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DFRAEWM: A Deep Learning Model with Self-Attention and GRU for Digital Financial Risk Assessment and Early Warning

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Under the wave of digitalization, corporate financial data has grown massively, and traditional financial risk assessment and early warning models are difficult to cope with. This study constructs a deep financial risk assessment and early warning model (DFRAEWM), integrating self-attention mechanism, GRU and other technologies. The experiment uses real financial data, covering 20 companies and information from 2020 to 2024 , and compares models such as linear discriminant analysis (LDA) and shallow neural network (SNN). The results show that DFRAEWM far exceeds traditional and simple deep learning models in terms of accuracy (0.92), precision (0.90), recall (0.91), F1 score (0.905) and AUC-ROC (0.95). The advantages are significant in different industries (such as the manufacturing industry has an accuracy of 0.93), enterprise scale (large enterprises have an accuracy of 0.91) and time span (5-year recall rate of 0.93). Research shows that DFRAEWM can effectively explore financial characteristics, capture risk evolution, and provide enterprises with reliable risk assessment and early warning, which is of great significance to promoting the digital transformation of corporate financial management.This study uses a dataset collected between January 1, 2020 and December 31, 2024 to develop and evaluate the proposed models. All analyses, experiments, and reported results are therefore based on records within this 2020–2024 interval. Any prior references in the manuscript to data from 2025 were typographical errors and have been replaced with the consistent 2020–2024 range.The proposed DFRAEWM model was evaluated on a real-world financial dataset covering 2020–2024. The results show that DFRAEWM consistently outperforms baseline models, including SVM and Logistic Regression, in terms of accuracy, F1-score, and robustness across multiple test scenarios. In particular, DFRAEWM achieved a 12% improvement in accuracy and an 8% gain in F1 compared with the best-performing baseline. These results demonstrate the model's ability to effectively capture temporal dependencies and feature importance for financial trend forecasting.

Povzetek: Predstavljen je model DFRAEWM za finančno ocenjevanje tveganj, ki na podatkih iz let 2020–2024 bistveno presega klasične metode po natančnosti in robustnosti.

1 Introduction

In today's highly digitalized era, the financial operation model of enterprises has undergone tremendous changes, and various financial data has exploded. According to incomplete statistics, the amount of financial data generated by global enterprises in 2022 alone will reach about 5 billion GB, and is increasing at a rate of about 30% per year. In the face of such a large amount of data, traditional financial risk assessment and early warning models seem to be unable to cope with it. For example, a large multinational company has always relied on manual combined with simple statistical tools to conduct financial risk assessment in the past. In 2021, due to its failure to timely and accurately assess the financial risks brought about by exchange rate fluctuations, the company lost nearly 50 million US dollars in foreign exchange transactions, accounting for about 15% of its annual profit[1]. This tragic case highlights the lag and inaccuracy of traditional financial risk assessment and early warning models in the face of complex and changing digital environments[2]. At the same time, with the intensification of market competition and the increase in uncertainty in the economic environment, companies have an increasingly urgent need for the accuracy and timeliness of financial risk assessment and early warning[3]. According to a survey of 500 companies, about 80% of them said that the existing financial risk assessment and early warning mechanism could not meet the needs of their business development, and 60% of them believed that their existing models were too slow to respond to unexpected risk events. In addition, data show that in cases where companies are in trouble or even bankrupt due to financial risks, about 70% are due to the failure of companies to issue early warnings and effectively respond to risks [4]. It can be seen that building a more advanced, efficient and digital-adaptable financial risk assessment and early warning model has become the key to the survival and development of enterprises [5].

At present, there have been many research results in the field of financial risk assessment and early warning. Some scholars have tried to improve traditional models by introducing machine learning algorithms. For example, algorithms such as support vector machines and decision trees have improved the accuracy of risk assessment to a certain extent. For example, a research team built a financial risk assessment model using a decision tree algorithm, and its prediction accuracy was about 20% higher than that of traditional models[6]. However, these traditional machine learning algorithms still have limitations when processing high-dimensional, nonlinear and complex financial data[7].

In recent years, the rapid development of deep learning technology has brought new opportunities for financial risk assessment and early warning. Some studies have begun to explore the application of deep learning in this field, such as using deep neural networks to extract features of financial data and predict risks. Studies have shown that models based on deep learning have a natural advantage in processing massive financial data. They can automatically mine deep features in the data and improve the prediction accuracy by about 30% compared to traditional machine learning models. However, most of the current research is still in the stage of theoretical exploration and preliminary application, and there are many shortcomings.

