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Enterprise risk assessment model based on graph attention networks

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Abstract

Enterprise risk assessment not only provides a crucial reference for enterprises' strategic and business decisions, but also forms a fundamental basis for the financing decisions of banks and other financial institutions. Furthermore, as a critical node within the industrial chain, the enterprise's risk may directly affect the stability of the entire industrial chain, highlighting the significance of researching enterprise risk assessment. Existing enterprise risk assessment methods need to be revised to account for the risk transmission between enterprises across different types of relationships. Consequently, it leads to the need for more utilization of industrial chain structure and interaction information between enterprises. To address this problem, an enterprise risk assessment model, which is based on attention mechanism and graph network, is proposed. Firstly, weights of associated enterprises under a particular relationship are focused on. Then, weights of different relationships are introduced. After that, feature aggregation is conducted. Finally, features are put into the classification network to determine the risk category of the target enterprise, and enterprise risk assessment is accomplished. Experiments using dataset in integrated circuit industrial chain are conducted to verify this method, and the result shows that the method can effectively assess enterprise risk.

Keywords Knowledge graph · Graph attention network · Enterprise risk assessment · Industrial chain · Integrated circuit

1 Introduction

Enterprise risk assessment [1–4] provides an important reference for its strategic and business decisions. As a critical node within the industrial chain, the risk of an enterprise can affect the stability of the entire industrial chain. Moreover, since the safety of industrial chain is the fundamental for ensuring high-quality development of China's economy, safeguarding the security of the industrial chain becomes a vital task in enhancing macroeconomic governance. Assessing enterprise risks can serve as a theoretical foundation for research on the discovery and prediction of risk in the industrial chain, highlighting its significant importance.

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Manufacturing is the leading industry in China's national economy. In 2022, the value increase of manufacturing accounted for 27.7% of the GDP. China's manufacturing sector has held the top globally for 13 consecutive years, with integrated circuits playing a crucial role. In 2019, the National Development and Reform Commission (NDRC) released the first batch of the national strategic emerging industry cluster construction list in 12 key regions, which included 66 industry clusters. Among them, the number of integrated circuit industry clusters ranked fifth. In addition, according to the 2022 A-share annual reports of the four central banks in China, the Industrial and Commercial Bank of China (ICBC), the Agricultural Bank of China (ABC), the Bank of China (BOC), and the China Construction Bank (CCB) reported non-performing loan ratios in the manufacturing industry of 3.02%, 2.59%, 1.89%, and 2.80%, respectively. These data are all higher than the average non-performing loan ratios of the four central banks of 2.08%, 2.00%, 1.32%, and 1.38% respectively, which indicates an overall elevated credit risk in the manufacturing enterprises. Therefore, researching manufacturing is of great importance. Given the crucial role of integrated circuits within manufacturing, this paper will focus on it as the subject of study.

The production and transaction interdependence among manufacturing enterprises contribute to a widespread transmission of risks [5–7]. Under different relationships, transferability of risks among enterprises may vary. However, existing research has yet to characterize this aspect thoroughly, and there needs to be more exploration of the utilization of interactive information among companies. Therefore, this paper has designed relevant models to assess the risks of associated enterprises in the integrated circuit industrial chain, considering various relationships such as competition, investment, and supply.

Based on attention mechanism [8–10] and graph convolutional network (GCN) [11–14], this paper raises an enterprise risk assessment model. With the aggregation of enterprises' features under different relationships, deeper layers of information are delved into, thereby facilitating the risk assessment of enterprises. This paper's model structure is divided into four layers: graph convolutional network (GCN), enterprise-level attention, relationship-level attention and enterprise classification. In more detail, the GCN layer is used to learn feature representations of enterprises from the local structure of the graph. The enterprise-level attention layer focuses on the attention weights between each enterprise and its associated enterprises under a specific relationship. By weighting the features of each associated enterprise, a new vector is obtained through feature aggregation. The relationship-level attention network layer is built upon the enterprise-level attention layer, focusing on the semantic information corresponding to the current relationship path, which integrates the semantic information along the current relationship path to learn more enriched feature vectors for enterprises. Finally, the feature vectors obtained after passing through the enterprise-level attention layer and the relationship-level attention layer under each type of relationship are aggregated. These aggregated vectors are then input into the classification layer for classification, determining the risk category of the target enterprise and achieving enterprise risk assessment.

This work identifies the risks of integrated circuits enterprises according to the enterprises' financial data, making the assessment more feasible and practical. By assessing the risks of enterprises and establishing a risk warning platform to release risk warning assessment reports promptly, the following roles can be fulfilled: From the perspective of the enterprises themselves, it can enhance their risk warning and prevention capabilities. From the banks' perspective, it can improve the risk assessment of financing enterprises, thereby reducing the non-performing loan ratio. From the perspective of investments, it can lower investment risks. From the perspective of the industrial and supply chains, it can ensure their stability, guarding against disruptions.

The main contributions and innovations of this paper are summarized as follows:

- Based on the characteristic that the risk transmissibility between enterprises may vary under different relationships, a risk assessment model is designed to consider multiple relationships between enterprises, such as competition, investment and supply. The effectiveness of the designed model was demonstrated through different experiments.
- By considering multiple relationships, industrial chain problem is transformed into a graph problem, effectively illustrating the pathways of risk transmissions. Utilizing metapaths of 'company-product-company', 'company-person-company', and 'company-raw material-company', the heterogeneous industrial chain graph is then converted into a homogeneous enterprise relationship graph.
- By incorporating the characteristics of GCN and introducing enterprise-level and relationship-level attention layers, the model proposed in this paper effectively integrates features from various relationships, which can achieve more comprehensive assessment due to the consideration of global information. The model provides a reliable method for evaluating enterprise risks.
- By interpreting the crucial parameters in the model and giving recommended values, predictive results of the model can accurately reflect the risk status of enterprises, offering essential reference points for implementing corresponding risk management measurements.

The rest parts of this paper is organized as follows: Section 2 reviews previous papers and technologies. Then, in Section 3, the overall framework and algorithm are introduced, followed by definitions and design ideas of the model. After that, in Section 4, experimental setups and results are explained, where an ablation study is held and comparison experiments are conducted. Finally, in Section 5, the contents of this paper are concluded with a summary. Moreover, the limitations of this work are presented and the future research directions are suggested.

2 Related work

2.1 Enterprise risk assessment

So far, the existing research on enterprise risk assessment can be divided into two main categories:

The first type is the risk assessment model based on traditional statistical methods. For example, Huo et al. [15] adopted a non-linear regression approach based on the Probit model to measure and predict the credit risk of listed manufacturing companies. Later, Lei and Zhao [16] applied Logistic regression model for assessing enterprise credit risks. Then, in the context of supply chain finance, Yu and Li [17] and Tian et al. [18] conducted assessments of the likelihood of financing defaults for small and medium-sized enterprises (SMEs) in the automotive and electronic manufacturing industries using the Logistic regression model. Between them, Yu et al. [17] employed backward stepwise regression to select essential variables, while Tian et al. [18] utilized factor analysis to identify the primary influencing factors and reduce the impact of multicollinearity. Wang et al. [19] proposed a dynamical assessment model of key manufacturers in manufacturing industrial supply chain based on C-POWA operator and weight multiplier. Song and Hu [20] focused on listed SMEs in Shandong Province and constructed a credit risk assessment model based on the TOPSIS method, combined with K-means clustering. Liu et al. [21] established an enterprise risk assessment model based on principal component regression and a hierarchical confidence rule library. Qin and Hou [22] employed analytic hierarchy process (AHP) to evaluate risks in the areas of marketing, finance, and investment for the companies. Min and Li [23] conducted an analysis of financial risks for SMEs using survival analysis models.

