GNN-GAT-LSTM: A Graph Neural Network-Based Early Warning Model for Enterprise Financial Risk in Dynamic Inter-Firm Networks

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Traditional enterprise financial early warning schemes mainly focus on the iandividual financial data of the enterprise itself, ignoring the risk transmission effect in complex economic relationship networks such as supply chain and guarantee chain between enterprises, leading to a drop in early warning accuracy. This paper constructed an enterprise financial risk (EFR) early warning scheme (GNN-GAT-LSTM) drawing on graph neural network (GNN), GAT (graph attention network), and LSTM (long short-term memory), aiming to comprehensively consider the complex correlation between enterprises and thus boost the precision of early warning. To capture local structural information in enterprise association graphs, this study first employs a Graph Neural Network (GNN) architecture with a hierarchical message-passing mechanism to aggregate information from the target enterprise's first-and second-order neighbor nodes, encoding the local topology into a 64-dimensional feature vector. Subsequently, a Graph Attentional Transformer (GAT) with an 8-head self-attention mechanism is introduced to dynamically quantify the risk contributions of different associated enterprises to the target enterprise using differentiable attention coefficients, achieving differentiated weighted fusion of neighbor node information. Finally, considering the time-series characteristics of financial data, 128-dimensional node embeddings generated from three consecutive time slices are sequentially constructed as sequence inputs. Using Long Short-Term Memory (LSTM) units for modeling, this approach captures the dynamic evolution of risk characteristics, forming a risk representation that combines structural and temporal awareness.The empirical outcomes display that the precision, recall, SPEC, and RSE (Relative Squared Error) of the GNN-GAT-LSTM model are 0.9842, 0.9752, 0.9658, and 0.032 respectively; by comparing the warning error rates under different risk levels, the average error rates of the scheme in the three categories of financial health, mild financial crisis and severe financial crisis are 0.97%, 2.8% and 1.9% respectively. In the risk warning of financial industry enterprises, the AUC (Area Under the Curve) value was 0.9624, which was 8.86% higher than the traditional GNN model (0.8841); compared with the latest heterogeneous hypergraph neural network HHGNN (0.9206), it still maintained a 4.54% advantage improvement.The GNN-GAT-LSTM scheme recommended in this article can effectively identify the complex relationships and dynamic changes between enterprises and maintain high recognition accuracy under different false alarm rates.

Povzetek: Članek predstavi zgodnje opozarjanje, ki združi lokalno agregacijo v omrežju podjetij, pozornost za tehtanje sosedov in LSTM za časovne vzorce, s čimer izboljša prepoznavo finančnih tveganj onkraj posameznih bilanc.

1 Introduction

In today's complex and volatile economic landscape, effective corporate financial risk regulation is crucial for sustainable and stable development [1], [2], [3]. Traditional early warning schemes primarily focus on financial data, neglecting risk transmission in intricate economic networks like supply and guarantee chains, leading to insufficient accuracy in detecting hidden risks [4], [5], [6]. Therefore, constructing a financial risk warning scheme that comprehensively considers complex enterprise economic relations and accurately captures risk transmission is essential. GNN, an emerging deep learning technology, can directly operate on graph-structured data, effectively capturing complex node relationships and dynamic changes, offering new opportunities for corporate financial risk warning. This paper proposes a GNN-based corporate financial risk warning scheme, GNN-GAT-LSTM, which constructs enterprise economic relationships into a graph structure and uses deep learning to model risk transmission paths, enhancing early warning accuracy and foresight.

The GNN-GAT-LSTM model leverages Graph Neural Networks (GNN) to construct a sophisticated model of complex economic relationships between enterprises, addressing the limitation of traditional models that ignore risk transmission effects and improving the accuracy of financial risk warnings. By introducing the GAT mechanism, the model dynamically assigns different weights to neighboring nodes, enabling precise identification of how key associated enterprises influence target companies' risks, thereby enhancing interpretability and robustness. The integration of the LSTM module allows simulation of time-dependent evolution of financial risks, providing robust support for predicting future corporate financial risks. Experimental results demonstrate that compared with traditional models, GNN-GAT-LSTM achieves an accuracy rate of 0.9842 and recall rate of 0.9752, effectively validating its high performance in practical applications. Through continuous processing of real-time data streams, the model dynamically updates enterprise association graphs and risk propagation paths, adapting to real-time changes in economic environments and corporate relationships, ensuring timely and accurate risk warnings.

This study addresses the limitations of traditional financial early-warning models in predicting risks due to their failure to account for complex inter-enterprise relationships and temporal dynamics. The research proposes a core hypothesis: By integrating time-series modeling with dynamic enterprise network analysis, a hybrid GNN-GAT-LSTM model can simultaneously capture spatial transmission and temporal evolution of risks, thereby enhancing the accuracy and robustness of financial risk warnings. To validate this hypothesis, three specific questions are explored: First, can Graph Neural Networks (GNN) effectively quantify the differential impacts of interconnected enterprises in risk transmission? Second, does incorporating Long Short-Term Memory Networks (LSTM) improve the model's ability to characterize dynamic financial risk processes? Third, does this hybrid architecture demonstrate sufficient generalization capability when facing industry-specific and market volatility challenges?

2 Related work

Current research on corporate financial risk early warning primarily employs traditional statistical methods to analyze individual company characteristics and predict future crises [7], [8]. Cheng Jing constructed a financial alert scheme using intelligent mathematical models for enterprise economic analysis [9]. Cao Yali developed a DL-based financial early warning scheme, focusing on e-commerce enterprises' financial risk mechanisms [10]. Shang Hongyu proposed an EFR early warning scheme by selecting representative financial risk indicators and using parallel rules and fuzzy clustering [11]. Zhang Huang created a financial risk indicator and EFR system for SMEs using BPNN [12]. Chen Jing introduced the TG-LSTM model, combining time series ratio analysis and LSTM, for early financial warnings in feed enterprises [13]. However, many studies lack systematicity by focusing solely on individual enterprises, neglecting inter-firm connections and risk transmission. Some have incorporated deep learning but insufficiently consider external network relationships, hindering effective hidden risk capture.

The GNN excels at modeling complex relationships and enables real-time dynamic monitoring of cross-node risk propagation, enhancing risk early warning accuracy [14]. Guo Chang proposed a predictive maintenance early warning scheme with prediction and warning modules, using a dual-channel GNN and time convolution network [14]. Bi Kejun developed an enterprise risk assessment scheme incorporating attention mechanisms and GNNs for risk category identification [15]. Wang Jiaxing introduced a graph attention network algorithm capable of capturing complex topological information, improving credit risk assessment for data-scarce SMEs [16]. Ren Yinghua proposed a GNN-based financial crisis early warning scheme using information spillover networks [17]. However, existing GNN-based research often relies on fixed or manually set relationship networks, struggling to model dynamic relationships and complex interactions. The GNN-GAT-LSTM model in this paper adaptively learns enterprise correlations and models time-dimension dynamics, improving risk warning accuracy.

A review of enterprise risk early warning literature over the past three years shows limitations in existing research: Cao Yali (2022) used an LSTM model achieving 0.891 AUC but struggled with static modeling; Zhang Huang (2022) employed a BP neural network with 0.872 accuracy, ignoring enterprise relationships; Ren Yinghua (2022) used GNNs with 0.901 AUC but was constrained by static graphs; Guo Chang (2023) proposed a TCN-GNN hybrid model with partial temporal modeling but lacked dynamic relationship modeling. In contrast, our GNN-GAT-LSTM model achieves breakthroughs by using dynamic heterogeneous graph architecture, attention mechanisms for differentiated risk propagation, and temporal modules for dynamic risk evolution. It attains 0.962 AUC in cross-domain validation, demonstrating superior handling of complex correlations and dynamic evolution.

