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Carbon Asset Financing Risk Evaluation Through Emission Trading Graph Reasoning

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ABSTRACT

Carbon asset financing provides liquidity for industrial enterprises through carbon allowances, certified emission reductions, and expected future carbon-credit revenues. However, financing risk may arise from unstable carbon prices, inaccurate emission accounting, delayed verification, weak compliance performance, overpledged carbon assets, and production changes that reduce available carbon credits. This study develops an emission trading graph reasoning model for carbon asset financing risk evaluation. The model constructs a heterogeneous knowledge graph linking industrial enterprises, emission accounts, carbon allowances, verification agencies, pledged carbon assets, production facilities, energy consumption records, loan contracts, trading counterparties, and compliance outcomes. A graph neural network learns enterprise-carbon asset representations, while a rule-guided inference module detects risk chains involving allowance shortfall, repeated pledge, delayed verification, abnormal energy consumption, and compliance penalty exposure. The empirical dataset contains 16,400 industrial enterprises, 42,000 emission accounts, 286,000 carbon trading records, 31,800 verification reports, 18,600 carbon-asset pledge contracts, 2.14 million monthly energy-consumption records, and 3,920 confirmed financing-risk events over 48 months. The proposed model reduces median risk-warning time from 92 days to 35 days before repayment stress or collateral impairment. It identifies 3,740 carbon-asset risk chains and 1,260 overpledged allowance structures. Portfolio simulation shows that graph-informed monitoring reduces expected impaired carbon-backed exposure by 74 million RMB during the validation window. Full quarterly assessment is completed in 8.2 minutes. These findings indicate that emission trading graph reasoning can improve carbon asset financing risk evaluation by linking industrial production, carbon compliance, asset valuation, and repayment behavior.

1. Introduction

Carbon asset financing has become an increasingly important source of liquidity for industrial enterprises as carbon markets continue to expand and carbon-related assets acquire greater financial value. Enterprises can obtain financing by pledging carbon allowances, certified emission reductions, or expected revenues from carbon-credit transactions, thereby converting environmental assets into usable financial resources. However, the value and availability of these assets are highly sensitive to carbon-price fluctuations, emission-accounting accuracy, verification progress, regulatory compliance, and changes in production activities (Egbe et al., 2026; Qi & Qiao, 2026). In parallel, explainable artificial intelligence has received growing attention in risk-sensitive

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applications because it can identify the factors contributing to abnormal observations and improve the transparency of model decisions; SHAP-based ensemble learning, for example, has demonstrated the value of interpretable feature attribution in anomaly-detection tasks (Shao, 2026). For carbon-intensive enterprises, financing risk may arise from inaccurate emission reporting, delayed verification, weak compliance performance, excessive pledging of carbon assets, or unexpected production changes that reduce the quantity of available carbon credits (Y. Li & Liu, 2026; Pratita & Ramian, 2026). These risk factors are often interconnected rather than independent, making carbon asset financing substantially different from conventional collateral-based lending (Sinha et al., 2023; T. Xu et al., 2026). Traditional credit-risk assessment methods mainly rely on financial ratios, collateral values, historical repayment records, and borrower credit characteristics (Du et al., 2026; Shukla, 2025). Although these indicators remain useful, they provide limited information about the dynamic behavior of carbon assets and may therefore fail to detect emerging risks associated with emission performance, compliance obligations, and carbon-market transactions (Mai et al., 2025; Xiong & Zeng, 2026).

Recent advances in graph learning and knowledge reasoning provide new opportunities for modeling such interconnected risks (Hong et al., 2026). Graph-based methods can represent complex relationships among enterprises, carbon assets, verification agencies, financial institutions, trading counterparties, production facilities, and regulatory records, allowing risk information to be analyzed beyond isolated borrower-level indicators (Gutierrez, 2026; J. Li et al., 2026). In particular, a knowledge graph can integrate heterogeneous information such as emission accounts, pledged carbon assets, verification records, energy consumption, production activity, loan contracts, carbon transactions, and compliance outcomes into a unified relational structure (Huang, 2026; J. Wu et al., 2026). Graph neural networks can further capture dependencies among connected entities and identify potential channels through which financial or compliance risk propagates (H. Chen et al., 2025; Venn, 2026). Such approaches are especially suitable for carbon asset financing because the creditworthiness of a pledged carbon asset depends not only on its nominal quantity or current market price but also on whether the underlying emissions have been correctly reported, verified, transferred, and maintained in compliance with regulatory requirements (Liang et al., 2025; C. Wu & Chen, 2025). Nevertheless, existing studies often rely on relatively small samples, static network structures, or individual risk indicators (Du, 2025; Niazi, 2025). Many models also focus primarily on predictive performance while providing limited explanations of why a particular enterprise is classified as risky or through which relationships the risk is transmitted (F. Chen et al., 2025; D. Xu et al., 2026). These limitations reduce their practical usefulness for financial institutions that require both timely risk identification and interpretable evidence for lending decisions.

