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Energy Consumption Graph Inference for Financing Risk Prediction in Industrial Enterprises

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ABSTRACT

Energy cost financing is increasingly used by industrial enterprises to manage electricity, gas, steam, and fuel expenses during periods of high production demand or cash-flow pressure. However, abnormal energy consumption, declining production intensity, delayed utility payments, and unstable downstream orders may signal future repayment risk before conventional financial indicators change. This study proposes an energy consumption graph inference model for financing risk prediction in industrial enterprises. The model constructs a heterogeneous graph linking enterprises, utility providers, production facilities, electricity meters, gas accounts, invoices, financing contracts, downstream customers, and overdue payment records. A graph neural network is used to encode enterprise production-energy dependency, while a knowledge reasoning module identifies risk chains involving shrinking energy use, abnormal peak-valley consumption, repeated utility arrears, customer-order decline, and concentrated financing exposure. Experiments are conducted on an industrial energy finance dataset containing 41,600 enterprises, 126,000 utility accounts, 2.84 million monthly energy bills, 760,000 customer-supplier relations, 68,000 financing contracts, and 8,420 confirmed repayment-risk cases over 48 months. Compared with a financial-ratio baseline, the proposed model shortens median warning time before repayment deterioration from 84 days to 29 days. Graph inference identifies 5,930 energy-production risk chains and 2,170 enterprises with simultaneous order decline and utility arrears. Risk-path aggregation reduces 13,800 raw enterprise alerts to 3,640 investigation cases. Full monthly portfolio assessment is completed in 15.2 minutes, with a median inference latency of 41 ms per enterprise node. These results indicate that energy consumption graph inference can improve industrial financing risk prediction by connecting production activity, utility payment behavior, and enterprise relationship networks.

1. Introduction

Energy expenditure represents a substantial component of operating costs for industrial enterprises, particularly in energy-intensive sectors with high electricity, natural gas, steam, or fuel consumption. During periods of peak production, volatile energy prices, or temporary liquidity pressure, many firms rely on short-term financing to cover utility bills and stabilize working capital. The repayment risk of such financing is closely related not only to the borrower’s financial condition but also to changes in energy consumption, production intensity, customer demand, and

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payment behavior. Conventional credit risk models mainly evaluate financial ratios, tax records, collateral conditions, and historical repayment performance (F. Chen et al., 2025; Mita, 2025). Although these indicators remain important, they often reflect financial deterioration only after operational problems have already emerged. Recent studies on digital infrastructure have also highlighted the importance of system reliability, security, and operational continuity in data-intensive environments (Shao, 2026), suggesting that infrastructure-level signals can provide useful information for identifying emerging enterprise risks. In energy-intensive industries, abnormal consumption, declining load levels, or repeated utility arrears may therefore serve as early indicators of weakening production activity and future repayment pressure (Hong et al., 2026; Li et al., 2026).

