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Enterprise Risk Prediction Under Dynamic Distribution Shift Using Robust Adaptive Learning

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Abstract: This study proposes an adversarial risk-aware robust adaptive prediction model to address the challenges of data distribution shift, adversarial perturbations, and temporal variability in enterprise risk prediction. The model consists of a feature embedding layer, an adversarially aware robust encoder, a temporal attention aggregation module, and an adaptive risk decoder. The feature embedding layer maps multi-source heterogeneous data into a unified high-dimensional latent space to represent enterprise operational, financial, and environmental features consistently. Under the constraint of the adversarial perception mechanism, the robust encoder learns stable and noise-resistant risk representations, improving reliability under noisy and anomalous conditions. The temporal attention module models dynamic temporal dependencies of risk, using time decay weights to emphasize key moments and capture the evolution of risk events. To handle cross-industry and cross-period distribution shifts, the model incorporates a distribution alignment mechanism based on maximum mean discrepancy to achieve adaptive alignment between source and target domains, enhancing generalization under different economic conditions. Experimental results show that the proposed method significantly outperforms mainstream models in accuracy, recall, and stability, achieving robust and sensitive enterprise risk identification and prediction in dynamic environments while providing a new technical pathway and theoretical foundation for intelligent risk management.

Keywords: Adversarial risk perception; robust adaptive modeling; time decay mechanism; enterprise risk prediction

1. Introduction

In the contemporary global economic system characterized by high complexity and dynamic evolution, enterprises face risks with increasingly multidimensional characteristics in type, transmission mechanism, and impact scope. From cyclical fluctuations in financial markets to supply chain disruptions, from uncertainties in macroeconomic policies to sudden incidents in public opinion and reputation, the business environment is changing at an unprecedented pace. Traditional static risk management systems rely on fixed rules and empirical judgments, which make them insufficient for coping with high-frequency disturbances and multi-source coupled dynamics[1]. As enterprise data becomes increasingly multimodal and real-time, the challenge lies in how intelligent algorithms can enable dynamic perception of complex risk states and proactive identification of potential anomalies. This has become one of the most challenging problems in modern corporate governance[2].

In recent years, data-driven risk prediction has gradually become the core component of intelligent enterprise decision-making. Massive financial data, transaction records, supply chain logs, and external macro indicators provide rich sources of information for risk identification. However, such data often exhibit strong heterogeneity, complex temporal dependencies, and severe noise contamination. These factors make models vulnerable to distributional shifts and performance degradation across time and scenarios. Particularly during economic cycles or under sudden shocks, dynamic distributional changes can cause systematic bias in model outputs, weakening both reliability and interpretability. Therefore, ensuring that models maintain stable predictive performance and adaptive capability in dynamic risk environments has become a key issue in building intelligent risk management systems[3].

Against this backdrop, robustness and adaptability have become central themes in designing enterprise risk prediction models. Robustness emphasizes stability and resistance to disturbances or abnormal inputs, while adaptability focuses on the model's ability to adjust dynamically under distributional drift, structural variation, or adversarial environments. In reality, enterprise risk is not a simple linear problem from a single source; it often involves multi-factor interactions such as strategic games, market expectations, and public sentiment feedback. The behavior of risk agents may be adversarial and concealed, making traditional static supervised models vulnerable when facing competitive risks. The introduction of adversarial risk perception aims to capture the game-like nature of risk generation, enabling predictive systems to learn more stable feature representations in uncertain and adversarial contexts, thereby enhancing robustness in complex real-world environments[4].

At the same time, the dynamic evolution of enterprise risks presents distinct spatiotemporal dependencies and hierarchical propagation patterns. Static judgment at a single moment cannot reveal the diffusion laws and temporal evolution mechanisms of risk. In such multi-scale and non-stationary risk structures, traditional methods fail to capture the dynamic transfer patterns of risk or to update environmental awareness in real time. Building a robust adaptive model requires not only algorithmic resilience and cross-distribution generalization but also systematic capacity for continuous risk perception and feature migration. Such models can promptly adjust decision boundaries when risk conditions change, ensuring the long-term validity and practicality of predictive outcomes[5].