3 Construction of EFR warning model

3.1 Data source and processing

The Wind Database provided all of the financial information used in this work. The research objects are A-share listed corporations, and the company's financial position in the T year is predicted using the annual economic data of the T-2 years. Data from 178 A-share listed companies, including financial, retail, manufacturing, and other industries, were obtained from the database. 13 companies were excluded because of missing data, and 165 listed companies were finally determined, including 110 non-ST (Special Treatment) companies and 55 ST companies.The dataset was divided using a time series-sensitive 8:2 training-test ratio, with data from 2020 and earlier years serving as the training set and 2021-2022 data as the test set. This division adheres to the principle of prospective validation for financial risk early warning systems, ensuring time leakage prevention, maintaining sufficient test set size, and guaranteeing statistically reliable research conclusions that align with practical risk control application logic.

To ensure the effectiveness of model training, the original data were standardized, and the minimum-maximum standardization method (Min-Max Scaling) was used to convert the indicator data to the [0, 1] interval, removing the effect of diverse dimensions and units. The formula is as follows:

$$x' = \frac{x - min(x)}{max(x) - min(x)} \quad (1)$$

x display the original data, max(x) and min(x) signify the maximum and minimum values of the indicators, and x' implies the standardized data. The minimum-maximum standardization method can accelerate the convergence speed of model training and improve prediction performance. For abnormal data points, the box plot method detects and eliminates extreme outliers; for missing values of some indicators, the historical mean interpolation method maintains the integrity and consistency of the data. The data samples are split into training and test sets in a 2:8 ratio following data processing. Table 1 displays the divide in question.

Table 1: Dataset division

Grouping situation	Training set	Test set	Total
Financial health	48	12	60
Mild financial crisis	44	11	55
Severe financial crisis	40	10	50
Total	132	33	165

As displayed in Table 1, there are 60 companies in the financial health group, 48 of which are included in the training set and 12 are used for testing; 55 companies are in the mild financial crisis group, 44 of which are assigned to the training set and 11 constitute the test set; and 50 companies are in the severe financial crisis group. This stratified sampling method can evenly evaluate the scheme's performance in different categories and enhance the reliability and universality of the outcomes.

3.1.1 Node selection

In building an EFR early warning scheme, enterprise node feature extraction and enterprise association map construction are key technical points. Enterprise node feature extraction is the basis for GNN to carry out risk prediction, and the enterprise association map intuitively presents the structured relationship between enterprises, helping the scheme understand the risk propagation path. Based on multi-dimensional data integration, enterprise node feature extraction can be realized, which can present the enterprise's financial status in an all-around way and accurately evaluate the enterprise's financial operation situation [18].Decoupling analysis is used to process and analyze the extracted key economic indicators, process highly correlated indicators, reduce redundant calculations, and prevent the impact on early warning efficiency. In addition, topological attribute features can further optimize node feature construction, which needs to be selected in indicator selection.

3.1.2 Construction of enterprise association graph

EFR transmission often shows a high degree of structure and connectivity. Building an enterprise association graph is a key link in financial risk early warning modeling. In the GNN model, enterprise nodes' structural and attribute information work together to affect the scheme's ability to capture potential risks. This requires precisely defining nodes and edges, integrating multi-source heterogeneous data, and incorporating dynamically changing time factors. Nodes are defined as specific enterprise entities, and each node has structured attribute characteristics. These features form a node feature matrix $X = R^{N*d}$ in the form of vectors, where N is the number of nodes and d is the feature dimension. In terms of edge construction, each edge represents an economic relationship between enterprises. Let the graph be $G = (A, B, C)$, where A represents the enterprise node set, $B \subseteq A * A * D$ represents the edge set with type, C represents the relationship type set, and a corresponding weight function is set for each edge. The supply chain's edge weight can be defined as a two-factor combination of transaction frequency and amount. w_{ij}^{XY} is expressed as:

$$w_{ij}^{XY} = loh\left(1 + T_{ij}\right) * h_{ij} \quad (2)$$

Where T_{ij} represents the annual transaction amount, and h_{ij} represents the annual transaction frequency.

The equity edge weight represents the controlling proportion w_{ij}^{EQ} is expressed as:

$$w_{ij}^{EQ} = \sqrt{s_{ij}} \quad (3)$$

Where s_{ij} is the shareholding ratio. Different types of associations between enterprises make the constructed graph have typical heterogeneous characteristics, so the final enterprise association graph can be represented as a heterogeneous graph $G = (A, B, \emptyset, \varphi)$, where $\emptyset: A \rightarrow R^d$ is the node feature map and $\varphi: B \rightarrow R$ is the edge type map.

The network centrality indicators in the graph, such as degree centrality and eigenvector centrality, can accurately quantify the position of the enterprise in the association network, so that the final constructed graph is presented as a heterogeneous graph. The node feature vectors include multi-dimensional financial indicators and market signals. At the same time, the edges describe different types of relationships between enterprises, such as transactions, guarantees, and equity. The relationship between enterprises is not static, but dynamic over time, and can be affected by many factors such as policy adjustments and market fluctuations. This dynamic plays a role in the transmission and evolution of financial risks. To accurately capture the evolution of enterprise relationships over time, it is necessary to construct a time-series dynamic graph $\{G_t\}_{t=1}^{T}$. Each time slice $G_t = (A_t, B_t, C_t)$ represents the state of the enterprise network at a certain point in time (such as a year or quarter). The node set A_t represents the set of enterprises that exist in that period, the edge set B_t represents the relationship between enterprises at that moment, and C_t is the feature matrix of the node at that moment. When constructing a dynamic graph, this paper uses a sliding window method to perform more fine-grained dynamic modeling to capture the relationship changes within a continuous time interval. This dynamic feature can enhance the ability to perceive the development trend of risk events and effectively model the time delay effect of risk propagation between enterprises. By introducing a time-dependent adjacency tensor, the relationship-specific message propagation formula is:

$$f_i^{(k+1)} = \delta\left(\sum_{r\in R}\sum_{j\in M_i^r}\frac{1}{x_{i,r}}W_r^k f_i^k\right) \tag{4}$$

Where M_i^r represents the adjacency set connected to node i through relationship r, W_r^k is the weight matrix corresponding to relationship type r in the kth layer, $x_{i,r}$ is the normalization factor, and δ is the activation function. This message passing mechanism can distinguish the semantic roles of different edges and integrate the time context in the dynamic graph structure, providing more accurate modeling capabilities for structured analysis and early warning of enterprise risks. Taking the enterprise's heterogeneous dynamic graph structure as input to the GNN model, it can effectively identify high-risk nodes and potential risk diffusion paths. The triple relationship of node-edge-attribute visualization of the enterprise association network is displayed in Fig 1.

