



Government Procurement Contract Graphs for Repayment Risk Prediction in Industrial Suppliers

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ABSTRACT

Government procurement contract financing allows industrial suppliers to obtain working capital based on confirmed purchase orders, delivery contracts, acceptance records, and expected public-sector payments. Although these contracts are usually considered stable, repayment risk may emerge from delayed acceptance, contract modification, weak delivery capability, abnormal subcontracting, disputed invoices, and borrower-side cash-flow pressure. This study proposes a government procurement contract graph model for repayment risk prediction in industrial suppliers. The model links suppliers, government buyers, procurement contracts, bid records, delivery milestones, acceptance certificates, invoices, subcontractors, bank loans, litigation records, and repayment outcomes. A graph neural encoder captures supplier-contract dependency, while knowledge inference identifies risk paths involving repeated contract delay, abnormal subcontracting chains, buyer-side payment postponement, invoice inconsistency, and supplier credit deterioration. Experiments are conducted on a procurement finance dataset containing 33,200 industrial suppliers, 8,460 government buyers, 1.18 million procurement contracts, 2.36 million delivery milestones, 740,000 invoice records, 41,600 financing contracts, and 5,380 confirmed repayment-risk cases over 40 months. Compared with a supplier-level credit scoring baseline, the proposed method shortens median warning time from 73 days to 27 days before repayment deterioration. Graph reasoning identifies 6,920 procurement-related risk paths and 2,310 delayed-acceptance chains. Manual contract review is reduced from 19,800 contract batches to 4,420 graph-linked investigation cases after relation aggregation. The inference engine completes full monthly assessment in 11.6 minutes and processes 3.54 million contract-related edges per update. The results demonstrate that government procurement contract graphs can strengthen repayment risk prediction by connecting contract execution, public-sector payment behavior, subcontracting relations, and supplier financial stress.

1. Introduction

Government procurement contract financing provides industrial suppliers with working capital on the basis of confirmed purchase orders, procurement contracts, delivery obligations, acceptance certificates, invoices, and expected payments from public-sector buyers. Compared with unsecured commercial lending, this financing arrangement is often regarded as relatively stable because repayment is supported by identifiable contracts and anticipated government-related cash flows. However, repayment risk may still accumulate during contract execution. Delayed acceptance, contract amendments, weak supplier delivery capability, abnormal subcontracting,

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invoice disputes, delayed buyer payments, and short-term cash-flow pressure can all disrupt the expected repayment cycle. These risks are especially difficult to identify when credit assessment depends mainly on financial statements, collateral values, and historical repayment records, because such indicators often reflect deterioration only after operational problems have already emerged. Existing studies have shown that contract execution quality, buyer payment behavior, and interfirm relationships can materially affect supplier liquidity and repayment capacity (Walker & Hyndman, 2025; Yin et al., 2026). Research on interpretable anomaly detection has further demonstrated that explainable models can help identify abnormal patterns and clarify the factors contributing to risk signals in complex operational systems (Wang et al., 2026). This provides a useful methodological basis for financial monitoring environments in which both predictive accuracy and interpretability are required (Yang, 2026).