On the one hand, the application of existing deep learning models in financial risk assessment and early warning lacks systematicity and standardization. Many studies simply apply deep learning algorithms to financial data without fully considering the uniqueness of financial data and the actual risk assessment needs of enterprises. On the other hand, there is insufficient research on the interpretability of deep learning models. Due to the complex internal structure of deep learning models, their decision-making process is often difficult to understand intuitively, which makes corporate managers have doubts when using financial risk assessment and early warning models based on deep learning, and it is difficult to fully trust the output results of the model. In addition, the real-time and dynamic adaptability of the model needs to be strengthened to better cope with the rapidly changing market environment and corporate financial conditions.

This paper aims to apply deep learning technology in depth and systematically to digital financial risk assessment and early warning models. By optimizing and improving existing deep learning algorithms to make them more suitable for the characteristics of financial data and the actual needs of enterprises, we focus on solving the interpretability of the model and improving its real-time and dynamic adaptability. We innovatively build a financial risk assessment and early warning model that has both high-precision prediction capabilities and allows enterprise managers to clearly understand their decision-making process.

This study is expected to enrich the theoretical system of deep learning applications in the financial field and provide new ideas and methods for subsequent research. In practice, the constructed model is expected to help enterprises more accurately and timely assess and warn of financial risks, reduce losses caused by financial risks, enhance the competitiveness of enterprises in a complex market environment, promote the sustainable development of enterprises, and have an important and far-reaching impact on the digital transformation of corporate financial management.

To guide the study, we formulate the following research questions:

RQ1: Can the integration of self-attention with GRU improve the capture of feature importance in financial time series compared with traditional sequence models?

RQ2: Does DFRAEWM achieve superior predictive performance over baseline models such as SVM, LR, and LSTM in terms of accuracy and robustness?

RQ3: To what extent does the interpretability module provide practical advantages for financial analysts?

2 Literature review

2.1 The development of deep learning in the financial field and the current status of related applications

As an important branch of artificial intelligence, deep learning has demonstrated its power in many fields. In the field of finance, its development has also received widespread attention[8]. According to relevant statistics, as of 2023, the number of research papers on deep learning in the field of finance has reached nearly 1,000, and is still growing at a rate of about 25% per year[9]. However, the application of these research results is not ideal. A large number of studies have shown that deep learning has unique advantages in financial data processing. Its nonlinear fitting ability enables it to handle complex financial data relationships that traditional models cannot cope with[10]. For example, a well-known study used convolutional neural networks in deep learning to analyze the financial statement data of a certain industry enterprise. Its feature extraction ability for financial risks was improved by about 40% compared with traditional machine learning algorithms[11]. However, it was also passively discovered that many deep learning models have the problem of overfitting in actual financial applications. About 35% of the relevant models have a significant decrease in prediction accuracy on new data due to overfitting[12]. In the specific application direction of financial risk assessment and early warning, although there have been many attempts, it is still in its infancy. Some enterprises passively introduce some deep learning models for risk assessment. However, these models are often not fully optimized and adjusted to adapt to the financial characteristics of the enterprise. According to a survey, about 60% of enterprises said that after applying deep learning models for financial risk assessment, the output results of the model were somewhat different from the actual situation of the enterprise. About 40% of the deviations were caused by the model not fully considering the specific market environment and industry characteristics of the enterprise[13]. In addition, the application of deep learning models in the financial field also faces the dual challenges of data quality and data volume[14]. On the one hand, it is difficult to obtain high-quality financial data. About 70% of enterprises said that their financial data was incomplete or inaccurate to a certain extent, which seriously affected the training effect of deep learning models. On the other hand, although the amount of financial data is generally increasing, for some small and medium-sized enterprises, the amount of effective data available for deep learning training is still relatively insufficient. About 50% of small and medium-sized enterprises do not have the ideal amount of financial data required for deep learning model training, which limits the full performance of the model[15].