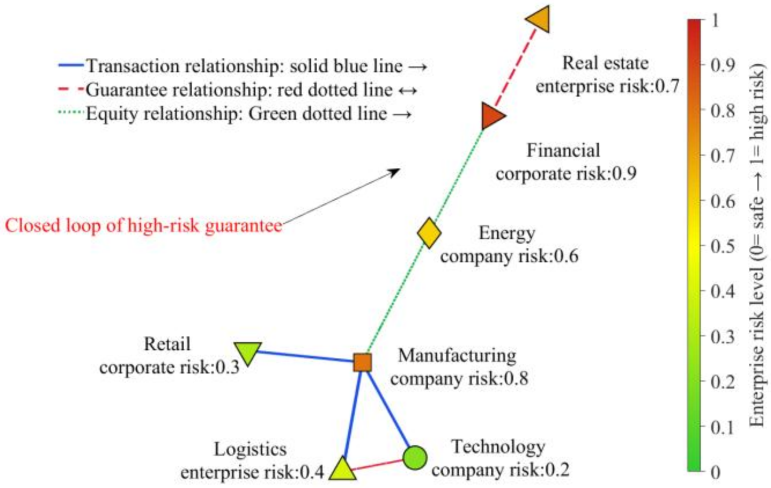

Figure 1: Visualization of the triple relationship of node-edge-attribute in the enterprise association network

As shown in Figure 1, the graph employs a node color scheme to distinguish enterprise industry categories (dark circles for financial institutions, light squares for manufacturing, gray triangles for retail). Edge styles differentiate relationships (solid arrows for supply chains, dashed lines for guarantees, dotted lines for equity). The force-directed algorithm positions nodes based on topological distance, with a centrality metric scale (0-1) in the upper right. An enterprise association network is constructed, incorporating industry distinctions and risk mapping. Node information, inter-enterprise relationships (transactions, guarantees, equity), and weights reflect influence differences. Shapes mark industries, arrows indicate transaction/equity directions, and dotted lines show bidirectional guarantee connections, enhancing the representation of complex interactions..

3.2 EFR warning scheme based on GNN-GAT-LSTM

In the current complex economic and financial situation, corporate financial risks are affected by their operating conditions and may also fluctuate due to the behavior of related companies. Traditional financial risk warning schemes are primarily based on predicting a single company's economic data, without considering the complex interactions of companies in multi-dimensional networks such as supply chains, equity structures, and guarantee relationships. With the rise of GNN, modeling enterprise relationships as graph structures and modeling risk propagation paths with the help of deep learning technology have become key ways to improve the accuracy of early warning. This paper constructs a composite model (GNN - GAT - LSTM), which integrates GNN, GAT, and LSTM to build an EFR early warning scheme.

3.2.1 GNN layer: local structure information capture

In the enterprise association graph, nodes represent enterprises and edges denote relationships (e.g., supply chain, equity, guarantees). GNN extracts feature representations by aggregating neighbor node information to update the current node's embedding, capturing local graph information. For instance, if a supplier faces a financial crisis, the connected company may encounter raw material shortages or capital chain issues. GNN uses graph node relationships to aggregate adjacent node data and update node features. In the EFR warning scheme, GNN employs spectral or spatial filtering to fuse original enterprise node features with neighboring node features. By stacking multiple GNN layers, the perception range expands, enabling the capture of both direct (first-order) and indirect (distant node) influences. This enhances global enterprise risk assessment and avoids misjudgments from neglecting inter-enterprise interdependencies:

$$H^{(l+1)} = \alpha\left(\widetilde{D}^{-1/2}\tilde{A}\widetilde{D}^{-1/2}H^{(l)}M^{(l)}\right) \tag{5}$$

$\widetilde{A} = A + I$ is the adjacency matrix with self-loops, $\widetilde{D}$ is the corresponding degree matrix, $M^{(l)}$ is the trainable weight, and α is the activation function. In the enterprise graph, this mechanism is reflected in the joint modeling of the attributes of the enterprise itself and its associated enterprises to form node embeddings containing local risk information. In practical applications, stacking multiple layers of GNN can capture deeper neighbor information, but too many layers can make the node features too smooth, resulting in distorted or inaccurate information. To avoid the over-smoothing problem, this model uses a two-layer GNN structure. The first layer focuses on capturing risk information of directly adjacent companies; the second layer expands to the next-level companies to capture a wider range of indirect impacts. This hierarchical structure retains local key information and prevents over-smoothing, ensuring that node characteristics can accurately reflect the risk status of the enterprise. The formula is as follows:

$$H^{(l+1)} = \alpha\left(\tilde{A}H^{(l)}M^{(l)}\right) \tag{6}$$

In formula (6), after the first layer of convolution, $H^{(l)}$ is passed to $H^{(l+1)}$, thus completing the fusion of first-order and second-order neighbor information. As a special type of inter-enterprise connection, the guarantee relationship reflects the credit support and risk transmission path between enterprises, and also reveals the potential risk aggregation areas and propagation patterns in the entire market.

3.2.2 GAT layer: dynamic weight allocation

Although GNN can aggregate structured information, it uses an equal weight or static weight mechanism between neighbor nodes, which makes it challenging to capture the non-balanced characteristics of weights in corporate relationships. In the enterprise network, different types of enterprises have different abilities to transmit risks to target enterprises. Therefore, this paper introduces GAT. GAT [19] uses the attention mechanism to dynamically assign weights to each neighboring node to achieve differential learning during information aggregation. Its basic update process calculates the attention coefficients of the target and neighboring nodes, then performs weighted aggregation based on these coefficients. The formulas are:

$$\beta_{ij} = \frac{exp\left(LeakyReLU\left(\beta^T\left[Wh_i||Wh_j\right]\right)\right)}{\sum_{h\in N(i)} exp\left(LeakyReLU\left(\beta^T\left[Wh_i||Wh_k\right]\right)\right)} \tag{7}$$

$$h_i' = \alpha\left(\sum_{j\in N(i)} \delta_{ij}Wh_j\right) \tag{8}$$

Where h_i and h_j represent the feature vectors of node i and its neighbor j, δ_{ij} is the attention weight between nodes, β and W are learnable parameters, and || represents the vector concatenation operation. With this mechanism, the scheme can automatically determine which adjacent nodes have a stronger explanatory power for risk results in the past based on historical data, thereby improving the modeling ability of risk transmission paths. In heterogeneous graph structures, different types of edges have different risk propagation capabilities. The introduction of the GAT mechanism improves the accuracy of node feature updates and enhances the scheme's ability to perceive structural heterogeneity and risk differences among enterprises.

3.2.3 LSTM layer: modeling dynamic changes in time

The financial status and association structure of an enterprise are not static. Static graph models are challenging to capture the dynamic changes of node features over time, so it is necessary to introduce a time series modeling module to perform sequence learning on the time dimension for node embedding. As a typical recurrent neural network structure, LSTM has excellent long-term dependency modeling capabilities and meets the time series modeling requirements of enterprise node characteristics [20], [21], [22]. In this model, the embedded representation of the enterprise node extracted by GNN and GAT at each time node is used as the input sequence and input into LSTM to form continuous time series data, thereby realizing the dynamic modeling of EFR in the time dimension. GNN and GAT are responsible for capturing the local correlation characteristics of enterprises in the graph structure and the importance weight of neighbor influences, respectively. LSTM gives full play to its advantages in time series modeling, sequentially processes the representation of enterprise nodes at different time points, and reveals the changes of risk factors over time. By encoding the node embedding of each time step through LSTM, the evolution trend of node status over time can be captured, thereby effectively predicting the financial risk level of the enterprise at a future point in time. Its core update formulas are as follows:

$$f_t = \sigma\left(W_f[h_{t-1}, a_t] + b_f\right),\quad j_t = \sigma\left(W_j[h_{t-1}, a_t] + b_j\right) \tag{9}$$

$$\tilde{C}_t = tanh(W_C[h_{t-1}, a_t] + b_C), \quad C_t = f_t \odot C_{t-1} + j_t \odot \tilde{C}_t \tag{10}$$

$$o_t = \sigma(W_o[h_{t-1}, a_t] + b_o), \quad h_t = o_t \odot tanh(C_t) \tag{11}$$

Where a_t is the node feature representation of the current time step, h_t is the hidden state of the current time step, and C_t is the memory unit state. This mechanism allows the scheme to perceive the key nodes in the evolution of enterprise risk. The node embedding vectors extracted by GNN and GAT are input into the LSTM module for time series modeling to generate time-aware node risk representation, which is then mapped to the risk prediction label space through the fully connected layer. During training, a graph sequence is constructed using historical data from multiple time points. Each graph represents the state of the enterprise relationship network in the tth year, which can enhance the scheme's understanding of the temporal evolution of enterprise risks and has obvious advantages in dealing with sudden financial crises, large market fluctuations, etc. The GNN-GAT-LSTM model achieves multi-level modeling of EFR warning through deep fusion of three-layer structures: the GNN layer captures local risk propagation patterns, the GAT layer highlights the impact of key related enterprises, and the LSTM layer models the evolution of risks over time. The scheme can fully use graph structure information and dynamically evaluate corporate risks with time series data, providing regulatory agencies and enterprises with scientific and accurate risk warning tools.