The second type is the risk assessment model constructed on the basis of machine learning. Compared to the traditional statistic method, machine learning has higher capability in non-linear processing, objectivity, and accuracy. For example, Zhao and Li [24], Xia [25], Chen and Tao [26] employed BP neural network, Sparse Least Squares Support Vector Machine (SVM-SLS) and multilayer perceptron (MLP) neural network to assess the credit risk of SMEs in the context of supply chain finance, respectively. Another implement for SVM is in the paper from Zheng et al. [27], which utilized SVM for ship collision risk assessment. The algorithm proposed overcame weaknesses of conventional methods and simulation results showed the advantage of this new risk assessment algorithm. On the other hand, for finance risk assessment of SMEs, Sang [28] used the SVM method optimized by genetic algorithm and BP neural network, which led to the fact that BP neural network has a better performance in classification accuracy. Moreover, Zhao and Li [29] also constructed a model with SVM and BP neural network algorithms for assessing credit risk of SMEs, while Du et al. [30] utilized a genetic algorithm to optimize the BP neural networks for assessing enterprises' internet credit finance risk. Feng et al. [31] employed optimized BP algorithm to assess risk of supply chain of the fresh graph industry. For analyse and early risk warning for the financial risk, artificial neural network (ANN) and genetic algorithm were used in [32]. Chen et al. [33] used MLP to conduct a risk assessment of taxation for large enterprises. Furthermore, other researchers employed ensemble algorithms. For instance, Xu and Li [34] constructed a stacking ensemble model including linear discriminant analysis (LDA), SVM, neural networks (NN), and random forest (RF) as base learners to classify and predict the credit risks of SMEs in the computer, communication, and other electronic equipment manufacturing industries. They further analyzed the impact of each feature using partial dependence plots (PDP). Zhu et al. [35] utilized the DS-RF model to achieve early warning of financial risk of enterprises. Liu et al. [36] proposed a multi-grained and multi-layered gradient boosting decision tree (GBDT) for credit scoring, in order to mangae credit risks for banks and institutions. Experiments showed that the multi-grained feature augmentation improved performance of credit scoring and provided more accurate results. Xia [37] applied a fuzzy integral SVM regression ensemble model to assess the credit risk of small and micro-enterprises. Rahid and Bhat [38] proposed a deep learning model that used GNN, which was called OlapGN and is integrated by deep learning and probabilistic nature to find overlapping communities and identify crucial nodes in complex networks effectively. Guo et al. [39] proposed GNN-RL model to increase risk situation perception capability of new power system, which effectively improved the efficiency of risk situation perception and contributed to full intelligence of risk perception in the new power system. And recently, Wang et al. [40] proposed a novel RGAT algorithm which effectively solved data incompleteness of SMEs. According to experiments, it was proved that the model had excellent predictive ability and potential economic benefits.

The methods mentioned above are primarily based on the structure features of the enterprises themselves. In this paper, however, we conduct enterprise risk assessment by considering the influence of associated enterprises on the target enterprise under various relationships, including competition, supply, and investment. Furthermore, due to the indeterminacy and non-uniqueness of the number and types of other enterprises associated with the same target enterprise, knowledge graphs (KG) and GCN may be better solutions for handling such unstructured features.

2.2 GCN and attention mechanism

Like convolutional neural networks (CNNs), GCNs are graph feature extractors. They extract features from graph node data and utilize them for the following tasks: node classification [41, 42] and link prediction [43]. For this reason, they have widespread applications. Besides, the attention mechanism often leads GCNs to assign different weights to the node neighbors due to the varying relevance of node neighbors.

For example, attention mechanism was applied in models for sentiment classification in [44–49]. In [44], a model called Sentiment Dependencies with Graph Convolutional Networks (SDGCN) was applied together with bidirectional attention mechanism, whereas in [45], sentiments were classified by using a Syntax- and Knowledge-based Graph Convolutional Network (SK-GCN) and applying multi-head positional attention (MHPA) mechanism. In [46], Cai et al. assigned features different weights in Attention-based Separate Pooling BRNN (ASP-BRNN) model and that was the first instance of applying attention mechanism in the the field of deep multi-task learning occurred at that time. In [47], Wang et al. adopted Multiple Attention Mechanism Network (MAMN), incorporating multi-head self-attention (MHSA) within level, and global attention together with feature focus attention (FFA) across level. In [48], Shan et al. employed retrieval-based attention mechanism to capture relevant information under specific aspect categories. In [49], Chen et al. [49] also utilized the multi-head attention in their network architecture called spatio-temporal representation learning enhanced speech emotion recognition (STRL-SER). It helped in fusion of representations and thus in retention of individual qualities of each feature type.

Except for sentiment classification, attention mechanism was also applied in many other research domains. In 2020, Yang and Dong [50] proposed a Hierarchical Attention GCN incorporating KG for Explainable Recommendation (HAGERec). They further used hierarchical attention mechanism to select important neighbor entities. Shi et al. [51, 52] applied graph attention networks (GAT) to separately assess the risks of food safety and indoor gas systems. Li et al. [53] applied GCN, incorporating self-attention layers to predict stock trends. Yang et al. [54] proposed a dynamic domain adaptation method based on deep multiple auto-encoders with attention mechanism (DMAEAM-DDA) for fault diagnosis, where attention mechanism is utilized for extracting feature. Lourenco and Paes [55] proposed a novel model named Attention-based Embeddings from Multiple Patterns (AEMP) and showed that attention mechanism perform well on improving entities' context representation. Hunag et al. [56] and Du et al. [57] both discussed relation extraction model using attention mechanism. Between them, [57] was proposed for manufacturing knowledge (MKREM). Liang and Wang [58] applied a GCN model consisting of GAT and GraphSAGE for personal credit risk prediction. Wang et al. [59] applied GCN and GRU to extract spatiotemporal features. They also added the attention mechanism into the spatiotemporal module, such that they could predict the risk of traffic accidents. Peng et al. [60] proposed a MB-AGCN model and optimized the behaviors of recommendation systems. Tan et al. [61] explored multiple attention mechanisms including graph self-attention, cross graph co-attention (GCA) and similarity-wise self-attention (SSA) for graph similarity learning. Xue et al. [62] proposed a External Attention-Based Feature Ranker for Large-Scale Feature Selection (EAR-FS), which contained a trained attention module, where attention mechanism was used for attention updating and importance ranking.

Consequently, in this paper, we introduce the attention mechanism into GCN. With the help of this attention mechanism, on the one hand, we take into account different importance between companies under specific relationships. On the other hand, we consider the relevance of companies under different relationships, thereby better integrating feature information.

3 Method

In this paper, an enterprise relationship graph is constructed, and based on it, an attention mechanism is applied to generate the enterprise risk assessment model under multi-relationship. The overall framework of this work is presented in Fig. 1. Information of graph structure is first learnt by

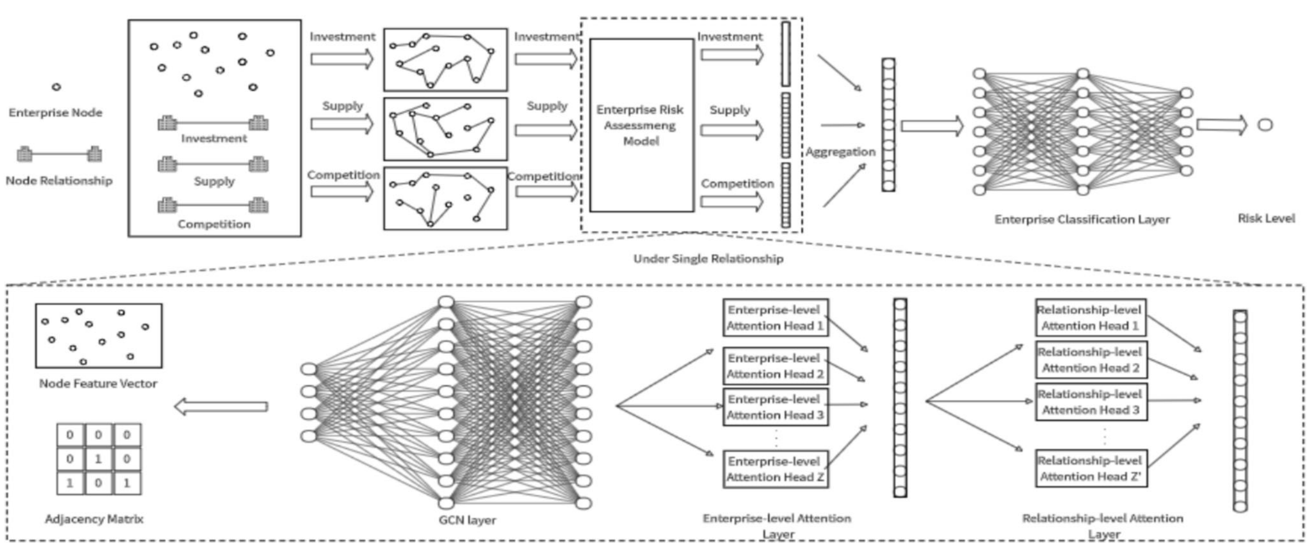


Fig. 1 Model overall framework using GCN with four layers.