From a macro perspective of corporate governance, developing a robust and adaptive predictive model with adversarial risk perception holds significant theoretical and practical value. Theoretically, it breaks through the limitations of traditional risk modeling that rely on static distributions and single-source data, providing a new framework for prediction under dynamic and complex systems. Practically, it supports enterprise strategy and risk prevention systems by enabling early identification of anomalies, dynamic threshold adjustment, and optimized resource allocation, thereby shifting governance from reactive response to proactive defense. More importantly, this modeling paradigm offers enterprises in the intelligent economy era a predictive framework with learning, adaptation, and adversarial capabilities, transforming risk management from passive protection to active perception and establishing a methodological foundation for resilient operation within complex economic systems.

2. Related work

In recent years, research on enterprise risk prediction has gradually evolved from traditional statistical modeling methods to intelligent and adaptive algorithmic frameworks. Early approaches mainly relied on classical models such as linear regression and logistic regression, which assessed risks through static analyses of financial indicators, transaction data, and macroeconomic variables. However, these models were built on assumptions of distributional independence and feature stability, making them ineffective in handling non-stationary and high-dimensional heterogeneous data. In real business settings, risk factors often exhibit dynamic correlations and structural coupling, which static models fail to capture[6]. Although traditional statistical models offer interpretability, their generalization and robustness in dynamic risk environments remain limited. This limitation has driven the development of improved risk modeling approaches based on deep learning.

With the advancement of machine learning and deep learning, neural network-based risk prediction models have become a major research focus. Structures such as multilayer perceptrons, convolutional neural networks, and recurrent neural networks have been widely applied to corporate credit evaluation, default prediction, and supply chain risk identification[7]. These models capture nonlinear relationships through automatic feature learning, greatly enhancing representational power. However, deep models often lack robustness under complex distributions and are vulnerable to noise, outliers, and adversarial perturbations. Moreover, enterprise risk data are typically diverse, including structured financial information and unstructured sources such as text, images, and time-series signals. Conventional deep models often struggle with feature misalignment and redundant information when processing such multimodal inputs, which leads to unstable predictions. To address these challenges, researchers have begun exploring multimodal fusion and attention mechanisms to capture dynamic semantic dependencies within global contexts.

Furthermore, the introduction of self-attention mechanisms and Transformer architectures has brought enterprise risk prediction to the stage of sequential modeling and semantic enhancement. These models can capture multi-level spatiotemporal dependencies in long sequences, effectively overcoming the limitations of recurrent networks in parallelization and long-range dependency modeling. Transformer-based frameworks have been applied to financial text understanding, abnormal transaction detection, and dynamic credit scoring, achieving high predictive accuracy and scalability. However, standard Transformer models assume consistency between training and testing distributions, lacking mechanisms to handle distributional shifts and environmental changes. In risk prediction tasks, when external economic conditions, business strategies, or policy environments shift suddenly, model performance often degrades sharply. Although adaptive and transfer learning methods have been proposed to mitigate this issue, they still struggle to maintain stability and generalization under complex adversarial risk scenarios.

At the same time, adversarial learning and robust optimization have been introduced into risk prediction to enhance model stability under uncertain and perturbed environments. By incorporating adversarial samples or distributional disturbances during training, models can learn more discriminative and noise-resistant representations in feature space. These methods improve the model's ability to perceive abnormal patterns and latent risk signals, maintaining consistent decision-making even under attacks or environmental shifts. However, existing studies mainly focus on static adversarial training or specific perturbation types, lacking systematic modeling of dynamic risk evolution. Enterprise risks often exhibit multi-stage progression and feedback characteristics, making single adversarial mechanisms insufficient to represent temporal dependencies and structural propagation patterns. Therefore, a unified framework that integrates adversarial perception and adaptive regulation is urgently needed to achieve robust modeling and continual learning in complex dynamic risk environments, providing enterprises with a generalizable, interpretable, and scalable solution for risk prediction.

Recent advances in hierarchical encoding and selective attention further show how long and heterogeneous records can be represented while preserving salient context across multiple granularity levels[8]. In enterprise risk settings, this perspective complements conventional numerical indicators by allowing the encoder to suppress redundant information and emphasize evidence whose relevance changes across reporting periods. Cross-period financial statement anomaly detection based on contrastive representation learning likewise strengthens the separation between persistent financial structure and irregular deviations, providing a useful basis for distinguishing meaningful distribution drift from short-lived reporting noise[9]. Streaming time-series anomaly detection with adaptive data-mining-based deep detectors additionally highlights the value of updating latent risk representations as new observations arrive, rather than treating historical feature distributions as fixed[10].