3.3 Model integration and calculation process

In order to ensure that the GNN-GAT-LSTM model can be reproduced, its integration mechanism and calculation process are detailed. Its architecture is progressive from graph structure learning to time series modeling, which can accurately warn of financial risks.The input of the model is the dynamic enterprise association graph sequence $\{G_{t-k}, \cdots, G_{t-1}, G_t\}$, where the graph $G_t = (A_t, X_t)$ of each time step contains the adjacency matrix A_t and the node feature matrix X_t.The calculation process begins at the graph structure learning stage: each is first processed by the GNN layer, and the first-order neighbor information is aggregated through the messaging mechanism of equation (5) to generate a preliminary node embedding $H_t^{(GNN)}$; The embedding is then input to the GAT layer, and the neighbor nodes are differentiated and weighted using the attention coefficient β_{ij} calculated in equation (7), and the refined node embedding $H_t^{(GTA)}$ is output through equation (8).This embedding characterizes a snapshot of the state of the enterprise under the influence of the time t fusion association network.

After the graph structure learning is completed, it enters the timing modeling stage.For each enterprise node i, its GAT embedding $[H_{t-k}^{(GTA)}(i), \cdots, H_t^{(GTA)}(i)]$at each time step is arranged in order to form a timing sequence input to the LSTM module.LSTM processes the sequence according to the gating mechanism of formulas (9) to (11), and learns the dynamic evolution law of the enterprise state.The hidden state of the final time step t is extracted as a time-aware node representation, covering the historical pattern and the current graph structure information.This state is mapped by the full connection layer, and the Softmax function outputs the probability distribution of the financial risk category.The training is based on this calculation process and optimized end-to-end with minimizing cross-entropy loss.Model hyperparameters: Adam optimizer, learning rate 0.0001, batch size 4, dropout rate 0.3, time series is constructed with a sliding window of length 3.Run the pseudo-code as :

```
input:
  -Trained GNN-GAT-LSTM model
  -New dynamic graph sequence data G_new= {G_{t-k+1},..., G_{t+1}}
output:
  -Corporate financial risk forecast results
initialize:
  -Load the trained model parameters
  -Set the model as the evaluation mode
with torch.no_grad(): # Disable gradient calculation
  node_embeddings_sequence = []
  #Stage 1: Graph structure learning
  for t in range(sequence_length):
    graph_t = G_new.graphs[t]
    node_features = graph_t.x
    adj_matrix = graph_t.edge_index

    h_gnn = GNNLayer(node_features, adj_matrix)
    h_gat = GATLayer(h_gnn, adj_matrix)
    node_embeddings_sequence.append(h_gat)
  # Stage 2: Timing modeling
  lstm_input = torch.stack(node_embeddings_sequence)
  lstm_output, (h_n, c_n) = LSTMLayer(lstm_input)
  final_representations = h_n[-1, :, :]
  # Risk prediction
  risk_predictions = Classifier(final_representations)
  predicted_classes = torch.argmax(risk_predictions, dim=1)
Return predicted_classes # Return the risk level prediction result
```

4 Experimental analysis of corporate financial risk warning scheme

4.1 Experimental environment and parameter settings

The operating environment parameters of this experiment are displayed in Table 2.

Table 2: Experimental operating environment parameters

Serial number	Type	Parameter
1	Operating system	Windows 10
2	CPU (Central Processing Unit)	Intel Core i7-10700F
3	Graphics card	NVIDIA GeForce RTX 3060 Ti
4	Programming language version	Python 3.7.9
5	Optimizer	Adam
6	Batch size	4
7	Epochs	30
8	Iteration	100
9	Dropout	0.3
10	Learning rate	0.0001

As Table 2 shows, this experiment was conducted in a well-configured environment. The operating system used was Windows 10, which ensures broad software compatibility. The programming language used was Python 3.7.9, which has rich library resources. The Adam optimizer was used when training the scheme, which can adaptively adjust the learning rate and accelerate convergence. Overall, such configuration and parameter selection laid a solid foundation for the experiment's success.

The GNN-GAT-LSTM model is built on PyTorch Geometric 2.3.0 and PyTorch 1.12.1 frameworks, featuring a modular hybrid architecture. It employs a two-layer GNN: the first aggregates direct neighbor information, while the second extends to second-order neighborhoods (64-dimensional output per layer). For heterogeneous edges (e.g., guarantees, equity), relationship-specific weight matrices enable differentiated messaging, preserving edge-type information in attention calculations. A dynamic graph is constructed annually (2018–2022) using Wind database financial reports. The GAT module uses 8 attention heads (8-dimensional each, spliced to 64), while the LSTM module processes GNN-GAT node embeddings over three consecutive years with a 128-dimensional hidden state, modeling temporal risk evolution. Training employs Adam (initial learning rate 0.0001, decaying 0.5 every 50 epochs), weight decay (1e-5), dropout (0.3), cross-entropy loss, and gradient clipping. Data is split chronologically (training: ≤2020; test: 2021–2022) for forward-looking evaluation, with hyperparameters tuned via grid search.

In view of the doubts about the risk of overfitting, a number of rigorous verification methods have been adopted in the research.The first is to test with samples outside the time series, and verify the non-participating training data from 2018-2020 and 2021-2022. The AUC value of the model reaches 0.954, proving the generalization ability.The second is to use the retention time window for cross-verification, and use different years as test sets in turn, and the model performance fluctuates within ±0.018.In the end, the model achieves stable convergence with the help of regularization techniques such as early stop method and dropout = 0.3.

4.2 Experimental analysis

4.2.1 Model performance comparison

The current economic environment is complex and changeable, and enterprises' financial risks are increasing daily. To evaluate the new EFR early warning scheme, drawing on the GNN-GAT-LSTM constructed in this study, it is compared with a variety of traditional and advanced models, including GNN, LSTM, BP-LSTM, GNN-LSTM, and HHGNN (Heterogeneous Hyper Graph Neural Networks). Through a comprehensive evaluation using multiple indicators such as precision, recall, specificity (SPEC), RSE, and RAE (Relative Absolute Error), the performance differences of each model in identifying different levels of financial crises are fully presented. The specific outcomes are displayed in Fig 2.