GCN, and embedding vectors of the enterprises are represented. Then, by introducing the attention mechanism, i.e., by simultaneously considering the enterprise-level attention and relationship-level attention, our model can adaptively calculate the importance weights between enterprises, thus better capturing complicated relationship patterns. Finally, feature vectors obtained in previous layer are input into the enterprise classification layer. As a result, our model can provide risk prediction information for enterprises and their decision-makers, helping them identify potential risks early on and take appropriate measures to ensure their business's stability and sustainable development. The corresponding algorithm of the model is shown in Algorithm 1.

Algorithm 1 Algorithm of Enterprise Risk Assessment Model.

Input: enterprise feature matrix $\mathbf{X}$, relationship matrix set $\mathcal{R}$

Initialize;

for $\tilde{\mathbf{R}}_j \in \mathcal{R} = \{\tilde{\mathbf{R}}_1, \tilde{\mathbf{R}}_2, \cdots, \tilde{\mathbf{R}}_m\}$ **do**

$\quad \vec{\mathbf{X}}_i' = \text{ReLu}(\tilde{\mathbf{D}}_j^{-\frac{1}{2}} \tilde{\mathbf{R}}_j \tilde{\mathbf{D}}_j^{-\frac{1}{2}} \vec{\mathbf{X}}_i \mathbf{W})$;

$\quad$ **for** $z = 1, \cdots, Z$ **do**

$\quad\quad a_{ii'}^{\tilde{\mathbf{R}}_j^z} = \frac{exp(\text{LeakyReLu}((\mathbf{W}^{\tilde{\mathbf{R}}_j})^T \cdot [\vec{\mathbf{X}}_i' || \vec{\mathbf{X}}_{i'}']))}{\sum_{s \in \mathbf{N}^{\tilde{\mathbf{R}}_j}} exp(\text{LeakyReLu}((\mathbf{W}^{\tilde{\mathbf{R}}_j})^T \cdot [\vec{\mathbf{X}}_i' || \vec{\mathbf{X}}_s']))}$;

$\quad\quad$ Calculate $a_{ii'}^z \cdot \mathbf{W}^z \cdot \vec{\mathbf{X}}_i'$;

$\quad$ **end for**

$\quad \vec{h}_i^{\tilde{\mathbf{R}}_j} = \text{Elu}(\frac{1}{Z} \sum_{z=1}^{Z} \sum_{i' \in \mathbf{N}_i^{\tilde{\mathbf{R}}_j}} (a_{ii'}^{\tilde{\mathbf{R}}_j^z} \cdot \mathbf{W}^z \cdot \vec{\mathbf{X}}_{i'}'))$;

$\quad$ **for** $z' = 1, \cdots, Z'$ **do**

$\quad\quad u_i^{\tilde{\mathbf{R}}_j} = \text{softmax}(\frac{1}{N} \sum_{i \in N} \mathbf{q}^T \cdot \tanh(\mathbf{W}_b \cdot \vec{\mathbf{h}}_i^{\tilde{\mathbf{R}}_j} + \vec{\mathbf{b}}))$;

$\quad\quad$ Calculate $u_i^{\tilde{\mathbf{R}}_j^{z'}} \cdot \vec{h}_i^{\tilde{\mathbf{R}}_j}$;

$\quad$ **end for**

$\quad \vec{o}_i^{\tilde{\mathbf{R}}_j} = \text{ReLu}(\frac{1}{Z'} \sum_{z'=1}^{Z'} \mathbf{u}_i^{\tilde{\mathbf{R}}_j^{z'}} \cdot \vec{\mathbf{h}}_i^{\tilde{\mathbf{R}}_j})$;

end for

$\vec{\mathbf{w}}_i = \sum_{j=1}^{m} \vec{\mathbf{o}}_i^{\tilde{\mathbf{R}}_j}$;

$P_i^c = \frac{exp(x_c)}{\sum_{c=1}^{C} exp(x_c)}, \; x_c \in \vec{\mathbf{w}}_i = \{x_1, \cdots, x_C\}$;

$\text{Loss} = -\frac{1}{N} \sum_{i=1}^{N} \sum_{c=1}^{C} y_i ln P_i^c$;

Backpropagation and update parameters;

Output: probability P_i^c of enterprise i belonging to risk category c

3.1 Enterprise relationship network

In the industrial chain, there exist both direct relationships and indirect relationships among enterprises, with the latter being connected through non-enterprise nodes. To comprehensively assess enterprise risks, we establish relationships among enterprises based on nodes such as enterprises, products, persons, and raw materials, representing the risk transmission within the industrial chain through graph. This approach provides an intuitive and visual representation of the industrial chain. Consequently, in this subsection, the enterprise risk assessment problem is first transformed into a graph problem, resulting in the creation of a heterogeneous graph comprising enterprises and their corresponding connection nodes. Subsequently, to more intuitively display the direct relationships between enterprises, the heterogeneous graph is converted into a homogeneous enterprise graph.

Based on the above analysis, this paper extracts the relationship graph according to the relationships between companys and the three connection nodes, namely products, people, and raw materials, following the three paths: 'company-product-company', 'company-person-company', and 'company-raw material-company'. Since the three connection nodes do not inherently possess risk characteristics, this paper utilizes the three metapaths to extract a homogeneous enterprise relationship graph from the heterogeneous industrial chain graph. An illustration is shown in Fig. 2.

Consequently, an enterprise-relationship graph $\mathbf{G} = (\mathbf{V}, \mathbf{E})$ is formed, where $\mathbf{V} = \{n_1, n_2, \cdots, n_N\}$ represents the set of enterprises and $\mathbf{E} = \{r_1, r_2, \cdots, r_m\}$ stands for the set of relationships. In this context, N is the number of enterprises, and m is the number of relationships. If enterprises operate in the same industry and produce the similar products, there will be a competitive relationship between them. If enterprises are located upstream or downstream within the industrial chain and have a raw material supply relationship, a supply relationship can be considered. If one company invests in another, meaning there is a direct equity relationship between them, then an investment relationship is formed. However, the "company-person-company" meta-path provides another form of indirect investment relationship. By analyzing indirect equity relationships, we can connect companies which do not directly hold shares in each other. Both indirect and direct investment relationships constitute the investment relationships studied in this research, and we integrate direct investment relationships into the extracted homogeneous subgraph of investment relations. Based on these rules, a graph of relationships among companies is established. The set of companies is: $V = \{n_1, n_2, \cdots, n_N\}$ and the set of relationships includes: $E = \{competition\ (r_1), supply\ (r_2), investment\ (r_3)\}$. An illustration of this graph is shown in Fig. 3.

3.2 Enterprise risk assessment model

This subsection will explain the model in the following four parts: GCN layer, enterprise-level attention layer, relationship-level attention layer, and enterprise classification layer.