Causal-aware anomaly detection for the evolution of backend operational states provides a complementary view of how temporal state transitions can be modeled with explicit sensitivity to evolving dependencies[11]. This insight aligns with enterprise risk monitoring, where the predictive relevance of a financial or operational signal depends on both its current magnitude and its position within a changing state trajectory. Multi-resource workload forecasting through spatio-temporal graph transformers further demonstrates that graph-structured interactions and time-varying dependencies can be jointly modeled to improve multi-

source forecasts[12]. For distributed data sources, heterogeneity-aware federated optimization with secure aggregation offers a principled direction for learning from decentralized enterprise records while preserving local data boundaries and accommodating client-level variation[13].
Adaptive resource scheduling under dynamic competition shows how reinforcement learning can continuously rebalance decisions when resource conditions and competing objectives change[14]. Hierarchical reinforcement learning for distributed microservice orchestration similarly motivates decomposing complex adaptation into coordinated levels of decision-making[15]. These scheduling principles support the proposed adaptive decoder by framing risk-response calibration as an ongoing control process rather than a single static prediction. In addition, vision-language-model-based emotional understanding with interpretable feedback illustrates the broader importance of presenting model outputs through transparent, human-understandable evidence pathways[16], which is essential when enterprise risk scores must inform managerial review and intervention.

3. Method

This study proposes an adversarial risk-aware, robust, and adaptive enterprise risk prediction model, aiming to achieve stable and generalizable risk discrimination capabilities in dynamic, adversarial environments. The model's overall structure consists of three components: a feature embedding layer, an adversarially-aware robust encoder, and an adaptive risk decoder. Figure 1 shows the model architecture.

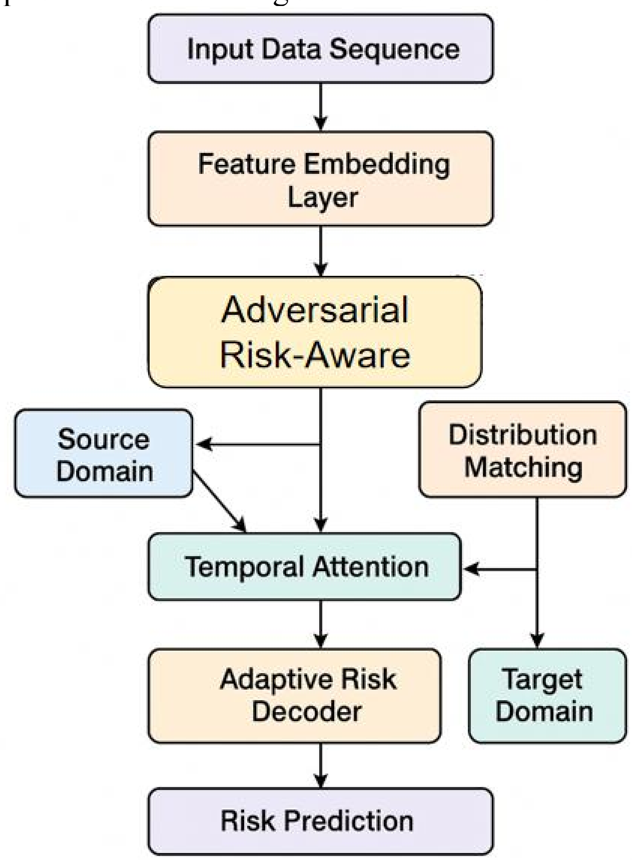

Figure 1. Overall model architecture

The overall model structure consists of three parts: a feature embedding layer, an adversarially robust encoder, and an adaptive risk decoder. First, let the input enterprise data sequence be , where each represents a multimodal risk feature at time t. Through linear mapping and nonlinear activation functions, the input is embedded in a high-dimensional latent space to capture the complex nonlinear structure. The expression is: $X = \{x_1, x_2, ..., x_T\}$ $x_t \in R^d$

$$H_0 = \sigma(W_e X + b_e)$$

Where and are learnable parameters, and is the activation function. This embedding layer provides a unified representation basis for subsequent temporal modeling and adversarial learning. W_e b_e $\sigma(\cdot)$