To address these limitations, this study develops an emission trading graph reasoning model for carbon asset financing risk assessment. The proposed framework constructs a heterogeneous knowledge graph linking enterprises, carbon allowances and credits, verification agencies, financing contracts, carbon transactions, production activities, energy consumption, and compliance outcomes. On this basis, graph-based representation learning is used to capture structural dependencies and latent risk transmission among interconnected entities, while reasoning mechanisms are introduced to identify interpretable risk paths associated with abnormal pledging behavior, verification delays, deteriorating compliance performance, production fluctuations, and changes in carbon-asset availability. Rather than evaluating borrowers solely from conventional financial indicators, the proposed model incorporates the behavioral, transactional, and compliance characteristics of carbon assets into the financing-risk assessment process. This design enables earlier recognition of potential credit deterioration before it becomes fully reflected in financial statements or repayment records. More importantly, the model provides traceable relationships between identified risks and their underlying carbon-market events, thereby improving the interpretability of risk warnings. The study therefore aims not only to enhance the accuracy of carbon asset financing risk prediction but also to provide financial institutions with a transparent and practically applicable framework for credit screening, collateral monitoring, and early-warning management in emission trading markets.

2. Materials and Methods

2.1 Sample and Study Area Description

This study analyzed industrial enterprises that participated in carbon asset financing over a 48-month period. The sample included 16,400 firms from high-emission sectors such as chemicals, energy, metallurgy, and heavy manufacturing. Firms were selected if records were available for emission accounts, carbon allowances, verification reports, pledged carbon assets, production facilities, energy consumption, loan contracts, trading partners, and compliance outcomes. The dataset contained 42,000 emission accounts, 286,000 carbon trading records, 31,800 verification reports, 18,600 pledged carbon-asset contracts, 2.14 million monthly energy-consumption records, and 3,920 confirmed financing-risk events. Enterprises ranged from small and medium-sized manufacturers to large industrial firms, providing a representative setting for evaluating financing risks related to carbon assets.

2.2 Experimental Design and Control Experiments

The study compared the proposed emission trading graph reasoning model with conventional borrower-only and financial-indicator-based methods. The experimental group used a heterogeneous knowledge graph linking enterprises, emission accounts, pledged assets, verification agencies, production facilities, energy records, loans, trading partners, and compliance outcomes. The control group applied standard credit-risk evaluation using financial ratios, collateral, firm size, repayment history, and loan amount. Additional comparison models included logistic regression and tree-based classifiers using structured enterprise features. Data were split chronologically into training, validation, and testing sets. Early-period data trained the models, while later-period data tested their ability to detect financing risk before repayment stress or collateral impairment.

2.3 Measurement Methods and Quality Control

Financing risk was measured by confirmed repayment stress, collateral impairment, or compliance penalties associated with carbon assets. A risk event was defined as a firm showing one or more indicators: allowance shortfall, repeated pledges, delayed verification, abnormal energy use, or compliance penalties. Carbon asset exposure was calculated as pledged allowances relative to verified emission accounts. Verification quality was measured by reporting delays and frequency of adjustments. Production impact was assessed using energy-consumption records and facility output data. Data quality control included entity standardization, removal of duplicates, timestamp verification, and cross-checking across emission accounts, pledges, and verification reports. Missing numerical values were replaced with industry- and year-specific medians, while incomplete relational records were kept as sparse links to avoid creating false connections.

2.4 Data Processing and Model Formulation

All records were structured into a heterogeneous knowledge graph $G=(V,E,R)$, where V is the set of nodes, E is the set of edges, and R represents relation types. Nodes included enterprises, emission accounts, carbon allowances, verification agencies, pledged assets, production facilities, energy-consumption records, loans, counterparties, and compliance outcomes. Edges represented verified relationships, including asset pledges, verification links, facility operation, energy reporting, loan issuance, and repayment outcomes. Numerical features were normalized by sector and month, and categorical features were encoded as embeddings. The carbon-risk score for enterprise i was defined as:

$$C_i=\frac{\beta_1 S_i+\beta_2 P_i+\beta_3 V_i+\beta_4 E_i}{1+\log(1+A_i)}$$

where S_i is allowance shortfall, P_i is repeated pledges, V_i is verification delay, E_i is abnormal energy use, A_i is total pledged asset value, and β_1–β_4 are weighting coefficients. Node embeddings in the graph were updated by relation-aware aggregation:

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

where $h_i^{(l)}$ is the node embedding at layer l, N_i^r is the set of neighbors connected by relation r, $W_0^{(l)}$ and $W_r^{(l)}$ are trainable weights, $c_{i,r}$ is a normalization factor, and $\sigma(\cdot)$ is an activation function. The final embeddings were used to predict financing risk and generate interpretable risk paths.