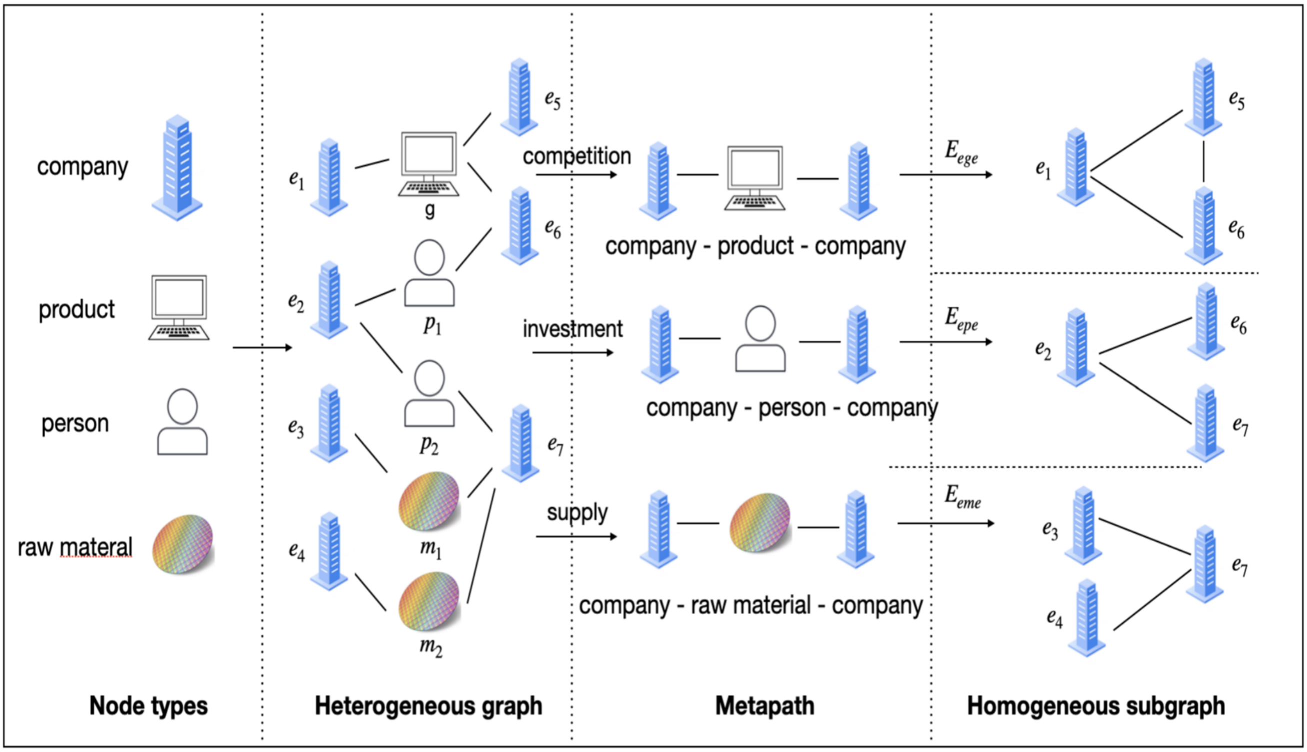


Fig. 2 Illustration of enterprise relationship graph generation

3.2.1 Definition of model

In the enterprise risk assessment model, each enterprise occupies several attribute features. Definitions of which are as follows:

Definition 1 Entity feature matrix is

$$\mathbf{X} = \{\vec{\mathbf{X}}_1, \vec{\mathbf{X}}_2, \cdots, \vec{\mathbf{X}}_i, \cdots, \vec{\mathbf{X}}_N\},$$

where N is the amount of enterprises and $\vec{\mathbf{X}}_i \in \mathbb{R}^{F_i}$. In this

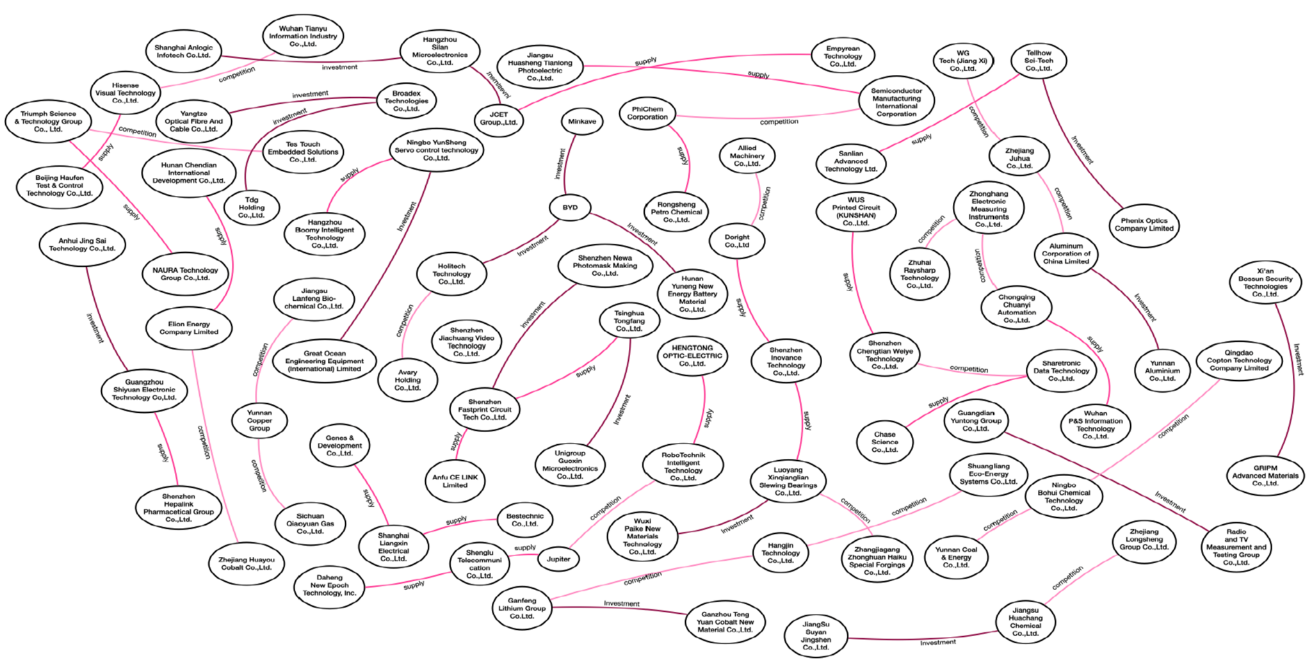


Fig. 3 Enterprise relationship graph connecting using competition, investment, and supply relationships

context, Superscript F_i represents the feature dimension of enterprise i.

Definition 2 Among companies, different relationship paths are formed under various relationships, leading to relationship matrix set

$$\mathcal{R} = \{\tilde{\mathbf{R}}_1, \tilde{\mathbf{R}}_2, \cdots, \tilde{\mathbf{R}}_j, \cdots, \tilde{\mathbf{R}}_m\},$$

where m is the amount of relationships and $\tilde{\mathbf{R}}_j$ is an adjacency matrix with a dimension of $N \times N$. If two companies are connected, the value is 1. Otherwise, it is 0.

Then, the feature matrix of companies and the adjacency matrix serve as inputs to the model.

3.2.2 GCN layer

GCN essentially serves the same purpose as CNN as a feature extractor. In this work, it is used for extracting features from enterprises. GCN can learn feature representations of enterprises from the local structure of the graph by aggregating neighbor information into a vector, thus obtaining the feature representation of each enterprise under the current relationship. The way to extract features is represented in as in Fig. 4.