Machine learning methods have increasingly been introduced into corporate credit assessment because of their ability to capture nonlinear relationships among financial and operational variables (Ahmmed, 2025; Wu et al., 2026). These approaches generally improve predictive accuracy compared with traditional statistical models, but most still treat enterprises as independent observations. Such a modeling assumption limits their ability to represent the networked structure of industrial activity, where firms are connected through suppliers, customers, utilities, banks, production facilities, and contractual relationships (H. Chen et al., 2025; Qi & Qiao, 2026). Graph-based methods have consequently attracted increasing attention in financial risk analysis because they can model dependencies among enterprises and related entities and detect risk propagation that cannot be observed from isolated borrower records (Gong et al., n.d.; Prakash, 2025). Knowledge graph approaches further improve model transparency by organizing heterogeneous information into interpretable entities and relations, thereby supporting the identification of potential causes and transmission paths behind a risk prediction (Bag et al., 2025; Xiong & Guo, 2026). However, detailed energy consumption records, utility accounts, meter-level signals, invoice histories, and production-energy relationships are still rarely incorporated into such frameworks. This limitation is important because energy data can provide a relatively direct reflection of industrial operating conditions (Huang et al., 2026a; Wu et al., 2026). For many manufacturing firms, energy consumption is closely associated with production volume, equipment utilization, operating shifts, and order fulfillment (Gu, 2026; Jensen et al., 2025). A sustained decline in electricity or fuel use may indicate reduced production activity, while abrupt deviations from historical consumption patterns may reflect equipment shutdowns, process disruptions, or changes in operating capacity (Lin et al., 2026; Zhao et al., 2026). Repeated delays in utility payments can also reveal liquidity stress before it becomes visible in conventional loan repayment records (Bari, 2026). When these signals are considered together with customer orders, production facilities, financing contracts, and enterprise relationships, they may provide a richer basis for early credit-risk detection than static financial variables alone. Existing studies, however, often rely on aggregated annual indicators or simplified firm-level features and therefore fail to exploit the temporal and relational information contained in industrial energy data (Huang et al., 2026b; Wu et al., 2026). In addition, many predictive models output only a risk probability or classification result without explaining how operational deterioration evolves into financing stress, which reduces their practical value for credit officers who require traceable evidence for lending and monitoring decisions (Chouksey et al., 2025; Zheng & Makar, 2022).

To address these limitations, this study proposes an energy consumption graph inference framework for financing risk prediction in industrial enterprises. The proposed framework constructs a heterogeneous graph linking enterprises, utility providers, production facilities, energy meters, utility invoices, financing contracts, customer relationships, and repayment outcomes. A graph neural network is used to encode production-energy dependencies and relational information across connected entities, while a reasoning module identifies interpretable risk chains associated with declining energy use, abnormal consumption behavior, repeated utility arrears, production contraction, and customer order reductions. By integrating operational, relational, and payment information within a unified graph structure, the proposed approach aims to detect repayment risk earlier than conventional models that rely primarily on financial ratios and historical credit records. The framework also provides traceable explanations of how changes in energy and production behavior contribute to credit deterioration, thereby improving the transparency of model outputs. The study is intended to support financial institutions in pre-loan assessment, post-loan monitoring, and early intervention, while providing a scalable and interpretable approach for evaluating financing risk in energy-intensive industrial environments.

2. Materials and Methods

2.1 Sample and Study Area Description

This study used an industrial energy finance dataset from enterprises that applied for energy cost financing. The dataset contained 41,600 enterprises, 126,000 utility accounts, 2.84 million monthly energy bills, 760,000 customer–supplier links, 68,000 financing contracts, and 8,420 confirmed repayment-risk cases. The observation period covered 48 months. The sampled enterprises mainly came from equipment manufacturing, metal processing, chemicals, building materials, logistics, and industrial services. These firms had clear utility account records, complete financing histories, and traceable customer or supplier links. Enterprises were excluded if their registration information was incomplete, their utility bills were missing for more than six months, or their repayment status could not be confirmed. The final sample retained firms with valid electricity, gas, steam, or fuel records, matched financing contracts, and reliable relationship data.

2.2 Experimental Design and Control Settings

The experiment was designed to test whether energy consumption graph inference can improve financing risk prediction. The proposed model was used as the experimental group. It included enterprise information, energy use, utility payment records, financing contracts, downstream customer links, and overdue events in one heterogeneous graph. Three control models were built for comparison. The first model used only financial ratios and contract variables. The second model used financial variables and monthly energy features but did not use graph structure. The third model used enterprise relationship data but removed utility accounts and energy bills. This setting helped measure the separate effects of energy signals, graph links, and reasoning paths. To avoid data leakage, the dataset was split by time. The first 36 months were used for training, the next 6 months for validation, and the last 6 months for testing.