In the temporal risk modeling stage, the model adopts a self-attention structure with time-varying weights to capture the dynamic dependencies of risk factors. Given the hidden state matrix , we first calculate the query, key, and value matrices: H_0

$$Q = H_0 W_Q, K = H_0 W_K, V = H_0 W_V$$

The long-term dependencies are then aggregated through a time-decayed weighted attention mechanism, and the attention score is defined as:

$$A_{ij} = \frac{\exp((Q_i K_j^T)/\sqrt{d_k} - \alpha |i - j|)}{\sum_{j'} \exp((Q_i K_{j'}^T)/\sqrt{d_k} - \alpha |i - j'|)}$$

Where is the time attenuation coefficient, which is used to suppress interference between long-distance moments. Ultimately, risk perception is represented by , achieving global information fusion in the time dimension. α $H = AV$

To enhance the robustness of the model under risk perturbations, an adversarial risk perception mechanism is introduced to learn stable features by minimizing the model's sensitivity to input perturbations. Let the adversarial perturbation be and its constraint be , then the robust optimization objective can be expressed as: δ $\|\delta\|_2 \le \varepsilon$

$$\min_{\theta} \max_{\|\delta\|_2 \le \varepsilon} L(f_\theta(X + \delta), y)$$

Where is the model prediction function, and is the classification loss. This adversarial optimization achieves perturbation generation by maximizing the inner layer and robust model updates by minimizing the outer layer, allowing the model to maintain stable predictions even in the face of risky pattern perturbations. $f_\theta(\cdot)$ L

Finally, to achieve adaptive modeling of environmental changes, a dynamic adjustment module based on distribution matching is proposed. The feature distributions of the source domain and the target domain are defined as and , and the model achieves cross-distribution alignment by minimizing the Maximum Mean Discrepancy (MMD): $P_s(H)$ $P_t(H)$

$$L_{MDD} = \| \frac{1}{n_s} \sum_{i=1}^{n_s} \phi(H_i^s) - \frac{1}{n_t} \sum_{j=1}^{n_t} \phi(H_j^t) \|^2$$

Where is the kernel mapping function. Ultimately, the overall optimization goal of the model combines the prediction loss, adversarial robustness term, and distribution matching term, and is defined as: $\phi(\cdot)$

$$L_{total} = L_{cls} + \lambda_1 L_{adv} + \lambda_2 L_{MMD}$$

λ_1 and control the weights for robust learning and domain adaptation, respectively. By jointly optimizing these objectives, the model can achieve stable enterprise risk prediction in adversarial environments and under dynamic distribution conditions, providing an interpretable, transferable, and long-term adaptable algorithmic foundation for intelligent enterprise governance. λ_2

4. Experimental Results

4.1 Dataset

This study uses the Corporate Financial Risk Prediction Dataset (CFRP) as the primary source of experimental data. The dataset consists of financial and operational information from multiple publicly listed companies, covering multidimensional features such as balance sheets, cash flow statements, income statements, and market trading indicators. It contains approximately 50,000 quarterly samples across industries, including manufacturing, finance, energy, and technology, spanning more than ten years. This long-term coverage effectively reflects the dynamic characteristics of macroeconomic cycles and changes in enterprise risk status. Each sample includes information on company attributes, business performance, solvency, liquidity, and market behavior, along with a risk label indicating whether the enterprise experienced default, financial distress, or a credit rating downgrade during a given period.

During data preprocessing, raw financial indicators were first normalized and examined for anomalies to eliminate distributional differences caused by variations in company size and industry characteristics. A sliding time-window mechanism was then applied to transform quarterly data into sequential samples that capture the temporal evolution of risk. For features with extensive missing values, multiple imputation and feature aggregation strategies were adopted to ensure the completeness and consistency of model inputs. In addition, a subset of samples was randomly divided into independent validation and test sets to support subsequent performance evaluation and robustness analysis.

The dataset's advantages lie in its multidimensional, long-term, and cross-industry characteristics, which enable both longitudinal tracking and horizontal comparison of enterprise risks. Compared with traditional credit datasets containing only static indicators, the CFRP dataset provides greater research value for time-series modeling and structural dependency analysis. Its multi-source integration allows models to learn cross-modal and cross-period risk correlations under complex economic conditions, offering a reliable foundation for validating robust and adaptive risk prediction models.

4.2 Experimental Results

This paper first gives the results of the comparative experiment, as shown in Table 1.