In GCN layer, a 2-layer GCN is utilized for feature extraction of enterprises under the current relationship. The corresponding computation of feature in each layer is as follows:

$$\vec{\mathbf{X}}_i' = \mathrm{ReLu}(\tilde{\mathbf{D}}_j^{-\frac{1}{2}} \tilde{\mathbf{R}}_j \tilde{\mathbf{D}}_j^{-\frac{1}{2}} \vec{\mathbf{X}}_i \mathbf{W}), \quad (1)$$

where $\vec{\mathbf{X}}_i \in \mathbb{R}^{F_i}$ stands for the input feature vector of enterprise i. Vector $\vec{\mathbf{X}}_i' \in \mathbb{R}^{F_i'}$ is the new feature vector after GCN layer. $\mathrm{ReLu}(\cdot)$ is a activation function. Matrices $\tilde{\mathbf{R}}_j$, $\tilde{\mathbf{D}}_j$ and $\mathbf{W}$ denote the adjacency matrix, its corresponding degree matrix and weight matrix, respectively.

3.2.3 Enterprise-level attention layer

After the GCN layer, feature representations of enterprise i under the current relationship $\mathbf{R}_i$ are learned from the local structure. With the aggregation of the neighbor's information into the new vector, a representation of each enterprise is obtained. In the next step in the enterprise-level attention layer, a multi-head attention mechanism is applied. Calculation of associated enterprises $i' \in \mathbf{N}_i^{\tilde{\mathbf{R}}_j}$ under the relationship $\tilde{\mathbf{R}}_j$ of an enterprise i is conducted to assign different importance weights to each enterprise, so that the model can focus on other companies with more substantial influence and choose information from associated companies more selectively during the information propagation process. In this multi-head attention mechanism, attention weight $a_{ii'}^{\tilde{\mathbf{R}}_j^z}$ of head $\tilde{\mathbf{R}}_j$ is between enterprise i and its associated enterprise i' is calculated as follows:

$$a_{ii'}^{\tilde{\mathbf{R}}_j^z} = \frac{exp(\mathrm{LeakyReLu}((\mathbf{W}^{\tilde{\mathbf{R}}_j})^T \cdot [\vec{\mathbf{X}}_i' || \vec{\mathbf{X}}_{i'}']))}{\sum_{s \in N^{\tilde{\mathbf{R}}_j}} exp(\mathrm{LeakyReLu}((\mathbf{W}^{\tilde{\mathbf{R}}_j})^T \cdot [\vec{\mathbf{X}}_i' || \vec{\mathbf{X}}_s']))}, \quad (2)$$

where current number of head of enterprise-level attention mechanism is represented by z. $\mathrm{LeakyRelu}(\cdot)$ is the activation function. $\mathbf{W}^{\tilde{\mathbf{R}}_j}$ is weight vector of the attention mechanism. Operation $||$ stands for concatenation. Parameter s belongs

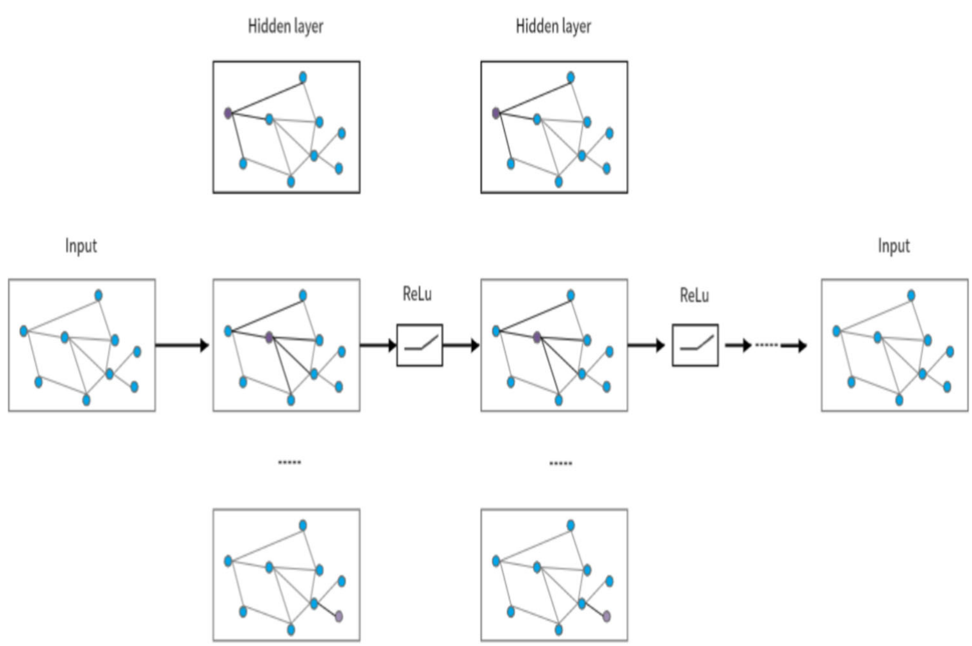


Fig. 4 Framework of GCN model with two hidden layers

Table 1 Dataset of integrated circuit industrial chain

Data	Enterprise Number	Feature Number	Relationship Type	Edge Number	Category Number
Graph			Competition	23,247	
	1,665	18	Investment	18,315	2
Structure			Supply	32,425	

to the set $N_i^{\tilde{\mathbf{R}}_j}$ of associated enterprises of enterprise i under the relationship $\tilde{\mathbf{R}}_j$.

The application of multi-head attention mechanism enriches the model's capabilities and stabilizes the training process. In the last layer of the enterprise-level attention layer, feature vectors of attention coefficient of each head applying to enterprise i are averaged to obtain the output vector $\vec{\mathbf{h}}_i^{\tilde{\mathbf{R}}_j}$ of enterprise-level attention layer:

$$\vec{h}_i^{\tilde{\mathbf{R}}_j} = \mathrm{Elu}\left(\frac{1}{Z}\sum_{z=1}^{Z}\sum_{i'\in\mathbf{N}_i^{\tilde{\mathbf{R}}_j}} (a_{ii'}^{\tilde{\mathbf{R}}_j^z} \cdot \mathbf{W}^z \cdot \vec{\mathbf{X}}'_{i'})\right), \tag{3}$$

where matrix $\mathbf{W}^z$ is the feature transformation matrix corresponding to the z-th attention head. $\mathrm{Elu}(\cdot)$ is the activation function.

3.2.4 relationship-level attention layer

Enterprises are connected with different paths under different relationships, i.e., they have different semantic information. A multi-head relationship-level attention layer is designed to learn different semantic expressions in each path and obtain enriched feature vectors of companies. Output from previous enterprise-level attention layer serves now as input of this layer. Based on learning at these two levels, the model can hierarchically obtain feature vectors for enterprises in different relationships and under different semantic information among associated companies. In single attention head, the calculation is conducted as in (4):

$$u_i^{\tilde{\mathbf{R}}_j} = \mathrm{softmax}\left(\frac{1}{N}\sum_{i\in N}\mathbf{q}^T \cdot \tanh(\mathbf{W}_b \cdot \vec{\mathbf{h}}_i^{\tilde{\mathbf{R}}_j} + \vec{\mathbf{b}})\right). \tag{4}$$

In each attention head, $\vec{\mathbf{h}}_i^{\tilde{\mathbf{R}}_j}$ is the normalized output of enterprise i under the relationship $\tilde{\mathbf{R}}_j$ after the enterprise-level attention layer. Vector q stands for attention vector. Matrix $\mathbf{W}_b$ is the parameterized weight matrix. Vector $\vec{\mathbf{b}}$ represents the biased vector. Parameter $\mathbf{u}_i^{\tilde{\mathbf{R}}_j}$ is the attention coefficient of enterprise i after the relationship-level attention layer, and $\tanh(\cdot)$ is the activation method. Then, again, apply the attention weights of Z'-th attention heads on the feature $\vec{\mathbf{h}}_i^{\tilde{\mathbf{R}}_j}$ to obtain the new feature vector representation, i.e.,

$$\vec{o}_i^{\tilde{\mathbf{R}}_j} = \mathrm{ReLu}\left(\frac{1}{Z'}\sum_{z'=1}^{Z'}\mathbf{u}_i^{\tilde{\mathbf{R}}_j^{z'}} \cdot \vec{\mathbf{h}}_i^{\tilde{\mathbf{R}}_j}\right), \tag{5}$$

where $u_i^{\mathbf{R}_i^{z'}}$ is the attention coefficient of enterprise i in the z'-th attention head.