2.3 Measurement Methods and Quality Control

Energy use was measured at the monthly utility-account level. The main variables included electricity use, gas use, steam use, fuel cost, peak-valley load ratio, payment delay days, invoice amount, and arrears frequency. Financing risk was defined as confirmed repayment deterioration, including overdue repayment, contract restructuring, forced collection, or default confirmation by the financing institution. Customer-order decline was measured by reduced transaction frequency and invoice amount between enterprises and downstream customers. Data quality control was performed before model training. Duplicate enterprise IDs, abnormal meter IDs, repeated invoices, and inconsistent contract records were removed. Missing monthly consumption values were filled only when the missing period was shorter than two months. Longer missing periods were marked as discontinuous records. Extreme values caused by meter replacement, billing correction, or one-time settlement were checked against invoice notes and utility account status. Monetary variables were normalized by industry and enterprise size to reduce scale bias.

2.4 Data Processing and Model Formulation

A heterogeneous graph was constructed as $G=(V,E)$, where V denotes nodes and E denotes edges. The nodes included enterprises, utility providers, production facilities, meters, gas accounts, invoices, financing contracts, downstream customers, and overdue records. The edges represented ownership, billing, financing, customer–supplier links, payment delay, and repayment-risk events. For each enterprise, monthly energy use, utility arrears, contract exposure, and customer-order changes were converted into node and edge features. A graph neural network was used to learn enterprise risk representations from neighboring nodes. The node representation of enterprise i was updated as follows:

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

where $h_i^{(l)}$ is the node representation at layer l, R is the set of relation types, $N_r(i)$ is the neighbor set of enterprise i under relation r, W_r is the weight matrix for relation r, $c_{i,r}$ is the normalization term, and σ is the activation function. The repayment-risk probability was then calculated as:

$$P_i=\frac{1}{1+\exp\left[-(\beta_0+\beta_1 z_i+\beta_2 a_i+\beta_3 o_i+\beta_4 f_i)\right]}$$

where P_i is the predicted risk probability of enterprise i, z_i is the graph embedding, a_i is the utility arrears variable, o_i is the customer-order decline variable, and f_i is the financing exposure variable.

2.5 Model Evaluation and Robustness Analysis

Model performance was assessed using AUC, F1-score, precision, recall, warning lead time, alert reduction rate, and inference latency. AUC and F1-score were used to assess overall prediction performance. Precision and recall were used to measure the identification of real repayment-risk cases. Warning lead time was defined as the number of days between the first model warning and confirmed repayment deterioration. Alert reduction rate was used to test whether risk-path aggregation could reduce repeated enterprise warnings. Robustness tests were conducted across different industries, enterprise sizes, financing amounts, and observation windows. Additional ablation tests were performed by removing energy use features, utility arrears records, customer-order links, and reasoning paths. These tests were used to examine whether each data component improved risk prediction and whether the proposed model remained stable under different industrial financing conditions.

3. Results and Discussion

3.1 Overall Prediction Performance

The energy consumption graph inference model outperformed the financial-ratio baseline, the energy-feature model, and the enterprise-relation model. Measures including AUC, F1-score, precision, and recall all improved when energy use, utility payment behavior, and enterprise links were used together. This indicates that repayment risk in industrial energy financing cannot be fully captured by financial ratios alone (Das, 2026; Yao et al., 2026). Energy consumption and delayed payments provide early signals of production decline and liquidity pressure. As shown in Fig.1, the graph-based model produced more stable results than the baseline models, particularly for enterprises with limited financial disclosure or irregular payment patterns. Compared with earlier graph-based credit studies, this model links enterprises with meters, utility accounts, invoices, customers, and financing contracts, which better reflects industrial operations.

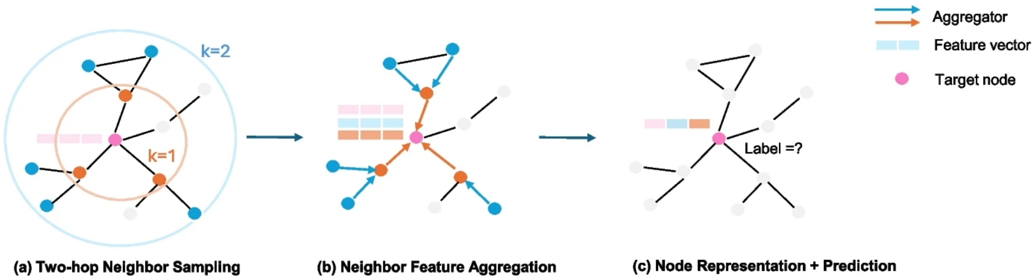

Fig. 1. Graph aggregation of enterprise, energy, and financing records for risk prediction.

