proposed graph-based model and baseline credit risk models in export order financing.

3.2 Early-Warning Results and Trade-Chain Signals

The early-warning results indicate that the proposed model identified repayment risk earlier than the exporter-level credit scoring model. The median warning time before repayment failure decreased from 66 days in the baseline model to 23 days in the proposed model. This result shows that trade-chain records can provide earlier risk signals. Delayed shipment, repeated order cancellation, abnormal customs declaration, and buyer-side payment delay were the most common warning factors [27,28]. This result is different from many traditional credit risk studies, which mainly evaluate models by accuracy, AUC, or F1-score. In export order financing, prediction accuracy alone is not sufficient. A useful model should also give warnings early enough for banks and credit officers to take action. Compared with the foreign trade credit risk framework proposed by Zhao et al. (2026), which focuses on firm-level credit classification and feature explanation, this study links each risk score with order records, customs data, logistics events, and repayment results. Therefore, the warning result is closer to the real review process in export financing.

3.3 Graph-Based Risk Path Interpretation

The graph reasoning module identified 8,760 cross-border trade risk paths and 2,180 buyer-concentration risk chains. As shown in Fig.2, most high-risk paths were related to exporter–buyer dependence, order–customs inconsistency, and shipment–repayment delay. In some high-risk cases, exporters had normal repayment records in the past, but their recent orders were highly dependent on one overseas buyer with repeated cancellation records. In other cases, the customs value did not match the purchase order amount, or the shipping route showed clear delays before repayment failure. These results show that export order financing risk often comes from weak points in the trade process, rather than from poor financial indicators alone [29,30]. This finding supports the view of Jamali et al. (2026) that foreign trade credit risk should be assessed with clear and explainable evidence. The proposed model provides more detailed support for this view because each warning can be traced to a specific buyer, order, customs record, or shipment event.

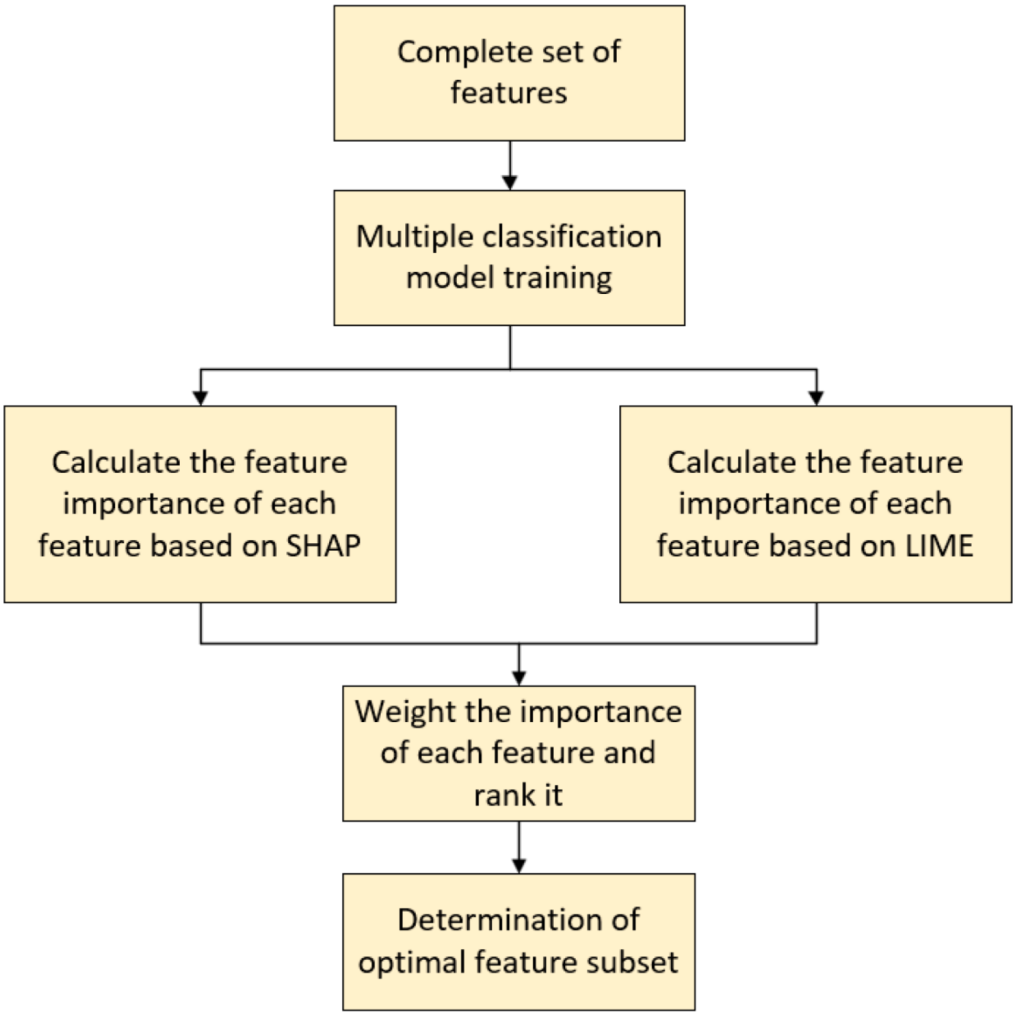

Fig. 2. Main risk paths related to buyer concentration, customs mismatch, shipment delay, and repayment failure.

3.4 Operational Value and Comparison with Existing Studies

The proposed method also improved the efficiency of manual review. Before graph-based screening, credit officers needed to review 24,300 order batches. After risk aggregation, the workload was reduced to 5,120 investigation cases, while most confirmed high-risk cases were still retained. This result indicates that the model can help financial institutions focus on cases with clear trade-chain risk. The full monthly assessment was completed in 12.1 minutes, and the median inference time was 44 ms for each exporter node. These results show that the method can be used in large-scale industrial finance settings. Compared with previous credit risk studies, this study has three practical improvements. First, the analysis unit is changed from a single exporter to the exporter–buyer–order–logistics chain. Second, the prediction result is linked with clear risk paths. Third, the evaluation considers both model accuracy and review efficiency. Overall, the results suggest that cross-border trade knowledge graphs can support export order financing risk prediction, especially when order authenticity, logistics evidence, and buyer repayment uncertainty need to be assessed together.

4. Conclusion

This study proposed a cross-border trade knowledge graph model for predicting export order financing risk. The results show that the model can improve early warning performance by connecting exporter credit status with buyer behavior, order records, customs declarations, shipping information, exchange-rate changes, tax rebate data, and repayment results. Compared with traditional exporter-level credit scoring models, the proposed method detected risk signals earlier and provided clearer evidence for credit review. It also identified major risk paths, including buyer concentration, order cancellation, customs mismatch, shipment delay, and repayment failure. These findings suggest that export financing risk should be assessed through the full trade process, rather than by financial indicators alone. The main contribution of this study is that it links cross-border trade evidence with graph-based risk assessment, providing a more complete and traceable method for checking order reliability and repayment risk. In practice, this method can help banks, supply chain finance platforms, and export credit institutions reduce review workload, improve risk screening, and make more reliable financing decisions for industrial exporters. However, this study has some limits. The dataset mainly used structured trade and financing records, while document text, market news, and policy changes were not fully included. In addition, the model was tested on historical export finance data, and its performance should be further examined in real-time financing systems and different trade regions. Future studies may include document text analysis, buyer credit tracking, and cross-market data to improve the stability and wider use of the model.

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