3.2.5 Enterprise classification layer

After the aforementioned layers, a feature vector under relationship $\tilde{\mathbf{R}}_j$ is obtained, where $j \in \{1, \cdots, m\}$. Thus, features of the m relationships need to be aggregated to obtain the final vector representation $\vec{\mathbf{w}}_i$ of enterprise i:

$$\vec{\mathbf{w}}_i = \sum_{j=1}^{m}\vec{\mathbf{o}}_i^{\tilde{\mathbf{R}}_j}. \tag{6}$$

The classification function of enterprise classification layer is achieved by inputting $\vec{\mathbf{w}}_i$ into two MLP layers, where MLP model is a kind of ANN. It can describe the complicated mapping relation between a set of input and output parameters by using a non-linear base function, which means that $\vec{\mathbf{w}}_i \in \mathbb{R}^{F'}$ can be mapped as $\vec{\mathbf{w}}'_i =$

Table 2 Dataset of domestic appliance industrial chain

Data	Enterprise Number	Feature Number	Relationship Type	Edge Number	Category Number
Graph			Competition	83934	
	2399	18	Investment	60403	2
Structure			Supply	92089	

Table 3 Data samples from integrated circuit industrial chain

Enterprise	Sales Net Profit Margin	Net Asset Liability Ratio	$\cdots$	Operating Income	Score
SMIC	18.0125	0.795253	$\cdots$	-13.8781	94
JCET	1.8759	0.508051	$\cdots$	-27.9928	82

$\{x_1, x_2, \cdots, x_c, \cdots, x_C\} \in \mathbb{R}^C$, where x_c being the feature value under the c-th risk category and C denotes the number of categories. The exact mapping method is shown in the following equation:

$$\vec{\mathbf{w}}_i' = \mathbf{W}_c \cdot (\mathrm{ReLu}(\mathbf{W}_h \cdot \vec{\mathbf{w}}_i)), \tag{7}$$

where $\mathbf{W}_c$ and $\mathbf{W}_h$ are parameter matrices in enterprise classification layer. Then, by passing the feature of $\vec{\mathbf{w}}_i'$ through the softmax function, the probability of the category to which the enterprise i belongs can be obtained by

$$P_i^c = \frac{exp(x_c)}{\sum_{c=1}^{C} exp(x_c)}, \ c \in [1, C], \tag{8}$$

where P_i^c is the probability of enterprise i belonging to the c-th risk category. In this model, cross entropy loss function is employed to assess and optimize the model, as shown in the following:

$$L = -\frac{1}{N} \sum_{i=1}^{N} \sum_{c=1}^{C} y_i ln P_i^c, \tag{9}$$

where $\mathbf{y}_i$ is the actual label vector of enterprise i and L denotes the loss of the model.

4 Experiments

4.1 Data source

The data used in this paper for integrated circuit and domestic appliance (used to validate the applicability of the model in other industries) industrial chain are sourced from WIND Financial Database (China's authoritative financial database), Tianyancha website (China's authoritative enterprise credit agency for enterprise information queries), and Tongdaxin Financial Terminal (China's securities information platform). The data includes enterprise relationship data, enterprise feature data, etc. Financial indicators and industrial chain upstream and downstream relationship data are from the WIND Financial Database. Investment relationship data is sourced from the Tianyancha website, and risk score data is obtained from the Tongdaxin Financial Terminal. Enterprise datasets have been constructed based on the industrial chain data, enterprise financial indicators data, enterprise investment relationship data, and enterprise risk score data. Data of knowledge graph for both industrial chains is shown in Tables 1 and 2.

4.2 Data preprocessing

Data is collected by referring to [63, 64] and selected based on practical situation of integrated circuit industrial chain and relevant manufacturing industry indicators. After discarding some indicators with less information, the financial indicator data primarily includes eighteen features for both integrated circuit and domestic appliance industrial chain. To eliminate the dimensionality differences between features, enhance the convergence speed and stability of the model, improve the model's performance, reduce the impact of outliers, and more accurately conduct data analysis and modeling, the feature values are standardized using z-score normalization. This results in a feature matrix with a dimension of $N \times 18$. According to the risk scoring of enterprises by Tongdaxin, the score ranges in [0, 100], where a higher score implies a lower risk level. In order to balance the proportion of positive and negative samples, a partition score of 90 was used [65, 66]. Enterprises with scores larger or equal to 90 were categorised as positive samples, i.e., 'low risk' with label '0', while enterprises with scores below 90 were

Table 4 Data samples from domestic appliance industrial chain

Enterprise	Sales Net Profit Margin	Net Asset Liability Ratio	$\cdots$	Operating Income	Score
Baoan	5.6665	3.3791	$\cdots$	44.7807	90
Ecobeauty	-28.3398	3.8505	$\cdots$	-32.6006	3

Table 5 Results of comparison experiment

Model	Acc		F1		AUC		Loss	
	IC	DA	IC	DA	IC	DA	IC	DA
GraphSage	0.620	0.617	0.623	0.726	0.621	0.564	0.768	0.689
GCN	0.620	0.604	0.623	0.738	0.621	0.537	0.783	0.680
GAT	0.687	0.600	0.658	0.739	0.689	0.535	0.606	0.693
DAGNN	0.675	0.592	0.675	0.738	0.675	0.540	0.875	0.700
TAGCN	0.699	0.588	0.716	0.714	0.701	0.534	0.832	0.682
Proposed model	**0.765**	**0.708**	**0.752**	**0.747**	**0.767**	**0.702**	**0.492**	**0.589**

Bold entries highlight the optimal results within each indicator

categorised as negative samples, i.e., 'high risk' with label '1', which means that C=2.

4.3 Enterprise relationship graph

The enterprise relationship network is constructed according to Section 3.1. The concrete knowledge graph datasets are represented in Tables 1 and 2. Data samples of Semiconductor Manufacturing International Corporation (SMIC) and JCET Group Co.,Ltd. are shown in Table 3, and data samples of China Baoan Group Co.,Ltd. and Shenzhen Ecobeauty Co.,Ltd. are shown in Table 4, where scores of risks are shown in the last column.

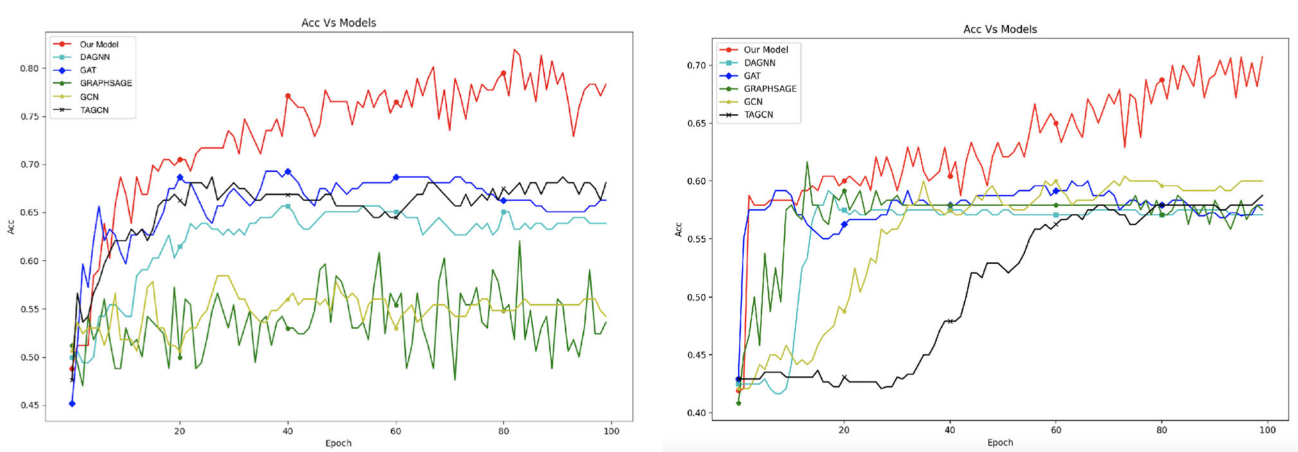
4.4 Parameter settings

For model training, the dataset is split into a training set of 80%, a validation set of 10%, and a test set of 10%. The training set is employed for model training, the validation set is employed for supervised model training and hyperparameter adjustment, and the test set is employed for the final evaluation of the model. Multiple repeated experiments are conducted to find suitable parameters for the model. During the iterative process of adjusting parameters, it was found that the model was optimized using the Adam optimizer with a learning rate of 0.002, weight decay of 0.0005, and iteration of 600 times. The number of both enterprise-level and relationship-level attention heads are 8. The unit number in hidden layer is 128. Simultaneously, a dropout mechanism with a probability of 0.4 is applied for discarding individuals randomly.