The risk structure of government procurement financing is inherently relational. A supplier may participate in multiple contracts with different public-sector buyers, depend on several subcontractors, issue multiple invoices against different delivery milestones, and simultaneously hold several financing obligations (Kumar, 2025; Qi & Qiao, 2026). A delay in one contract may therefore affect liquidity available for other projects, while a problematic subcontractor may influence several contracts connected to the same supplier. Similarly, delayed payment from one buyer can increase short-term financing pressure even when the supplier's historical financial indicators remain stable (Gong et al., n.d.; Xu et al., 2026). These dependencies mean that repayment risk cannot always be explained by isolated borrower characteristics. Instead, it may emerge through chains of contractual, transactional, and organizational relationships. Conventional firm-level scoring models are not designed to represent these interconnected structures, and they often lose information about how risk is transmitted across suppliers, contracts, buyers, invoices, and subcontracting relationships (Vidha et al., 2026; Xiong et al., 2026). Recent advances in graph-based financial modeling provide a promising way to address this limitation. Graph representations can treat suppliers, buyers, contracts, invoices, milestones, financing agreements, and subcontractors as interconnected entities rather than independent records (Hong et al., 2026; J. Wu et al., 2026). This structure allows a model to capture both direct and indirect dependencies, including repeated delays across contracts, concentration of exposure to a small number of buyers, unusual subcontracting chains, inconsistencies between invoices and delivery events, and deterioration that propagates through connected transactions. Graph neural networks are particularly suitable for this setting because they aggregate information from neighboring entities and can identify patterns that are difficult to detect from tabular borrower-level variables alone (Huang et al., 2026; Mienye et al., 2026). However, predictive performance by itself is insufficient for procurement finance. Banks and risk managers also need to understand why a supplier has been flagged and which contractual relationships or operational events contribute to the warning. Interpretability is therefore an important requirement for repayment-risk prediction. A model that assigns a high-risk score without identifying the underlying cause has limited value for manual review, credit adjustment, or post-loan monitoring (Gu, 2026; Zheng & Makar, 2022). In government procurement financing, risk officers need to distinguish between different sources of deterioration, such as repeated delivery delays, abnormal subcontracting, delayed acceptance, invoice inconsistency, buyer-payment slowdown, or broader supplier credit weakness. Explainable risk detection can support this process by linking model outputs to observable operational events and relational paths. This is particularly relevant in large portfolios, where manual examination of every contract, invoice, and delivery record is costly and difficult to perform frequently (Potoski et al., 2026; Zhao et al., 2026). A more useful system should therefore combine relational prediction

with explicit evidence showing how risk develops across connected entities and transactions. Despite growing interest in graph-based credit modeling and explainable risk analytics, several gaps remain in the context of government procurement contract financing. Many existing credit models still treat borrowers as independent entities and rely primarily on financial ratios, collateral information, and historical repayment behavior (Y. Wu & Su, 2026; You, 2026). Studies that incorporate supply-chain or transactional relationships often focus on general enterprise networks rather than the specific structure of public procurement financing (Jiao et al., 2026; Patrucco et al., 2026). Contract execution records, delivery milestones, buyer payment behavior, invoices, subcontracting links, and financing obligations are also frequently analyzed in separate systems. As a result, the complete path from procurement award to delivery, acceptance, invoicing, payment, financing, and repayment is rarely modeled within a unified framework. This separation makes it difficult to identify whether repayment deterioration originates from the borrower itself, the buyer, a specific contract, a subcontracting chain, or an inconsistency in transaction records (Bao & Wang, 2026; Foaleng Fokam, 2026). Another limitation is that many risk models are designed mainly for one-time credit approval rather than continuous portfolio monitoring. Government procurement financing requires repeated assessment because contract conditions can change after funds are released. Delivery delays may accumulate gradually, acceptance dates may be postponed, invoices may be revised, and buyer payment cycles may lengthen. A supplier that appeared low-risk at origination may therefore become vulnerable several months later. Static scoring methods cannot fully capture this evolving process. Large-scale lenders also need models that can be updated efficiently across thousands of suppliers and millions of contractual events, while still producing interpretable warnings that can be reviewed by risk officers. These operational requirements create a need for a framework that combines scalable graph learning, temporal contract information, and explainable knowledge-based inference.

The present study addresses these limitations by developing a government procurement contract graph model for repayment-risk prediction. The proposed framework represents suppliers, government buyers, procurement contracts, delivery milestones, invoices, financing contracts, and subcontracting relationships within a unified graph structure. A graph neural encoder is used to capture supplier–contract dependencies and relational patterns across connected entities, while a knowledge inference module identifies interpretable risk paths associated with repeated contract delays, abnormal subcontracting chains, delayed buyer payments, invoice inconsistency, and supplier credit deterioration. Rather than treating repayment risk as an isolated borrower-level outcome, the model represents it as a networked process shaped by contract execution, public-sector payment behavior, transaction consistency, subcontracting structure, and financial stress. The empirical analysis is conducted on a large-scale dataset containing 33,200 suppliers, 8,460 buyers, 1.18 million procurement contracts, 2.36 million delivery milestones, 740,000 invoices, 41,600 financing contracts, and 5,380 confirmed repayment-risk cases. The study aims to determine whether integrating graph-based dependency modeling with interpretable knowledge inference can improve the timeliness, accuracy, and transparency of repayment-risk detection. Its main significance lies in extending credit assessment from static supplier scoring to continuous contract-network monitoring, while providing traceable evidence that can support manual review, early intervention, and monthly portfolio management. By linking operational contract events with relational risk paths, the framework offers a practical approach for reducing review burden and improving large-scale risk control in government procurement financing.