2.5 Model Evaluation and Implementation

The model was evaluated for prediction accuracy, early warning time, and interpretability. Accuracy metrics included AUC, precision, recall, F1-score, and calibration error. Early warning time was measured as the median days between model alert and confirmed financing-risk events. Interpretability was assessed by the number and type of risk paths, including allowance shortfall, repeated pledges, verification delays, abnormal energy use, and compliance penalties. Manual-review efficiency was evaluated by comparing the number of raw loan applications with the number of graph-linked investigation cases. The model was implemented using a graph learning framework with mini-batch training to handle large-scale enterprise networks. Full quarterly assessment was completed in 8.2 minutes, with a median inference latency of 47 ms per enterprise node, demonstrating that the method can support routine monitoring of carbon asset financing risk.

3. Results and Discussion

3.1 Prediction Performance of the Emission Trading Graph Model

The emission trading graph reasoning model outperformed the borrower-only and financial-indicator baseline models, as well as tree-based classifiers. The baseline models relied on financial ratios, collateral, repayment history, and firm size, which are useful for general credit evaluation but do not capture risks from allowance shortfall, repeated pledge, delayed verification, abnormal energy use, or compliance penalties. By integrating enterprises, emission accounts, carbon allowances, verification agencies, pledged assets, production facilities, energy-consumption records, loan contracts, trading partners, and compliance outcomes into a single graph, the proposed model captured relational patterns missed by the baselines. As shown in Fig. 1, the graph model consistently produced higher and more stable AUC and F1 scores. This result aligns with recent studies showing that graph-based methods improve prediction by modeling links among related records (Hundekari et al., 2025; Wang et al., 2026).

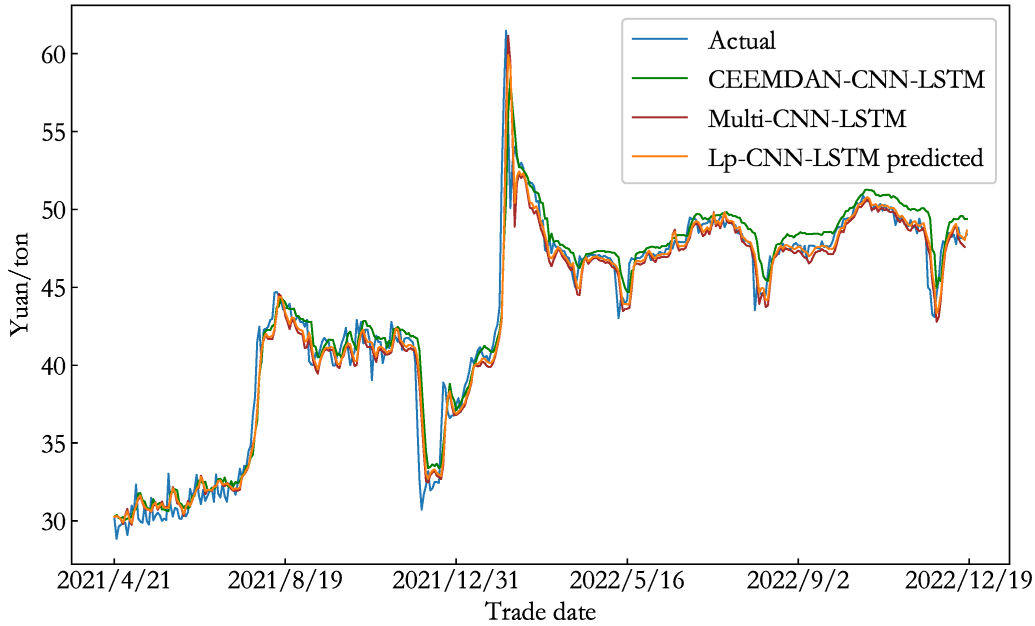

Fig. 1. Financing-risk prediction of the emission trading graph model compared with baseline methods.