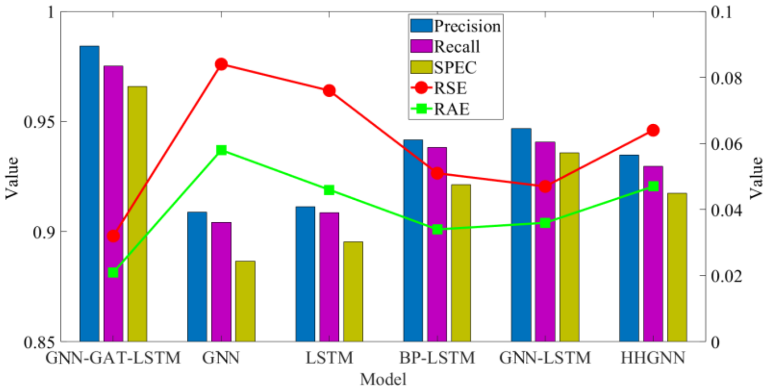

Figure 2: Performance comparison of different EFR warning schemes

As shown in Figure 2.The GNN-GAT-LSTM model demonstrates superior performance across all evaluation metrics compared to other models. It achieves precision (0.9842), recall (0.9752), and specificity (0.9658) values significantly outperforming competitors, highlighting its effectiveness in distinguishing healthy and crisis-prone enterprises. In error evaluation, its RSE (0.032) and RAE (0.021) values are substantially lower than those of GNN, LSTM, BP-LSTM, GNN-LSTM, and HHGNN, indicating higher prediction accuracy, stability, and generalization. While GNN excels in structural modeling, its precision and recall lag behind deep learning alternatives. LSTM struggles with inter-enterprise relationship modeling, limiting its performance. BP-LSTM and GNN-LSTM improve accuracy but fail to integrate graph dynamics effectively. HHGNN, despite its complex heterogeneous hypergraph structure, underperforms GNN-GAT-LSTM. The proposed model leverages GNN's graph-processing capabilities, enhances node interactions via GAT, and incorporates LSTM's temporal modeling, enabling comprehensive capture of enterprise risk propagation paths and significantly improving early warning performance.

In the field of EFR early warning, the GNN method is becoming an emerging and effective way. The GNN-GAT-LSTM model constructed in this paper is compared with other models. These models' loss value and accuracy comparison outcomes are displayed in Fig. 3.

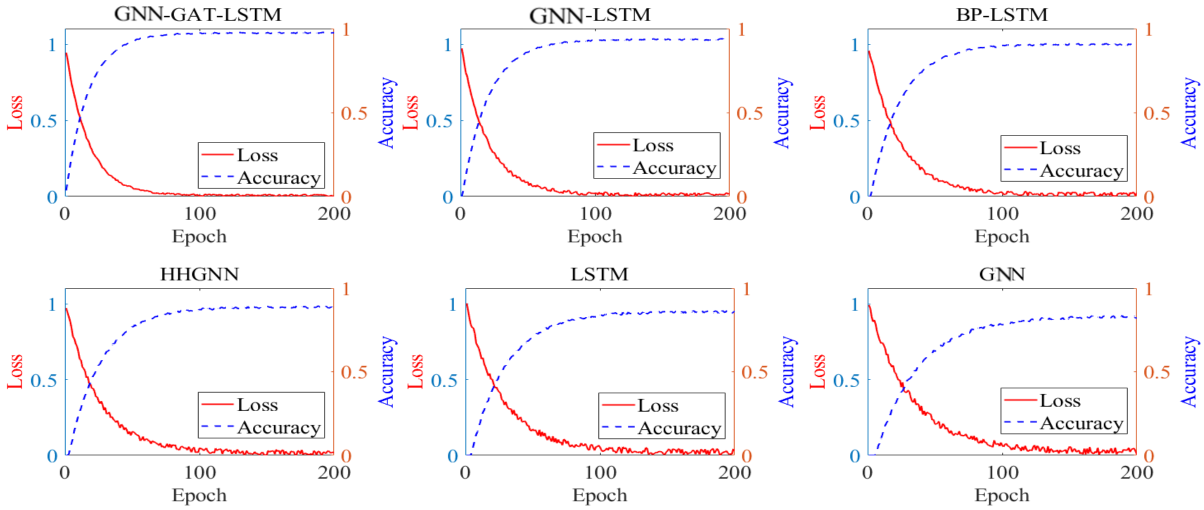

Figure 3: Comparison of loss values and accuracy curves of different models

As displayed in Figure 3, the experiment set 200 training rounds, and the GNN-GAT-LSTM model performed best. Its loss value dropped rapidly and stabilized at the lowest level. Its accuracy was the first to approach 98%, demonstrating the scheme's powerful feature extraction ability and learning stability. The traditional GNN model has a simple structure and cannot capture time dependencies. The loss decreases slowly, and the final accuracy is relatively low, ranking last. This performance gap verifies the advantages of the proposed method of integrating GNN, GAT, and LSTM. GNN-GAT-LSTM can use the graph structure to depict the complex relationships between enterprises, strengthen the influence of key nodes through GAT, and use LSTM to capture the dynamic changes of financial status over time. Although HHGNN has certain advantages in heterogeneous information modeling, it has high computational complexity, slow convergence speed, and slightly lower accuracy than GNN - GAT - LSTM.

To establish a more comprehensive benchmarking framework, this study introduces three advanced models specifically designed for dynamic graph structures: T-GCN (Temporal Graph Convolutional Network), DySAT (Dynamic Self-Attention Temporal Graph Network), and ST-GAT (Spatio-Temporal Graph Attention Network) as comparative benchmarks. While the GNN-LSTM baseline model only incorporates basic graph convolutional and LSTM modules, our proposed GNN-GAT-LSTM model demonstrates key innovations through its multi-head graph attention mechanism. This mechanism dynamically learns differentiated weighting factors for different neighboring nodes in assessing enterprise risks. Experimental results are presented in Table 3.

Table 3: Comparative results of dynamic graph models

Model	RSE	AUC	Precision
GNN-LSTM	0.047	0.913	0.938
T-GCN	0.041	0.925	0.947
DySAT	0.038	0.934	0.953
ST-GAT	0.035	0.943	0.962
GNN-GAT-LSTM	0.032	0.962	0.984

Table 3 demonstrates performance differences among dynamic graph models in corporate financial risk early warning tasks. The GNN-GAT-LSTM model outperforms others with 0.032 RSE, 0.962 AUC, and 0.984 accuracy, validating its effectiveness in modeling corporate risk propagation. The experiment reveals progressive performance trends: T-GCN achieved initial improvements through temporal graph convolution, DySAT enhanced with self-attention mechanisms further improved results, while ST-GAT converged to the model's level after integrating spatiotemporal attention. This indicates that refined modeling of heterogeneous relationships in corporate networks is crucial for improving risk prediction accuracy. Our model surpasses GNN-LSTM by leveraging customized heterogeneous graph structures and relationship-specific attention mechanisms to differentiate the influence of various relationships in risk propagation. Through deep encoding of business logic, it captures dynamic risk transmission while understanding economic semantics of relationship types, achieving both low error rates and precise identification of high-risk enterprises.

4.2.2 Comparison of early warning performance heat map

In the research on early warning of corporate financial risks, accurately identifying corporate financial conditions is significant in preventing potential crises. To evaluate the performance of different models on this task, 165 samples in Table 1 were used and divided into three groups. By comparing the prediction outcomes of the two models, the research method of this paper is compared with the traditional GNN model, as displayed in Figure 4.