2. Materials and Methods

2.1 Sample and Study Area Description

This study used a government procurement finance dataset containing 33,200 industrial suppliers, 8,460 government buyers, 1.18 million procurement contracts, 2.36 million delivery milestones, 740,000 invoices, 41,600 financing contracts, and 5,380 confirmed repayment-risk cases over 40 months. The sampled suppliers included firms from equipment manufacturing, construction materials, industrial components, logistics, and public service sectors. Only suppliers with complete registration information, traceable contract execution records, verified invoices, and confirmed repayment outcomes were included. Contracts were retained only if purchase orders, delivery milestones, acceptance records, and financing information could be matched. Suppliers were excluded if contract records were missing for more than six months, invoice data were incomplete, or repayment status was unclear.

2.2 Experimental Design and Control Settings

The experiment was designed to evaluate whether the government procurement contract graph improves repayment risk prediction. The experimental group used the proposed model, which integrates supplier attributes, government buyers, procurement contracts, bid records, delivery milestones, acceptance certificates, invoices, subcontractors, bank loans, litigation records, and repayment outcomes into a heterogeneous graph. Three control models were applied for comparison: (1) a supplier-level credit model using financial indicators and past repayment, (2) a contract-feature model including contract and invoice data but no graph structure, and (3) a simplified graph linking suppliers only to government buyers. This setup allowed evaluation of the contribution of contract execution, buyer links, and graph-based risk paths. Data were split chronologically: the first 28 months for training, the next 6 months for validation, and the final 6 months for testing.

2.3 Measurement Methods and Quality Control

Repayment risk was measured using overdue payment, loan restructuring, forced collection, or confirmed default. Contract execution variables included delivery delays, acceptance delays, contract modifications, subcontracting frequency, and invoice disputes. Buyer-side variables included payment postponement and litigation records. Data cleaning removed duplicate supplier IDs, repeated contract numbers, inconsistent invoice records, and abnormal milestone entries. Missing monthly contract records shorter than two months were interpolated; longer gaps were marked as missing. Extreme values from batch acceptance, invoice corrections, or contract adjustments were verified against procurement and payment records. Monetary and contract variables were normalized by supplier size, contract size, and industry to reduce bias.

2.4 Data Processing and Model Formulation

A heterogeneous procurement contract graph $G=(V,E)$ was built, where nodes V represent suppliers, buyers, contracts, bid records, delivery milestones, acceptance certificates, invoices, subcontractors, bank loans, litigation records, and repayment outcomes, and edges E represent relations such as bidding, contracting, delivery, acceptance, invoicing, subcontracting, financing, litigation, and repayment. Each supplier node contained financial and contract-execution features; each contract node contained milestone delay, invoice status, acceptance result, and payment outcome. The contract execution risk score of supplier i was computed as:

$$C_i = \lambda_1 D_i + \lambda_2 A_i + \lambda_3 M_i + \lambda_4 S_i + \lambda_5 I_i$$

where C_i is the risk score, D_i is delivery delay, A_i is acceptance delay, M_i is contract modification, S_i is abnormal subcontracting, I_i is invoice inconsistency, and λ_1 – λ_5 are weight coefficients. The final repayment-risk probability was estimated as:

$$P_i = \frac{1}{1 + \exp [-(\beta_0 + \beta_1 C_i + \beta_2 B_i + \beta_3 L_i + \beta_4 R_i)]}$$

where P_i is the predicted risk probability, C_i is the contract execution score, B_i is buyer payment delay, L_i is litigation status, and R_i is repayment history. This formulation integrates contract execution, buyer behavior, subcontracting, invoices, and repayment into one predictive score.