4.5 Result analysis

4.5.1 Indicator selection

In classification tasks, common evaluation metrics include accuracy (Acc), F1 score ($F1$), recall ($Recall$), and precision ($Precision$). This study has used these metrics to conduct experiments and evaluate the designed model. Among these metrics, the accuracy is the proportion of correctly classified samples to the total number of samples, providing the most intuitive measure of the model's classification performance. The recall represents the proportion of correctly predicted samples in a particular category of all samples, and higher recall indicates more positive samples the model identifies.



(a) integrated circuit industrial chain. (b) domestic appliance industrial chain.

Fig. 5 Line chart of accuracy

Table 6 Time comparison of different models

Model	competition		investment		supply		total time	
	IC	DA	IC	DA	IC	DA	IC	DA
GraphSage	0.537	0.744	0.470	0.721	0.712	0.788	1.719	2.253
GCN	0.123	0.147	0.119	0.209	0.126	0.186	0.368	0.552
GAT	2.671	3.188	2.637	3.113	2.854	3.654	8.162	9.955
DAGNN	0.126	0.131	0.140	0.214	0.144	0.158	0.410	0.503
TAGCN	0.140	0.165	0.105	0.110	0.253	0.364	0.498	0.639
Proposed model	-	-	-	-	-	-	6.568	7.594

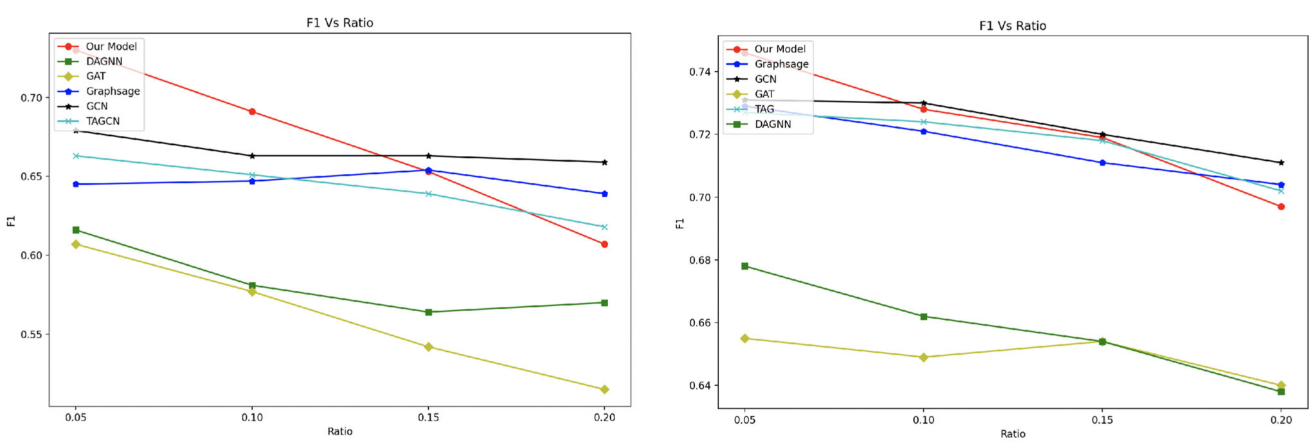
The precision measures the proportion of samples predicted by the model as belonging to a certain category that actually do belong to that category. F1 score is the harmonic mean of precision and recall, considering both precision and recall. In multi-classification tasks, precision, recall, and F1 score are calculated for the distribution of multiple categories, and their averages are taken as overall evaluation metrics.

4.5.2 Baselines

To validate the generalization performance of the proposed model on different datasets, we compared it with existing models such as GraphSage [67], GCN [68], GAT [69],DAG-NN
[70], and TAGCN [71].

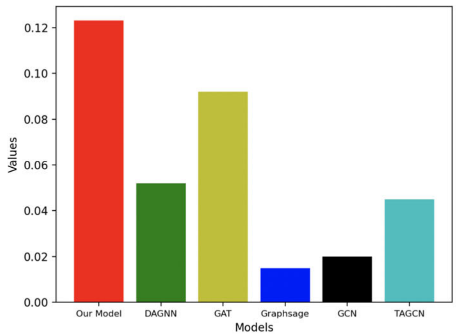
- GraphSage is a GNN model based on random walks, aggregating information by sampling features of neighboring nodes. It is notable for its ability to effectively handle heterogeneous and large-scale graphs, capturing long-range dependency relationships between nodes.
- GCN is a classic graph neural network model that processes graph data through convolutional operations. The main feature of it is to use the adjacency matrix for convolutional operations on the graph, capturing interactions between nodes.
- GAT is a GNN with an attention mechanism, interacting through attention weights between nodes. Unlike GCN, GAT can adaptively select important neighboring nodes for information propagation, better capturing complex patterns in the graph.
- DAGNN is an adaptive deep GNN model that decouples the Transformation and Propagation operations in the traditional GCN model. It is able to adaptively acquire information from large sensory fields for node representation learning.
- TAGCN is a GNN that uses topologically adaptive GNNs that perform convolutional operations on graphs using fixed-size learnable filters to provide a significant classification accuracy advantage in semi-supervised graph vertex classification problems.

By comparing with the models above, one can comprehensively assess the performance and characteristics of the proposed model.

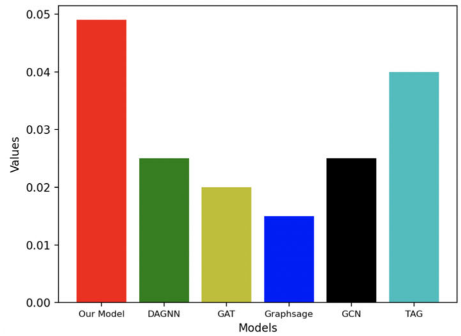


(a) integrated circuit industrial chain. (b) domestic appliance industrial chain.

Fig. 6 Line chart of F1 score under different disturbance ratios



(a) integrated circuit industrial chain.



(b) domestic appliance industrial chain.

Fig. 7 Histogram of F1 score under different disturbance ratios

4.5.3 Comparison experiments

Due to the complexity of the industrial chain dataset, baseline models cannot handle multiple risk transmission relationships simultaneously. Therefore, this study designed different implementations for the proposed model and the baseline models. For fair comparison, same parameters were chosen, namely 100 epochs were taken and a learning rate lr=0.001 was used. The results of the comparison experiments are shown in Table 5, where IC indicates integrated cirucit industrial chain and DA indicates domestic appliance industrial chain.