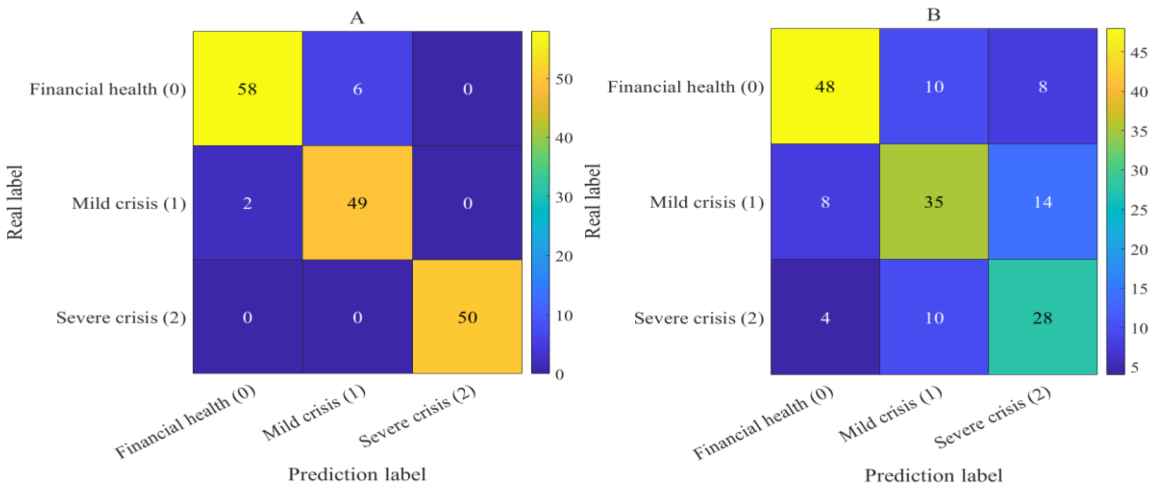

Fig. 4A. GNN-GAT-LSTM
Fig. 4B. GNN

Figure 4: Comparison of GNN-GAT-LSTM and GNN model warning performance heat map

As displayed in Fig. 4, the performance of the scheme GNN-GAT-LSTM studied in this paper is better than that of other models. As shown in Figure 4A, GNN-GAT-LSTM was studied, and the scheme performed well in financial health, with 58 samples correctly classified as financially healthy and only two samples misclassified as mild crisis. For the 55 samples of mild financial crisis, the scheme successfully identified 49, but 6 were misclassified as financially healthy. In predicting 50 samples of severe financial crisis, the scheme achieved all correct classifications; this shows that the GNN-GAT-LSTM model performs well in identifying severe financial crisis and accurately distinguishes financial health from mild financial crisis. As displayed in Figure 4B, the performance of the traditional GNN model is relatively poor. In the identification of financially healthy samples, only 48 samples were correctly classified, and 8 and 4 samples were misclassified as mild and severe financial crisis samples, respectively. For samples with mild financial crisis, only 35 were accurately identified. In the identification of severe financial crisis samples, only 28 samples were correctly classified. These data fully demonstrate that the traditional GNN model is far inferior to the GNN-GAT-LSTM model in classification accuracy, especially when dealing with mild and severe financial crisis samples, where the performance gap is more significant. The GNN-GAT-LSTM model studied in this paper performs better, mainly due to its unique architectural design. The scheme combines the structured data processing capabilities of GNN, GAT's adaptive weight allocation capabilities, and the time series analysis capabilities of LSTM. This combination enables the scheme to more accurately capture the complex relationships and dynamic changes in corporate financial data, thereby improving the accuracy of corporate financial status forecasts. In addition, the scheme can effectively distinguish different types of financial crisis samples, improve the overall classification performance, and provide strong support for corporate financial risk management in practical applications.

4.2.3 Comparison of warning error rates

Table 1 divides corporate financial risks into three levels, and warns of the three levels of risks to obtain warning error rates. The error rate of the method studied in this paper is compared with other model methods, and for the scientific nature of the experiment, 10 experiments are conducted. The specific comparison outcomes are displayed in Figure 5.

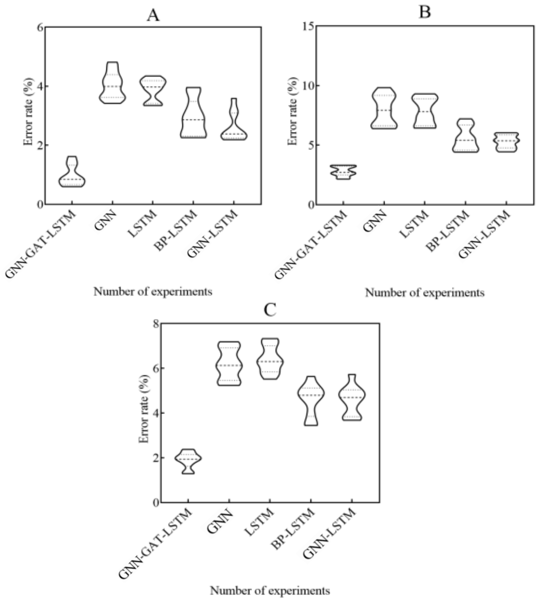

Fig. 5A. Financial health
Fig. 5B. Mild financial crisis
Fig. 5C. Severe financial crisis

Figure 5. Comparison of warning error rates of different models

As displayed in Figure 5, the performance of the GNN-GAT-LSTM model constructed in this paper at different risk levels is far better than that of several other methods. As shown in Figure 5A, in the early warning error rate analysis of financially healthy enterprises, 10 experiments were conducted. The average error rate of the GNN-GAT-LSTM model was 0.97%, which was 3.05%, 2.92%, 1.97%, and 1.64% lower than the error rates of the GNN, LSTM, BP-LSTM, and GNN-LSTM models, respectively. This gap demonstrates the scheme's ability to handle complex relationship networks and dynamic changes. As shown in Figure 5B, the GNN-GAT-LSTM model also performed well in terms of the early warning error rate of companies in mild financial crisis, with an average error rate of 2.8%, which was 5.16%, 5.07%, 2.77%, and 2.49% lower than the error rates of the GNN, LSTM, BP-LSTM, and GNN-LSTM models, respectively. This shows that the scheme can accurately identify potential risks and support corporate risk management even in more complex financial situations. As displayed in Figure 5C, in companies with severe economic crises, the average value of the GNN-GAT-LSTM model is 1.9%, which is lower than that of other models. This further proves the effectiveness of the scheme in high-risk early warning. It can capture local risk propagation patterns and accurately predict the risks that companies may encounter in the future by combining time series data. Based on the comparative analysis of the early warning error rates of companies with three different risk levels in 10 experiments, the GNN-GAT-LSTM model performs well at all levels. Therefore, whether the enterprise is in a relatively stable financial health state or facing different degrees of monetary crisis, GNN-GAT-LSTM can provide more scientific and accurate risk warning services to help enterprises respond quickly and ensure sustainable and healthy development.

To systematically evaluate the statistical significance of model performance, 10 independent experiments were conducted on all comparison models under identical data partitioning and random seed conditions, with average values and standard deviations of key metrics recorded. For validation methods, rigorous time series cross-validation was employed, with training and test sets being annually rolled over to ensure evaluation protocols fully align with real-world business requirements for predicting future risks using historical data. This approach guarantees the reliability and generalizability of performance improvement conclusions. Additionally, Wilcoxon sign-rank tests were applied to analyze differences in evaluation metrics between GNN-GAT-LSTM and benchmark models, with results presented in Table 4.

Table 4: Statistical significance analysis of model performance

Model	RSE	RAE	AUC
GNN	0.084 ± 0.005	0.062 ± 0.004	0.884 ± 0.008
GAT	0.068 ± 0.004	0.049 ± 0.003	0.901 ± 0.006
GNN-LSTM	0.047 ± 0.003	0.035 ± 0.002	0.913 ± 0.005
HHGNN	0.043 ± 0.003	0.031 ± 0.002	0.921 ± 0.004
GNN-GAT-LSTM	0.032 ± 0.002**	0.021 ± 0.001**	0.962 ± 0.003*

Note: **p <0.01, *p <0.05.

Table 4 demonstrates the superiority of the GNN-GAT-LSTM model in corporate financial risk early warning. This model significantly outperforms the baseline model across all key indicators, showing remarkable reductions in RSE (0.032) and RAE (0.021) compared to other models ($p<0.01$), indicating smaller prediction errors. The AUC value of our model reaches 0.962, markedly higher than other models ($p<0.05$), highlighting its exceptional capability to distinguish enterprises with different risk levels. The performance improvement stems from the model architecture's alignment with corporate risk transmission characteristics. Its stable and excellent performance under time series cross-validation proves that its advantages are not accidental but stem from its ability to capture the essential patterns of risk transmission, providing reliable technical support for financial risk control applications.