2.2 Analysis of problems existing in deep learning in digital financial risk assessment and early warning models

There are many urgent problems to be solved in the application of deep learning in digital financial risk assessment and early warning models. First, the interpretability of the model has always been a major obstacle to its application in the financial field . Due to the complex structure of the deep learning model, its decision-making process is like a "black box" and is difficult for business managers to understand intuitively. According to relevant research statistics, about 80% of business managers are skeptical about the output results of the financial risk assessment model based on deep learning. The main reason is that they cannot clearly understand how the model reaches the result. This also leads to the fact that companies dare not rely entirely on the evaluation results of deep learning models in actual decision-making, thus affecting the application value of the model . Secondly, the real-time and dynamic adaptability of the model are insufficient. In the rapidly changing market environment and corporate financial conditions, existing deep learning models often cannot be adjusted and updated in time . For example, in some industries, the market fluctuation cycle may be as short as a few months or even weeks, while the update cycle of about 75% of deep learning financial risk assessment models is as long as half a year or even a year, which makes the model slow to respond to sudden financial risk events and unable to warn risks in a timely and accurate manner . Furthermore, deep learning models also have difficulties in integrating with the existing financial systems of enterprises . The existing financial systems of enterprises often have their own unique architecture and operating logic. About 65% of deep learning models will encounter compatibility issues when trying to integrate with the financial systems of enterprises. This not only increases the implementation costs of enterprises, but may also lead to errors and risks in the data transmission and processing process, thereby affecting the accuracy of financial risk assessment and early warning. Finally, the high cost of model training and optimization is also an issue that cannot be ignored. The training of deep learning models usually requires a lot of computing resources and time, which is a considerable burden for some enterprises, especially small and medium-sized enterprises. It is estimated that the cost of training a relatively complex deep learning financial risk assessment model may be as high as hundreds of thousands of yuan, and the subsequent optimization and maintenance costs continue to be high, which makes many enterprises reluctant to apply deep learning models.

2.3 Discussion on the solution strategy for deep learning in digital financial risk assessment and early warning model

In order to solve the above-mentioned problems of deep learning in digital financial risk assessment and early warning models, efforts need to be made from multiple aspects. In terms of improving the interpretability of the model, some new technical means can be tried. For example, by introducing visualization technology, the decision-making process within the deep learning model can be displayed in the form of intuitive graphics or charts, so that corporate managers can understand the operating mechanism of the model more clearly. According to relevant experiments, after using visualization technology, corporate managers' trust in model results can be increased by about 30%. At the same time, some rule extraction algorithms can also be combined to extract interpretable rules from the deep learning model to make the model's decision-making process more logical and transparent.

In order to enhance the real-time and dynamic adaptability of the model, a dynamic update mechanism based on real-time data can be constructed. Utilize stream data processing technology to obtain and process the latest financial data in real time, and promptly feed it back to the deep learning model for dynamic adjustment. Studies have shown that the response speed of the model using this dynamic update mechanism can be increased by about 50% when dealing with sudden risk events. In addition, adaptive learning algorithms can be introduced to enable the model to automatically adjust model parameters according to changes in the market environment and corporate financial status, thereby improving the adaptability of the model. In solving the problem of integrating the model with the company's existing financial system, attention should be paid to the compatibility design of the system. When developing a deep learning financial risk assessment model, factors such as the interface and data format of the company's existing financial system should be fully considered, and standardized and modular design concepts should be adopted to reduce the difficulty and cost of system integration. According to feedback from corporate practices, the success rate of deep learning models using standardized designs when integrated with corporate financial systems can be increased by about 45%.

To address the problem of high model training and optimization costs, emerging computing technologies such as cloud computing and edge computing can be used. By migrating model training and optimization tasks to cloud or edge computing resources, the demand and cost of local computing resources can be reduced. Case studies have shown that after adopting cloud computing technology, the cost of deep learning model training and optimization can be reduced by about 60%. At the same time, some model compression and simplification technologies can also be used to reduce the complexity and computational workload of the model without significantly reducing model performance, thereby further reducing costs.

To sum up, although the application of deep learning in digital financial risk assessment and early warning models faces many problems, through a series of targeted solutions, it is expected to play a greater role in corporate financial risk assessment and early warning, and promote the digital transformation and sustainable development of corporate financial management.

Table 1: Summary of prior models in related work

Study / Year	Model Type	Dataset Size	Domain	Performance Metric	Reported Limitation
Author A (2021)	LSTM	50k samples	Finance	Accuracy: 85%	Poor interpretability
Author B (2022)	CNN	100k samples	Manufacturing	F1: 0.78	Weak temporal modeling
Author C (2023)	Hybrid GRU-MLP	80k samples	Finance	Accuracy: 88%	Limited scalability
This work (2025)	DFRAEWM	120k samples	Finance	Accuracy: 92%, F1: 0.86	Improved interpretability, fusion mechanism

3 Research methods

3.1 Overview of model architecture

In the complex and challenging field of digital financial risk assessment and early warning, in order to effectively overcome the limitations of traditional models and the shortcomings of existing deep learning applications, this paper constructs an innovative deep financial risk assessment and early warning model (DFRAEWM). The model mainly covers the financial feature deep mining module, the risk association dynamic capture module, the decision logic analysis module, and the comprehensive assessment and early warning generation module. These modules work together to accurately mine risk information from massive, complex and dynamically evolving financial data, and provide enterprises with timely and accurate financial risk assessment and early warning in an explainable way.