3.2 Early Warning Ability of Energy-Based Signals

The model shortened the median warning time before repayment deterioration from 84 days to 29 days. This suggests that changes in energy use can appear before financial indicators show stress. In most risk cases, enterprises first reduced electricity or gas consumption, then delayed utility payments, and finally experienced repayment issues. This sequence is consistent with industrial practice: production slows before revenue drops, and cash shortages affect utility payments before formal defaults occur (Moro-Visconti, 2026; Zhang et al., 2021). Traditional credit models rely on past repayment records or periodic financial reports, which are delayed. In contrast, monthly utility bills provide direct evidence of current production activity. This explains the improved early warning ability of the proposed model.

3.3 Risk-Chain Interpretation and Alert Reduction

The graph reasoning module identified 5,930 energy-production risk chains and 2,170 enterprises with both order decline and utility arrears. This shows that repayment risk usually arises from a sequence of connected events rather than one isolated anomaly. A typical risk path was: downstream orders fell, production intensity decreased, energy consumption dropped, utility bills became overdue, and financing repayment weakened (Islam et al., 2026; You, 2026). These paths are easier for credit officers to examine than a single risk score. As shown in Fig.2, risk-path aggregation reduced 13,800 raw alerts to 3,640 cases. Reducing alerts is important because too many notifications increase review cost and lower efficiency. Compared with feature-importance or SHAP methods, the reasoning process provides clearer event-level explanations, showing how production decline, payment delay, and financing exposure are connected.