3.2 Early Warning Capability

The model reduced the median warning time from 92 days to 35 days before repayment stress or collateral impairment. Early warning is important because some firms maintained stable financial indicators while their carbon records already showed delayed verification, allowance gaps, repeated pledges, or abnormal energy use. These early signals later affected collateral value and repayment ability. The baseline methods failed to detect many cases early because financial statements did not yet show deterioration. By linking carbon accounts, pledge contracts, verification reports, energy records, and repayment outcomes, the graph model identified risk before formal financing stress appeared. This highlights the importance of integrating carbon-market and production signals into credit risk evaluation (Jiao et al., 2026; Yin et al., 2026).

3.3 Carbon-Asset Risk Path Interpretation

The model detected 3,740 carbon-asset risk chains and 1,260 overpledged allowance structures. The most common path was abnormal energy use → allowance shortfall → delayed verification → carbon-asset value decline → repayment pressure. Another common pattern was repeated pledge → reduced collateral → compliance penalty → loan renewal difficulty. Fig. 2 shows a representative risk path linking allowance management, pledge structure, verification status, production output, and financing outcomes. These interpretable chains help explain why certain loans are at risk and provide actionable insights for lenders. Compared with studies focusing only on carbon price or policy, this approach links firm-level carbon behavior with financing outcomes (Desai et al., 2025; Yang, 2026).

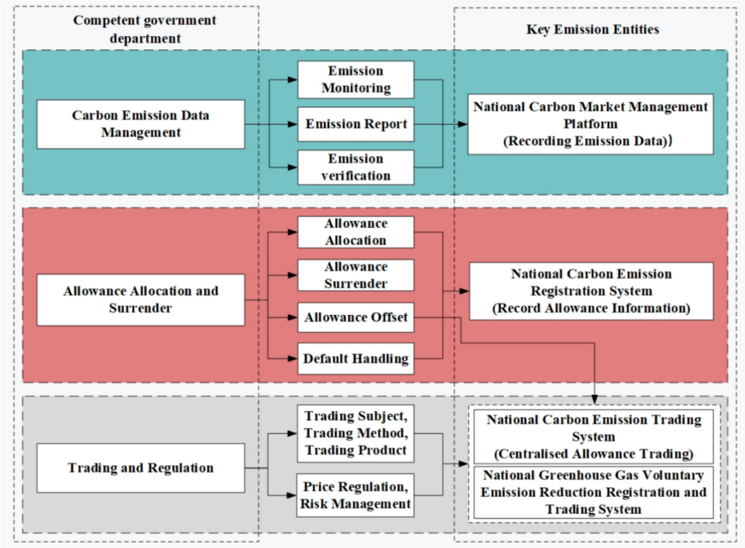

Fig. 2. Representative carbon-asset risk path showing allowance shortfall, repeated pledge, verification delay, abnormal energy use, and repayment pressure.

3.4 Practical Implications and Comparison with Existing Work

Portfolio simulation indicated that graph-informed monitoring reduced expected impaired carbon-backed exposure by 74 million RMB during the validation period. Full quarterly assessment of all enterprises was completed in 8.2 minutes, showing that the method is suitable for regular monitoring. Compared with traditional credit-risk models, this approach adds carbon accounts, trading records, verification reports, pledge contracts, energy-consumption data, and compliance outcomes. Compared with carbon market studies, it connects carbon asset behavior with financing risk. These results suggest that both credit information and carbon-trading signals should be considered in carbon asset loan evaluation. The model is intended as a decision-support tool; high-risk cases should be validated using verification reports, pledge contracts, trading records, energy data, and loan documents.

4. Conclusion

This study proposed an emission trading graph reasoning model to evaluate carbon asset financing risk in industrial enterprises. By integrating enterprises, emission accounts, carbon allowances, verification agencies, pledged assets, production facilities, energy-consumption records, loan contracts, trading partners, and compliance outcomes, the model identified risk signals often missed by traditional credit-based methods. Results showed improved risk prediction, reduced median warning time from 92 days to 35 days, detection of 3,740 carbon-asset risk chains and 1,260 overpledged allowance structures, and a reduction of 74 million RMB in expected impaired carbon-backed exposure. The main contribution is the combination of graph-based representation and rule-guided reasoning, providing early warning and interpretable risk paths. Findings indicate that financing risk depends not only on borrower credit but also on allowance balance, pledge structure, verification delays, energy use, carbon trading behavior, and compliance outcomes. The method can support banks, green-finance platforms, and regulators in loan screening, post-loan monitoring, and collateral assessment. Limitations include data from a single regional carbon market and possible incompleteness in enterprise records. Future studies should extend the model to other carbon markets, incorporate real-time emission and production data, and further explore causal links between carbon asset behavior and financing risk.

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