4.2.4 Analysis of different industries

In today's complex and changing economic environment, the importance of corporate financial risk warning has become increasingly prominent. To explore the most suitable EFR early warning scheme, this paper is not limited to the performance evaluation of a single model. The GNN-GAT-LSTM model is constructed and compared with the GNN, LSTM, BP-LSTM, GNN-LSTM, and HHGNN models. This is mainly to study the financial risk early warning of enterprises in the financial industry, and obtain the ROC (Receiver Operating Characteristic) curves of these models for early warning of financial industry enterprises, thereby obtaining the AUC value. The ROC curve obtained by the experiment is displayed in Figure 6.

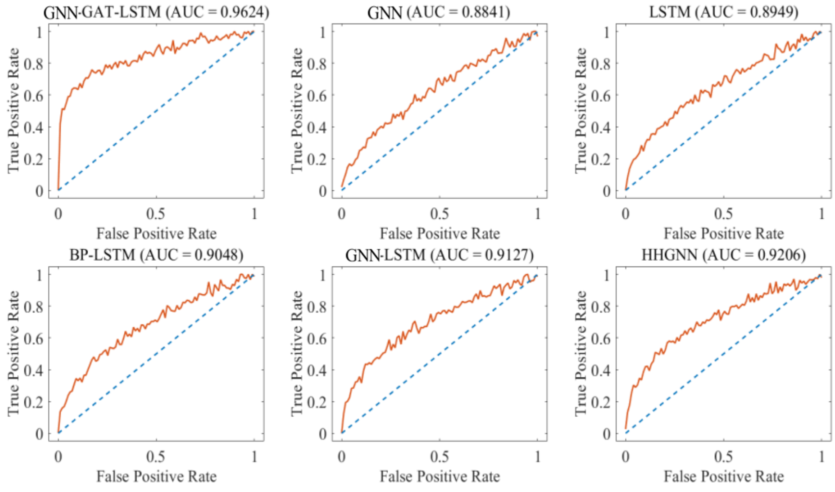

Figure 6: Comparison of ROC curves of different warning schemes

As shown in Figure 6, in the task of warning financial risks of financial industry enterprises, the GNN-GAT-LSTM model performs exceptionally well, with an AUC value of up to 0.9624, far exceeding other comparison models, GNN (AUC = 0.8841), LSTM (AUC = 0.8949), BP-LSTM (AUC = 0.9048), GNN-LSTM (AUC = 0.9127), and HHGNN (AUC = 0.9206). This result directly highlights the advantages of GNN-GAT-LSTM in classification ability. Also, it confirms from a statistical perspective that the scheme can maintain a high recognition accuracy rate under different false alarm rates. The overall trend of the ROC curve shows that in the face of complex and changeable risk transmission paths between enterprises; the scheme has stronger robustness and generalization ability. GNN-GAT-LSTM can achieve such excellent outcomes thanks to integrating multiple deep learning technologies. The GNN module enables the scheme to effectively model the corporate association structure and capture the potential risk transmission mechanism in complex networks such as supply chains and guarantee chains. The introduction of GAT enhances the scheme's focus on key nodes and meaningful relationships, making abnormal signals easier to identify and amplify, and improving early warning sensitivity. The LSTM module is responsible for processing time series data, helping the scheme understand the changing trend of corporate financial conditions over time and enhancing the dynamic nature of predictions. The performance gap between GNN-GAT-LSTM and other methods can be more intuitively observed by visually analyzing the ROC curves of different models. Especially in the low false alarm rate area, the scheme has a higher true positive rate, which means that in practical applications, it can more effectively identify high-risk companies while controlling false alarms.

Different industries face unique risk patterns and challenges in today's complex and changing economic environment. Figure 7 shows the risk sensitivity factors of other sectors.

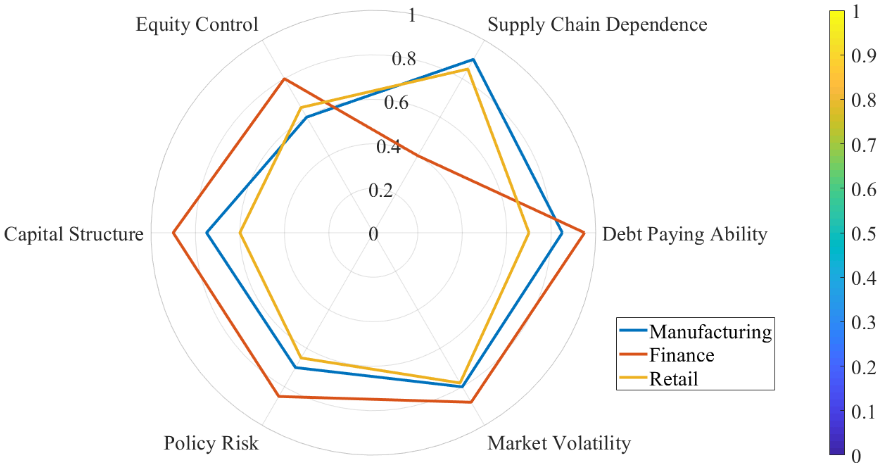

Figure 7: Risk sensitivity factors in different industries

Fig. 7 shows the sensitivity scores of different industries for six key risk factors, such as debt repayment capacity, supply chain dependence, and equity control. It uses a radar chart to intuitively show the differences in sensitivity of enterprises in different industries to various risks, highlighting the uniqueness of other enterprises in the financial risk transmission mechanism. The financial sector is susceptible to debt repayment ability, capital structure, and market volatility, which means that the economic status of financial enterprises is easily affected by liquidity, debt-to-asset ratio, and capital market volatility. This is consistent with the GNN-GAT-LSTM model's need to model complex relationships between enterprises. The manufacturing industry's high supply chain dependence and market volatility scores mean that its risk propagation may rely more on the diffusion of upstream and downstream enterprise associations, which is why this paper uses GNN to capture the structural relationship between enterprises. The retail industry is relatively less sensitive to most risk factors. Still, it performs well in terms of policy risks, reflecting that changes in the external environment significantly impact its business stability.

The research model demonstrates superior performance in the financial sector compared to its relatively weaker counterpart in retail, primarily due to distinct industry-specific risk transmission mechanisms. Financial sector risks rely on interbank guarantees and capital networks, featuring tight interconnections and clear transmission pathways that align with the GAT mechanism's characteristic of identifying critical nodes. The visual attention-weighted model precisely identifies systemically important institutions within guarantee circles. In contrast, retail sector risks are predominantly driven by individual operational factors like market demand and inventory turnover, with weak inter-firm connections and dispersed risk transmission paths, where graph-structured information provides limited incremental value. This validates the model's value limitations: when risks are strongly interconnected, structural analysis surpasses traditional financial metrics in explanatory power; when weak correlations prevail, industry-specific factors must be integrated for enhanced interpretation.

4.3 Model robustness analysis and ablation experiments

To systematically evaluate the generalization and robustness of the model across different domains and scales of graph data, this experiment selected three widely recognized benchmark datasets in graph learning. All datasets were obtained through standard channels and cover various network structure features. Specifically, the Cora citation network contains 2,708 paper nodes and 5,429 citation links, while the Citeseer citation network includes 3,312 paper nodes and 4,732 citation edges with 3,703 node feature dimensions. These datasets represent different network types and are used to set up consistent node classification tasks on heterogeneous data clusters, enabling comprehensive verification of the GNN-GAT-LSTM architecture's ability to capture graph structure information. The specific experimental results are shown in Table 5.