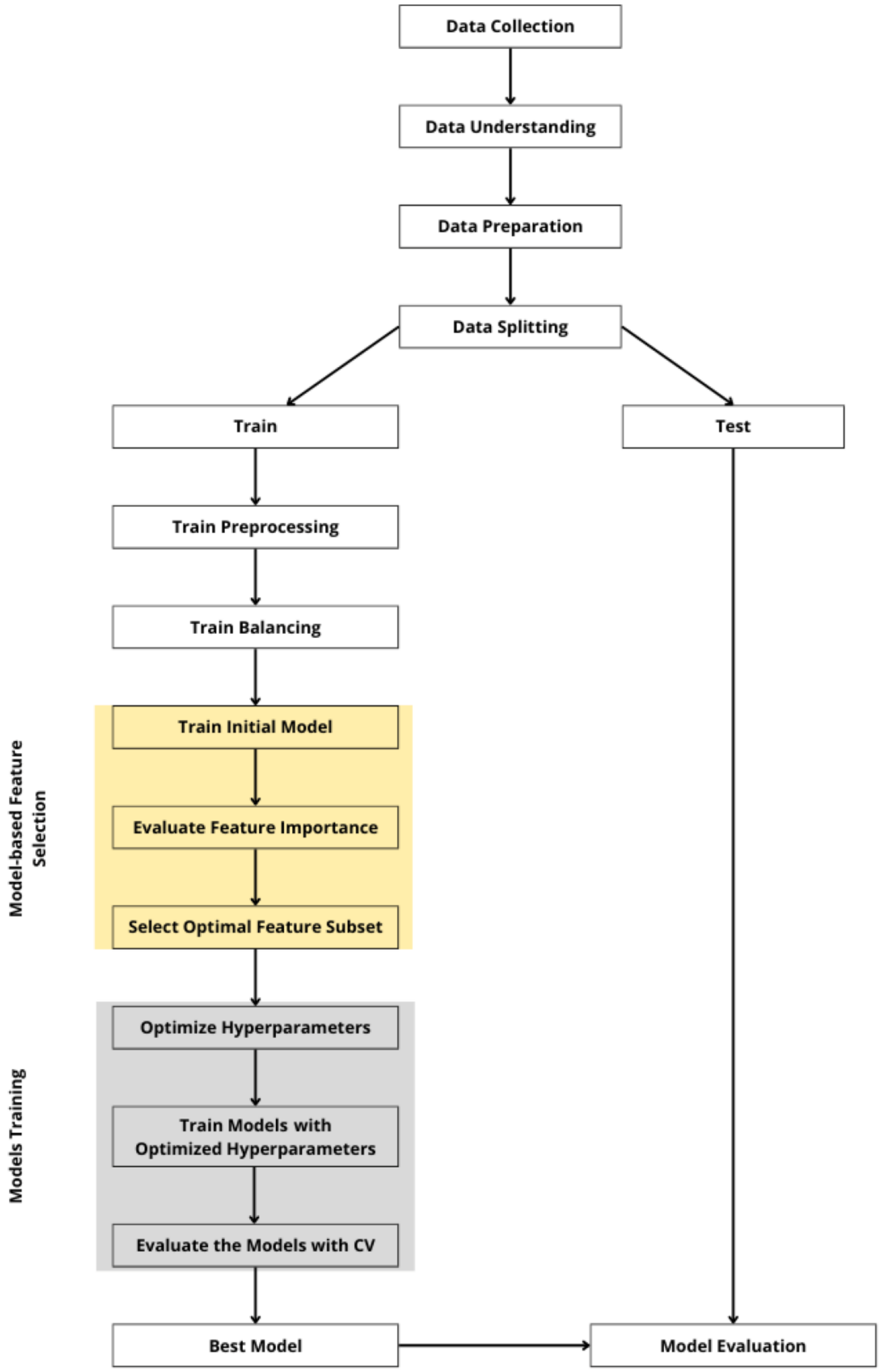

Fig. 2. Risk path detection and alert reduction process in industrial energy finance.

3.4 Comparison with Existing Studies and Practical Implications

The results differ from earlier credit risk studies in several ways. First, previous models mainly target bank loans, credit cards, or listed firms. This study focuses on industrial energy financing, where repayment risk is linked to production activity and utility payment behavior. Second, most graph neural network models build borrower similarity graphs, supply chain graphs, or corporate relation graphs. Here, a heterogeneous graph includes enterprises, utility providers, meters, gas accounts, invoices, financing contracts, customers, and overdue records. Third, prior studies mainly report prediction accuracy. This study also evaluates warning lead time, risk-chain explanation, alert reduction, and inference speed. Full monthly portfolio assessment completed in 15.2 minutes, with median inference latency of 41 ms per enterprise node. This shows the model can support large-scale monthly risk screening. Limitations remain: incomplete utility bills or fragmented billing systems may reduce stability. Future work should test the model in more regions, industries, and real-time energy monitoring scenarios.

4. Conclusion

This study developed an energy consumption graph inference model for financing risk prediction in industrial enterprises. The results show that energy use, utility payment records, customer-order changes, and financing exposure can provide early signs of repayment deterioration. Compared with the financial-ratio baseline, the proposed model improved prediction performance and reduced the median warning time from 84 days to 29 days. It also detected 5,930 energy-production risk paths and reduced 13,800 raw alerts to 3,640 review cases. These results indicate that the model can improve both prediction accuracy and review efficiency. The main contribution of this study is the construction of a heterogeneous graph that connects enterprises, utility accounts, meters, invoices, financing contracts, customers, and overdue records. This graph links production activity, payment behavior, and credit risk in a clear structure. The findings suggest that energy consumption data can support early warning in industrial finance. In practice, the model can be used by banks, energy finance platforms, and industrial parks for monthly risk screening and credit review. However, the model depends on complete utility records and reliable customer-order data. Missing bills, delayed invoice updates, and separated energy systems may reduce prediction stability. Future studies should test the model in more regions and industries, use real-time energy data, and improve its performance under different financing conditions.

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