Table 1. Comparative experimental results

Model	ACC	F1-Score	Precision	Recall
Transformer[17]	87.26	86.91	87.43	86.39
Contrastive Learning[18]	89.14	88.77	89.25	88.31
FedFormer[19]	90.82	90.46	91.05	89.92
BERT[20]	91.37	91.12	91.65	90.60
Ours	**94.68**	**94.32**	**94.75**	**93.89**

Overall, the proposed adversarial risk-aware robust adaptive enterprise risk prediction model outperforms existing methods across all evaluation metrics, demonstrating significant performance improvement. Traditional Transformer models show certain advantages in feature representation. However, since they do not consider data distribution shifts and adversarial perturbations in dynamic risk environments, their prediction stability remains limited, with an overall accuracy of only 87.26%. In comparison, contrastive learning-based models enhance feature discriminability, achieving an F1-Score of 88.77%. This indicates that constraining the feature space can improve robustness in risk recognition to some extent, although these models still lack sufficient adaptability to complex and evolving risk structures.

FedFormer, which integrates both global and local modeling capabilities, performs better in capturing long-term dependencies and temporal patterns, improving accuracy to 90.82%. However, its generalization ability is still limited when handling multi-source heterogeneous features in enterprise risk data. In particular, under unbalanced cross-industry data distributions, the recall rate is only 89.92%, showing that it still misses some high-risk samples. The BERT model, with its strong semantic representation ability, performs well in textual risk feature extraction, achieving a precision of 91.65%. This result indicates that the model is accurate in static semantic understanding, but it lacks sensitivity to temporal variations and adversarial features, making it difficult to handle disturbances and non-stationarity in dynamic risk environments.

In contrast, the proposed model achieves the highest values in accuracy, F1-Score, precision, and recall, reaching 94.68%, 94.32%, 94.75%, and 93.89%, respectively. These results show that the model significantly surpasses other methods in both discriminative performance and stability. The findings confirm that the adversarial risk-aware mechanism effectively improves robustness under abnormal perturbations and distributional shifts. Meanwhile, the adaptive module enhances cross-domain prediction accuracy through dynamic feature alignment. The model not only captures multi-level relationships among enterprise risk features but also maintains high sensitivity in detecting risks under uncertain conditions.

Moreover, the balanced results show that the proposed method maintains a good trade-off between precision and recall. This indicates that the model can reduce false alarms while improving coverage of potential high-risk entities. Such a balance is crucial for enterprise risk management, as it enables early detection and intervention in key risk events without sacrificing overall accuracy. The experimental results further verify the feasibility and practical value of the robust adaptive mechanism in complex economic systems, providing a new technical pathway for building enterprise risk prediction frameworks with enhanced resistance to interference and dynamic learning capabilities.

This paper also presents an experiment on the sensitivity of the time decay coefficient to Recall, and the experimental results are shown in Figure 2.