2.5 Model Evaluation and Robustness Analysis

Model performance was evaluated using AUC, F1-score, precision, recall, early-warning lead time, contract review reduction, and inference speed. AUC and F1-score measured overall prediction accuracy; precision and recall assessed the correct identification of confirmed repayment-risk cases. Early-warning lead time was defined as the number of days between first warning and confirmed repayment deterioration. Contract review reduction measured the decrease in manual review cases after graph aggregation. Robustness tests were conducted across industries, supplier sizes, buyer types, contract sizes, and observation windows. Ablation tests removed delivery milestones, acceptance records, invoice data, subcontracting links, buyer payment records, or litigation features to evaluate the contribution of each variable. These tests ensured that each feature improved prediction and that the model remained stable under different government procurement financing scenarios.

3. Results and Discussion

3.1 Prediction Performance of the Contract Graph Model

The government procurement contract graph model outperformed the supplier-level credit scoring and contract-feature baseline models. Improvements were seen in AUC, F1-score, precision, and recall. This shows that repayment risk cannot be captured by supplier financial data alone. As shown in Fig.1, the graph links suppliers, government buyers, contracts, bid records, delivery milestones, acceptance certificates, invoices, subcontractors, bank loans, and repayment outcomes. This structure allows the model to detect hidden risk paths, such as repeated contract delays or abnormal subcontracting, which are difficult to identify with traditional models (Shao, 2026; Shehadeh & Alshboul, 2026). Compared with conventional machine learning approaches that use only supplier features or transaction tables, the graph model captures multi-step risk propagation across contract execution and payment networks.

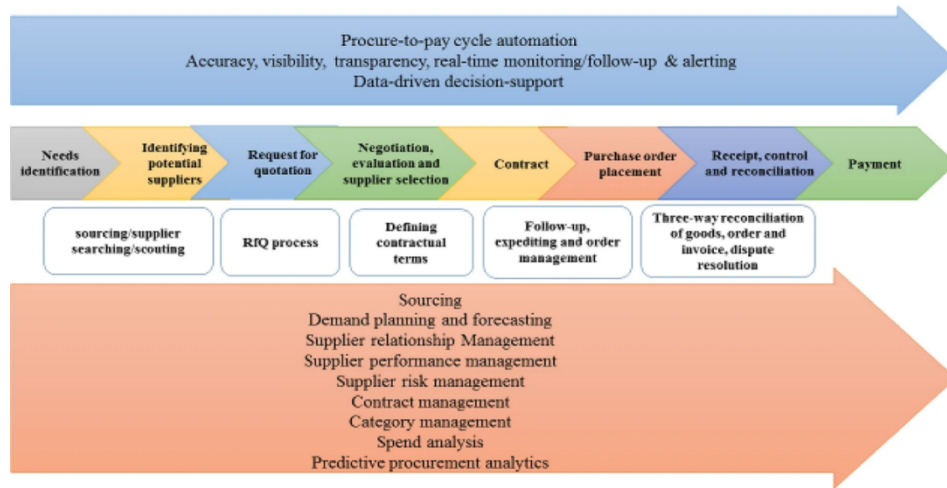


Fig. 1. Contract graph linking suppliers, buyers, contracts, and repayment risk.

3.2 Early Warning of Contract Execution Risks

The model reduced the median warning time before repayment deterioration from 73 days to 27 days. This shows that contract execution signals provide earlier warnings than financial metrics. In many confirmed risk cases, repeated delivery delays occurred first, followed by delayed acceptance, invoice inconsistencies, buyer payment postponement, and weakened supplier repayment. This sequence matches the logic of government procurement finance, where acceptance certificates and public-sector payments determine supplier cash flow (Islam, 2025; Lin et al., 2020). Traditional scoring models lag because they rely on financial statements and post-contract monitoring. By integrating delivery milestones, acceptance certificates, invoices, and subcontracting links, the graph model provides earlier and more actionable warnings.