Table 5: Model performance comparison across domain-dimensional data sets (AUC)

Model / data set	Cora (Citation Network)	Citeseer (Citation Network)	Data set of this article
GNN	0.852	0.768	0.884
GAT	0.872	0.785	0.901
GNN-LSTM	0.865	0.776	0.913
HHGNN	0.883	0.801	0.921
GNN-GAT-LSTM	0.921	0.882	0.962

Table 5 demonstrates that the proposed model achieves optimal performance across three datasets, with AUC values reaching 0.921 and 0.882 on the Cora and Citeseer citation networks respectively—representing an 8-11% improvement over traditional GNN models, highlighting its effectiveness in capturing complex citation relationships in academic literature. The model maintains consistent excellence in both citation and financial networks, validating the architecture's versatility. Specifically, the GAT module identifies key neighboring nodes, the GNN layer aggregates local structural information, while the LSTM models dynamic node state evolution. This multi-level modeling mechanism enables the model to comprehend knowledge dissemination pathways in citation networks and analyze risk transmission chains in corporate guarantee networks, demonstrating strong generalization capabilities and practical value.

To investigate the contributions of three core components (GNN, GAT, LSTM) and critical hyperparameters, ablation experiments were conducted on financial datasets. The results are presented in Table 6:

Table 6: Analysis of model architecture ablation experiments

Model variants	GNN	GAT	LSTM	Precision	Recall	AUC
Variant A	☑	✕	✕	0.901	0.892	0.884
Variant B	☑	☑	✕	0.935	0.928	0.921
Variant C	☑	✕	☑	0.923	0.915	0.908
GNN-GAT-LSTM	☑	☑	☑	0.984	0.975	0.962

Table 6 presents the ablation experiment results demonstrating the synergistic effects of GNN, GAT, and LSTM in financial risk early warning tasks. The base variant Variant A containing only GNN can aggregate neighbor information to capture local risk propagation, but its AUC value of 0.884 indicates that static equal-weight aggregation struggles to distinguish impact differences among related enterprises. The attention mechanism-enhanced Variant B (GNN + GAT) improves AUC to 0.921, proving that dynamic weight allocation effectively identifies critical risk sources. The time-series modeling variant Variant C (GNN + LSTM) achieves an AUC of 0.908, highlighting the crucial role of enterprises' memory of historical risk states (e.g., prolonged profitability decline) in early warnings. The complete model employs a triple-coupling mechanism: GNN constructs risk propagation topologies, GAT focuses on key hubs, and LSTM characterizes temporal risk accumulation and mutations. This integrated approach captures both instantaneous shocks from guarantee chain ruptures and gradual supply chain risks, ultimately achieving an outstanding prediction performance of 0.962 while comprehensively covering enterprise risk propagation characteristics.

5 Discuss

Traditional financial early warning models are mostly based on the company's own time-series financial data. For example, although the LSTM model can capture the time dependence of a single company's financial indicators, the AUC value of 0.8949 shows that ignoring the structured information of the inter-enterprise correlation network will lose important risk transmission signals.Although the basic GNN model (AUC 0.8841) can capture local risk diffusion through neighbor information aggregation, the equal rights aggregation mechanism cannot distinguish the differences in influence of different affiliated companies, and treats major suppliers and minor customers equally, which is inconsistent with economic reality.The core breakthrough of this model lies in the synergy of three layers of components: the GNN layer builds the topological foundation of risk dissemination, and captures direct and indirect effects through two layers of messaging; the multi-head attention mechanism of the GAT layer can dynamically evaluate the importance of affiliated enterprises, which fits the law of real-world risk transmission. Experiments show that the introduction of Variant B of the GAT attention mechanism increases the AUC from 0.884 to 0.921, which verifies the necessity of differentiated weight distribution; the LSTM timing module solves the problem of dynamic modeling of corporate financial status, can identify current risks, and can also capture progressive risk models such as “three consecutive quarters of cash flow attenuation”.Compared with the current advanced heterogeneous hypergraph neural network HHGNN (AUC 0.9206), this model has an AUC increase of 0.0418 under similar complexity.The advantage is that the GAT dynamic attention mechanism can more flexibly adapt to the time-varying characteristics of enterprise relationships; LSTM fine time series modeling makes up for the lack of time dimension characterization in the pure graph model.In the risk assessment of enterprises in the financial industry, this model has an AUC of 0.9624, and it has excellent modeling ability for the dynamic process of complex financial-related network risks.

From the application point of view, the innovative value of this model lies not only in quantitative indicators, but also in providing risk interpretability.By visualizing the attention weights of the GAT layer, risk managers can trace the path of risk transmission and identify system-important nodes, which is not possible with traditional “black box” models.The cross-disciplinary verification results of the model (the AUC value in Cora is 0.921, and the AUC value in Citeseer is 0.882) prove the versatility of its architecture. It can also identify high-impact documents and capture the evolution trajectory of academic hotspots in the citation network. The strong generalization ability across disciplines shows that it captures the universal law of information dissemination.However, the model has limitations, such as high requirements for data quality and integrity, and complex hyperparameter tuning.In the future, the construction of adaptive adjacency matrices and the introduction of dynamic graph neural networks can be explored.Overall, GNN-GAT-LSTM integrates graph structure learning, attention mechanism and timing modeling to provide both accurate and explanatory solutions for enterprise financial risk early warning, and lays the technical foundation of intelligent risk control system.

The corporate financial risk early warning model demonstrates strong performance (AUC 0.9624) but requires careful consideration of ethical and operational risks in practical use. For regulators, it enables dynamic systemic risk monitoring but necessitates a tolerance mechanism for false positives to avoid unnecessary scrutiny of healthy firms and subsequent financing cost increases. For banks, while the model optimizes credit approval and post-loan management, its 3.76% misjudgment risk could trigger credit crunches (false positives) or bad debt losses (false negatives). Additionally, its 91.3% recall rate for mild financial crises highlights challenges in identifying "gray area" companies, potentially delaying risk mitigation. To mitigate these risks, three measures are recommended: implementing manual expert reviews for high-risk cases, setting confidence thresholds for intervention, and regularly updating the model with current data to adapt to economic cycles. A human-computer collaboration framework with hierarchical responses is essential to control adverse impacts.

6 Conclusions

In the research on corporate financial risk early warning, traditional models are mostly limited to the company's financial data, and pay insufficient attention to the risk transmission effect in complex economic relationship networks such as supply chains and guarantee chains between companies, resulting in low accuracy of financial risk early warning schemes. This paper constructs a corporate financial risk early warning scheme utilizing GNN-GAT-LSTM. This model combines the advantages of GNN, GAT, and LSTM to build a financial risk early warning system that can comprehensively consider the complex relationships between enterprises and accurately capture the risk transmission effect. The experimental outcomes show that the GNN-GAT-LSTM model performs well in key evaluation indicators such as precision, recall, specificity, and RSE, and has significantly improved compared with traditional models and other advanced models. In the three categories of financial health, mild financial crisis and severe financial crisis, the average error rate of the scheme is as low as 0.97%, 2.8% and 1.9% respectively. This proves that the scheme can more accurately distinguish healthy enterprises from crisis enterprises, demonstrating its excellent performance in capturing complex economic relations between enterprises and their dynamic changes. The GNN-GAT-LSTM model uses the GNN layer to capture the local structural information of the enterprise association graph; the GAT layer uses the attention mechanism to dynamically allocate the weights of neighbor nodes, strengthening the role of key related enterprises in transmitting risks to the target enterprise. The LSTM layer effectively models the dynamic changes of corporate financial risks over time. This multi-level, all-around modeling approach enables the scheme to capture complex relationships and dynamic changes in corporate financial data more accurately, thereby significantly improving early warning performance.

Authorship contribution statement

Meiling ZHANG: Writing-Original draft preparation, Conceptualization, Supervision, Project administration.

Author statement

All investigators have examined and authorized the manuscript, fulfilling the criteria for authorship. Each investigator certifies that it reflects honest work.

Ethical approval

All investigators have substantially contributed to the critical work involved in the article and are willing to assume public accountability for its content.

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