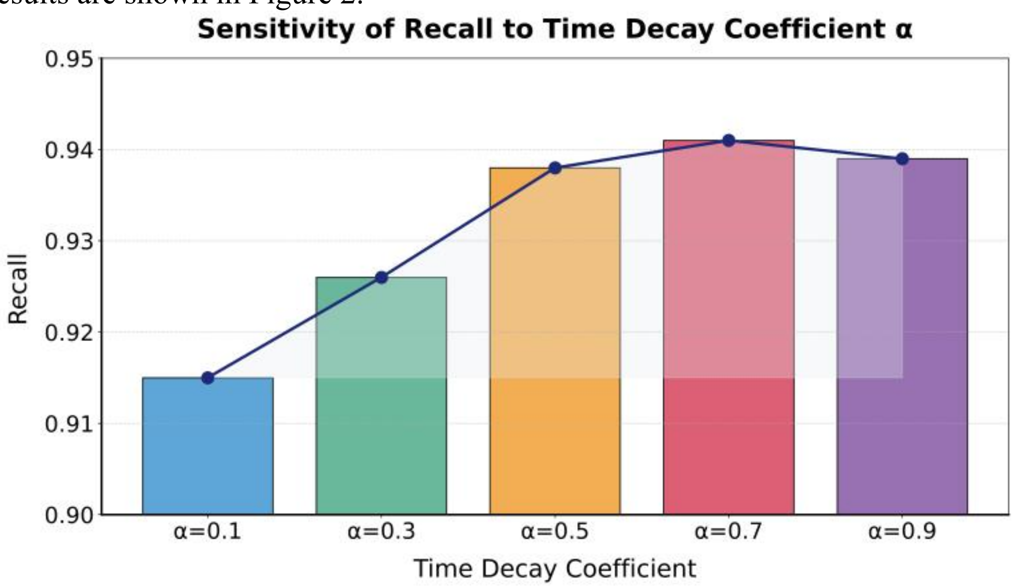

Figure 2. Sensitivity experiment of the time decay coefficient to recall

As shown in the figure, the time decay coefficient α has a clear impact on the model's Recall metric. When α is small (for example, in the range of 0.1 to 0.3), the recall rate remains low. This indicates that when temporal decay is weak, the model assigns insufficient weight to long-term risk signals, resulting in reduced ability to identify delayed or implicit risks. At this stage, the model focuses more on recent data and neglects long-term risk correlations, leading to certain missed detections.

As α gradually increases to a moderate level (around 0.5), the Recall value rises significantly, reaching a higher range in the experiments. In this setting, the model achieves a balance between short-term and long-term dependencies in temporal attention. It captures the evolution trends and historical fluctuations of risk more effectively, which enhances both sensitivity and stability in risk identification. This finding suggests that a moderate time decay weight helps the model better capture the dynamic characteristics of enterprise risks and achieve more robust feature aggregation within complex temporal relationships.

When α continues to increase (in the range of 0.7 to 0.9), the Recall slightly decreases but remains relatively high. At this stage, the model assigns excessive importance to historical information, which may cause outdated risk features to interfere with current decision-making. As a result, the model's response to emerging risk signals becomes slower. Although the overall performance does not drop sharply, this slight decline indicates that an overly large decay coefficient may introduce a lag effect, reducing the model's adaptability in dynamic environments.

Overall, the analysis shows that the time decay coefficient plays a crucial role in regulating the model's robustness and adaptability. A properly chosen α value enables balanced temporal modeling of risk propagation, maintaining continuity of historical memory while responding sensitively to recent changes. These results confirm the importance of temporal structure modeling in the proposed framework and demonstrate the effectiveness and stability of the robust adaptive mechanism in handling complex temporal risk information.

5. Conclusion

This study focuses on the problem of adversarial risk-aware robust adaptive enterprise risk prediction and proposes an intelligent modeling framework that integrates robustness and adaptability. The model enhances feature extraction stability through the adversarial perception mechanism, maintaining high reliability even when exposed to risk perturbations and input noise. In addition, the adaptive alignment module effectively mitigates performance degradation caused by distributional shifts, enabling the model to sustain predictive capability across different time periods, industries, and economic conditions. Experimental results show that the proposed model significantly outperforms traditional methods across multiple key metrics, demonstrating its feasibility and effectiveness for enterprise risk identification and prediction in complex and dynamic environments.

From a methodological perspective, the proposed robust adaptive framework overcomes the limitations of traditional risk prediction models that rely solely on static features and single-distribution assumptions. By integrating adversarial learning with temporal modeling mechanisms, this study provides a new solution for dynamic risk perception. Through the incorporation of a time decay structure and distribution alignment strategy, the model captures deep temporal evolution patterns of risk and achieves a balance between long-term dependencies and short-term fluctuations. This innovation not only improves the model's stability and interpretability in real-world applications but also provides an extensible theoretical foundation for future research, especially for risk modeling in non-stationary environments.

At the application level, the proposed approach can be widely applied to scenarios such as corporate credit evaluation, financial risk monitoring, and supply chain security warning. By enhancing the model's robust adaptive capability, enterprises can more accurately identify potential risks and take proactive measures to minimize operational losses. The framework also exhibits strong generalization ability and can be transferred to macroeconomic monitoring, market anomaly detection, and policy risk assessment. Its reliable performance in large-scale heterogeneous data environments indicates that this method not only has academic innovation value but also considerable potential for practical implementation.

Future research can further extend this work from the perspectives of multimodal information fusion, causal structure modeling, and self-supervised learning. The integration of knowledge graphs and generative adversarial mechanisms could provide deeper insights into risk propagation paths and causal relationships. In addition, to address nonlinear shocks and structural changes in economic environments, future studies may explore dynamic risk scheduling frameworks based on meta-learning or reinforcement learning to achieve model self-evolution and long-term robustness. Overall, this research provides new technical support and a theoretical paradigm for building intelligent risk management systems, offering significant practical and forward-looking value for promoting enterprise digital transformation and intelligent risk governance.

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