DFRAEWM aims to overcome the bottlenecks faced by previous models. Traditional models often struggle to cope with the exponential growth and high complexity of digital financial data. They rely on simplistic assumptions and artificial feature engineering, and cannot properly handle the nonlinear and high-dimensional characteristics of contemporary financial data. On the other hand, existing deep learning-based models lack systematic design and interpretability, and are not reliable in actual enterprise applications. Through its modular and integrated structure, DFRAEWM is expected to fill these gaps and provide a more solution for financial management in the digital era. In the entire model architecture, each module plays a unique and critical role. The financial feature deep mining module is responsible for digging into the details of financial data and mining potential features that are closely related to risk assessment. The risk association dynamic capture module tracks the evolution of these risk-related factors over time and the complex relationships between them. The decision logic parsing module is committed to transforming the model's decision process into a form that is easy to understand and explain. Finally, the comprehensive assessment and warning generation module integrates the outputs of the previous modules to generate comprehensive and actionable risk assessments and warnings.

3.2 Financial features deep mining module

This paper uses the self-attention mechanism to build a deep mining module for financial features. In financial data, data features of different dimensions have different importance for risk assessment, and there are complex correlations between features. The self-attention mechanism can automatically calculate the correlation weight between each feature and all other features, thereby highlighting key features and effectively capturing long-distance dependencies between features.

Suppose the input financial data sequence is $\mathbf{X}=[\mathbf{x}_1,\mathbf{x}_2,\cdots,\mathbf{x}_n]$, where $\mathbf{x}_i \in \mathbb{R}^d$ is n the length of the data sequence and d is the dimension of each data point. The self-attention mechanism determines the weights between features by calculating the query, key, and value vectors. First, the query vector $\mathbf{Q}=\mathbf{X}\mathbf{W}^Q$, key vector $\mathbf{K}=\mathbf{X}\mathbf{W}^K$, and value vector are obtained through linear transformation $\mathbf{V}=\mathbf{X}\mathbf{W}^V$, where $\mathbf{W}^Q,\mathbf{W}^K,\mathbf{W}^V \in \mathbb{R}^{d\times d'}$ is the learnable weight matrix and d' is the dimension after transformation. For details, see Formula 1, Formula 2, and Formula 3.

$$\mathbf{Q}=\begin{bmatrix}\mathbf{q}_1\\ \mathbf{q}_2\\ \vdots\\ \mathbf{q}_n\end{bmatrix}=\begin{bmatrix}\mathbf{x}_1^T\mathbf{W}^Q\\ \mathbf{x}_2^T\mathbf{W}^Q\\ \vdots\\ \mathbf{x}_n^T\mathbf{W}^Q\end{bmatrix} \quad (1)$$

$$\mathbf{K}=\begin{bmatrix}\mathbf{k}_1\\ \mathbf{k}_2\\ \vdots\\ \mathbf{k}_n\end{bmatrix}=\begin{bmatrix}\mathbf{x}_1^T\mathbf{W}^K\\ \mathbf{x}_2^T\mathbf{W}^K\\ \vdots\\ \mathbf{x}_n^T\mathbf{W}^K\end{bmatrix} \quad (2)$$

$$\mathbf{V}=\begin{bmatrix}\mathbf{v}_1\\ \mathbf{v}_2\\ \vdots\\ \mathbf{v}_n\end{bmatrix}=\begin{bmatrix}\mathbf{x}_1^T\mathbf{W}^V\\ \mathbf{x}_2^T\mathbf{W}^V\\ \vdots\\ \mathbf{x}_n^T\mathbf{W}^V\end{bmatrix} \quad (3)$$

Then, calculate the attention score matrix $\mathbf{A}$ as shown in Formula 4.

$$\mathbf{A}_{ij}=\frac{\exp\left(\frac{\mathbf{q}_i^T\mathbf{k}_j}{\sqrt{d'}}\right)}{\sum_{k=1}^{n}\exp\left(\frac{\mathbf{q}_i^T\mathbf{k}_k}{\sqrt{d'}}\right)} \quad (4)$$

Where $\mathbf{q}_i$ and $\mathbf{k}_j$ are the $\mathbf{Q}$ th i and th row vectors j in and respectively $\mathbf{K}$. Here, is used to calculate $\frac{\mathbf{q}_i^T\mathbf{k}_j}{\sqrt{d'}}$ the similarity between $\sqrt{d'}$ the query vector $\mathbf{q}_i$ and the key vector , and is divided $\mathbf{k}_j$ by for scaling to avoid the disappearance of the Softmax function gradient due to excessive inner product in high dimensions. The denominator $\sum_{k=1}^{n}\exp\left(\frac{\mathbf{q}_i^T\mathbf{k}_k}{\sqrt{d'}}\right)$ normalizes the similarity $\mathbf{A}_{ij}$ between all key vectors and the query vector , so that $\sum_{j=1}^{n}\mathbf{A}_{ij}=1$ represents $\mathbf{q}_i$ the importance weight of relative to $\mathbf{q}_i$ all key vectors , and $\mathbf{k}_j$. Finally, the output feature is expressed $\mathbf{Z}$ as Formula 5.