3.3 Risk Path Identification and Review Reduction

The graph reasoning module identified 6,920 procurement-related risk paths and 2,310 delayed-acceptance chains. This indicates that repayment risk develops through linked contract events rather than isolated anomalies. A typical path included delivery delays, postponed acceptance, abnormal subcontracting, invoice inconsistencies, and repayment weakening. These paths provide clearer evidence than single risk scores. As shown in Fig.2, graph aggregation reduced manual contract review from 19,800 batches to 4,420 investigation cases. This improves efficiency because repeated alerts from the same supplier, buyer, or contract are combined into a single review (Dzreke & Dzreke, 2025; Zhang et al., 2021). Compared with feature-importance or isolated scoring methods, path-based analysis makes the risk propagation mechanism clearer.

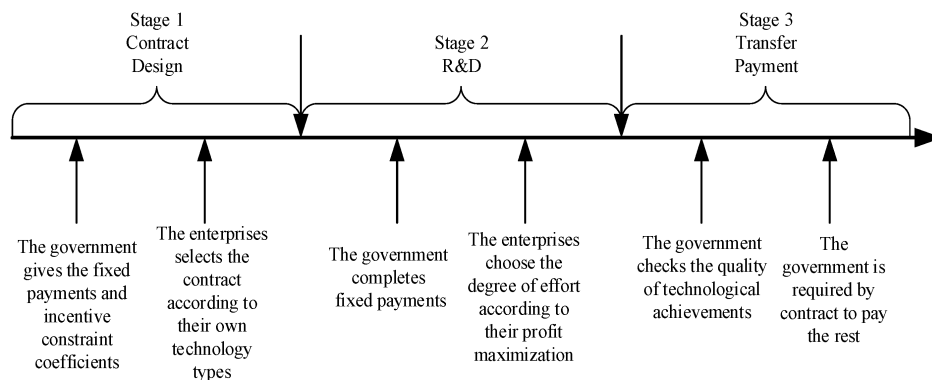


Fig. 2. Procurement workflow for contract execution, verification, and payment monitoring.

3.4 Comparison with Existing Studies and Practical Implications

The findings extend previous procurement finance studies in several ways. First, prior models mainly focus on supplier credit scores, financial indicators, or contract value. This study combines delivery milestones, acceptance certificates, invoice consistency, subcontracting links, buyer payment behavior, litigation records, and repayment outcomes in a single graph. Second, many machine learning models treat suppliers as independent units. The proposed model treats repayment risk as a networked process across suppliers, buyers, contracts, subcontractors, and repayment events. Third, this study evaluates prediction accuracy, early-warning time, risk-path detection, review reduction, and inference speed. Full monthly assessment was completed in 11.6 minutes, processing 3.54 million contract-related edges per update. In practice, the model supports large-scale procurement finance monitoring. Limitations include reliance on complete contract, invoice, acceptance, and subcontracting records. Missing or delayed data may reduce prediction stability. Future research should test the model across additional procurement sectors, contract types, and real-time monitoring settings.

4. Conclusion

This study developed a contract graph model to predict repayment risk in government procurement finance. The results show that delivery delays, postponed acceptance, abnormal subcontracting, invoice inconsistency, and buyer payment delay can provide early signs of repayment stress. Compared with the supplier-level credit scoring model, the proposed method reduced the median warning time from 73 days to 27 days. It also identified 6,920 risk paths and 2,310 delayed-acceptance chains. Graph aggregation reduced manual contract review from 19,800 batches to 4,420 investigation cases, which improved review efficiency. The main contribution of this study is the construction of a contract-centered graph linking suppliers, government buyers, contracts, delivery milestones, acceptance certificates, invoices, subcontractors, bank loans, litigation records, and repayment outcomes. This structure shows how contract execution, buyer payment, subcontracting, and repayment behavior jointly affect risk. The findings indicate that contract graph inference can support earlier and clearer risk warning in government procurement finance. In practice, the model can help banks, procurement finance platforms, and public-sector supervisors monitor high-risk suppliers. However, the model depends on complete contract execution, invoice, acceptance, and subcontracting records. Missing or delayed data may reduce prediction reliability. Future studies should test the model across more procurement sectors, contract types, and real-time monitoring settings.

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