According to the above experiment, the following can be observed: (1) For IC industrial chain, it it shown that the proposed model outperforms other models on all indicators in the IC industrial chain dataset. On the indicator *Acc*, the accuracy is improved by at least 11.35% compared with other models. On the indicators F1 and AUC scores, the proposed model improves at least 5.03% and 9.42%, respectively. In addition, on the indicator Loss, the overall loss of the proposed model is reduced by at least 18.81% compared with the existing models, which further proves that it is better than the existing models for the risk assessment of enterprises in the IC industrial chain. (2) For DA industrial chain, it is shown that the proposed model also has fair performance in another industry. On the indicator *Acc*, the accuracy increases at least 14.75% compared to baselines. And the indicator F1 and AUC score demonstrate an increase of 9.47% and 24.47% respectively, which serves to illustrate the superiority of the proposed model in classification. With regard to the indicator Loss, the proposed model also performs well, exhibiting a reduction in loss error of 13.38%. So it can be concluded that the proposed model is able to mine the structural information of the industrial chain and the interaction information between enterprises more comprehensively, and has better classification performance.

Then, in order to further demonstrate the advantages of the proposed model in terms of accuracy, *Acc* of the different models in each round was compared to obtain a line graph of accuracy, as shown in Fig. 5, which shows that the proposed model has optimal accuracy in most epochs. In addition, as the number of training epochs increases, the classification accuracy of the proposed model becomes significantly better than the existing models.

In the comparison algorithm, we calculated the time complexity of the baseline models based on the enterprise relationship graph for individual relationships in the IC and DA datasets, where IC indicates integrated circuit industrial chain and DA indicates domestic appliance industrial chain. Finally we summed up the time complexities of the baseline models under all relationships, and compared them with the time complexity of the Proposed model. As can be seen from Table 6, GCN network has the best performance in time complexity due to its simple structure. Secondly, TAGCN and DAGNN networks realize efficient processing of time series data by adaptively adjusting the weight of graph convolu-

Table 7 Ablation study results of integrated circuit industrial chain

GCN	*Enterprise-Attn*	*Relation-Attn*	*Acc*	Loss	F1	AUC
×	✓	✓	0.693	0.606	0.721	0.696
✓	×	✓	0737	0.543	0.733	0.717
✓	✓	×	0.752	0.575	0.735	0.720
✓	✓	✓	**0.765**	**0.492**	**0.752**	**0.767**

Bold entries highlight the optimal results within each indicator

Table 8 Ablation study results of domestic appliance industrial chain

GCN	*Enterprise-Attn*	*Relation-Attn*	*Acc*	Loss	F1	AUC
×	✓	✓	0.610	0.689	0.709	0.633
✓	×	✓	0.654	0.621	0.667	0.676
✓	✓	×	0.668	0.623	0.672	0.685
✓	✓	✓	**0.708**	**0.589**	**0.747**	**0.702**

Bold entries highlight the optimal results within each indicator

tion. Their structural designs allow the model to avoid too deep and too many layers in the process of feature aggregation, thus reducing the time complexity. DAGNN uses the directed acyclic graph structure to represent the dependency between data. This structure design is helpful to reduce the redundant calculation and improve the calculation efficiency of the model. However, GAT and the Proposed model are designed based on multi-head attention mechanism, which requires a large number of operations under each attention head to calculate the attention coefficient of all nodes. Therefore, these models are highly complex. Compared with GAT, which has the highest time complexity, the Proposed model is optimized structurally so that it is not necessary to calculate the attention coefficients of all nodes under each head, instead, each head is only responsible for the calculation of a part of nodes. Moreover, other structural designs of the proposed model greatly improve the algorithm accuracy and performances of other classification indicators at the cost of time complexity. In the Proposed model, the algorithm complexity is $O(m*(|E|*F*F'+|V|*F'+|E|*Z'*F')+C)$, where $|E|$ is the number of edges, F is the size of the input layer, F' is the size of the hidden layer, and $|V|$ is the number of nodes.

The above results show that the proposed model performs well in classification. Compared to the existing models, it can assess enterprises' risk more accurately and more effectively.

4.5.4 Disturbance experiment

In order to verify the sensitivity of the proposed model against risk transmission, a disturbance experiment has been designed. A specific proportion of enterprise nodes were selected and their risk labels were modified. For example, if the risk label of the enterprise is '1', indicating 'high risk', then its risk label was modified to '0', which was assumed to be a 'low risk' enterprise, thus disturbing the classification of the model. In the test set, the disturbance ratio was set to {0.05, 0.10, 0.15, 0.20} respectively for the experiments. F1 scores and magnitude of change of each model under different ratios were recorded. Experimental results are shown in Figs. 6 and 7.

According to Figs. 6 and 7, F1 scores of each model decrease as the disturbance ratio increases. In comparison, it can be observed that the proposed model changes most significantly. According to the adjustment of the disturbance ratio, risk profile of the enterprise changes and risk characteristics that can be learned by the model also change accordingly. This result indicates that the model has good sensitivity in capturing risk transmission between enterprises compared to the other baseline models, and therefore can achieve more accurate risk assessment.

4.5.5 Ablation study

To validate the effectiveness and rationality of various modules of the proposed model, ablation experiments have been conducted by removing specific modules, and deconstruction experiments have been performed under the same training parameter settings. *Enterprise-Attn* represents the enterprise-level attention layer and *Relation-Attn* represents the relationship-level attention layer. The experiment results present the accuracy (*Acc*), Loss, F1 score (F1) and AUC score.

After removing certain layers, the model's performance shows varying degrees of decline, indicating that the addition of each module effectively enhances the performance of the enterprise risk assessment model. According to Tables 7 and 8, the following conclusions can be drawn: (1) The significant changes in indicators after removing the GCN layer means that adding the GCN layer enables the model to extract crucial features. (2) The deterioration in indicators observed following the removal of the enterprise- and relationship-level attention layer shows that the model may either lose attention to associated nodes or fail to consider the overall structure of the industrial chain, which implies that associated nodes and the industrial chain structure may influence enterprise risk in a mutually reinforcing manner.

5 Conclusion and future work

In this work, various relationships among enterprises are considered, acknowledging that the transferability of risk between companies may vary under different relationships. Consequently, various enterprise relationships such as competition, investment, and supply are constructed, an enterprise-level attention layer that focuses on the neighborhood and a relationship-level attention layer that considers the entire network are designed. Finally, the importance of enterprises under different relationships is assessed to conduct a risk level evaluation. Experimental results demonstrate that the model exhibits good stability and accuracy. Predicting enterprise risks can provide valuable references for related companies, contributing significance to individual enterprises and the entire industrial chain's risk research.

However, this study still has certain limitations. One limitation is that the relationships among enterprise nodes are not only limited to competition, supply, and investment. Furthermore, establishing relationships between enterprises is based on an idealized scenario, while in actual situations, the industrial chain may dynamically change over time with the addition or removal of enterprise nodes. Moreover, the composition of an industrial chain is not solely comprised of enterprise nodes and situation changes in different industrial chains. Therefore, future work will primarily focus on the following aspects:

(1) Although the design of multi-level attention layers has improved the model's utilization of information, but it has also increased the risk of overfitting. The GCN layer also faces the challenge of oversmoothing. Thus, future research could explore more effective model structures, such as preprocessing graph data through subgraph partitioning and designing more efficient convolutional calculation methods.
(2) Introduce the time dimension to study the dynamic graph classification task in industrial chain analysis. In reality, the structure of industrial chains evolves, and adding new nodes leads to changes in the entire graph structure. The model designed in this study lacks certain scalability. For this reason, the next research step is to explore the fusion of temporal data and dynamic graph data, e.g. by adding RNN, Transformer, etc. for data processing, to make the designed model more applicable to real world scenarios.
(3) Consider a scenario closer to the real-world situation for design by adding various types of non-enterprise nodes and incorporating relationship constraints. Explore the construction of industrial chain structures that closely resemble real-world scenarios. Furthermore, consider data from different industries during training process to improve the universality of the model.

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Data availability The data are not publicly available because they were acquired from third parties (WIND, Tianyancha and Tongdaxin) and are subject to relevant intellectual property rights requirements.

Materials availability Not applicable.

Code availability The code is available from the corresponding author on reasonable request.

Declarations

Competing interests The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Ethics approval and consent to participate Not applicable.

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