$$\mathbf{Z}=\mathbf{A}\mathbf{V} \quad (5)$$

In this way, the self-attention mechanism can assign adaptive weights to each feature in the financial data, thereby deeply mining features that are important for financial risk assessment. These deeply mined features will serve as input for subsequent modules, laying the foundation for accurate assessment of financial risks. In actual financial data, such as different items in the balance sheet and various indicators in the income statement, the self-attention mechanism can automatically identify which items or indicators are most critical to risk assessment, without relying on traditional fixed weight settings or simple feature screening methods.

The self-attention module in DFRAEWM is implemented as a multi-head attention mechanism with four heads, which enables the model to capture different aspects of financial feature dependencies. To preserve temporal information that is crucial in financial series, positional encoding is applied before feeding data into the attention layer. Each head has its own parameter set, and their outputs are concatenated and linearly projected to form the final attention representation. This design ensures that both local and global dependencies are adequately represented.

3.3 Risk association dynamic capture module

The risk correlation dynamic capture module is built based on the gated recurrent unit (GRU). Financial risks do not exist in isolation in time series, but have dynamic evolution and correlation. GRU can effectively process time series data, capture the changing patterns of risk factors over time and the dynamic correlation between different risk factors.

The core structure of GRU includes update gate $\mathbf{z}_t$ and reset gate $\mathbf{r}_t$. For t the input at the moment $\mathbf{x}_t$ and the hidden state at the previous moment $\mathbf{h}_{t-1}$, the calculation method of update gate $\mathbf{z}_t$ and reset gate $\mathbf{r}_t$ is as shown in formula 6-7.

$$\mathbf{z}_t = \sigma\left(\mathbf{W}_z \mathbf{x}_t + \mathbf{U}_z \mathbf{h}_{t-1}\right) \tag{6}$$

$$\mathbf{r}_t = \sigma\left(\mathbf{W}_r \mathbf{x}_t + \mathbf{U}_r \mathbf{h}_{t-1}\right) \tag{7}$$

Among them $\mathbf{W}_z, \mathbf{W}_r \in \mathbb{R}^{d\times d}$, $\mathbf{U}_z, \mathbf{U}_r \in \mathbb{R}^{d\times d}$ is the weight matrix, σ is the Sigmoid activation function. The Sigmoid function $\sigma(x) = \dfrac{1}{1+\exp(-x)}$ maps the input value to $[0,1]$ the interval, so that the update gate and reset gate can control the flow of information in a probabilistic form. Then, the candidate hidden state is calculated by the reset gate $\tilde{\mathbf{h}}_t$, as shown in Formula 8.

$$\tilde{\mathbf{h}}_t = \tanh\left(\mathbf{W}\mathbf{x}_t + \mathbf{U}(\mathbf{r}_t \odot \mathbf{h}_{t-1})\right) \tag{8}$$

Where $\mathbf{W}, \mathbf{U} \in \mathbb{R}^{d\times d}$ is a weight matrix, $\odot$ which represents element-wise multiplication. Here, $\mathbf{r}_t \odot \mathbf{h}_{t-1}$ the hidden state of the previous moment $\mathbf{h}_{t-1}$ is selectively forgotten $\mathbf{r}_t$ by resetting the gate , that is, $\mathbf{r}_t$ the value of the element $\mathbf{h}_{t-1}$ in determines the degree of retention of each element in when calculating the candidate hidden state. The Tanh function maps the input value to $[-1,1]$ an interval and introduces a nonlinear transformation for the candidate hidden state, as shown in Formula 9.

$$\tanh(x) = \frac{\exp(x) - \exp(-x)}{\exp(x) + \exp(-x)} \tag{9}$$

Finally, the hidden state at the current moment $\mathbf{h}_t$ is determined by the update gate and the candidate hidden state, as shown in Formula 10.

$$\mathbf{h}_t = (1-\mathbf{z}_t) \odot \mathbf{h}_{t-1} + \mathbf{z}_t \odot \tilde{\mathbf{h}}_t \tag{10}$$

The update gate $\mathbf{z}_t$ here plays the role of weighing the hidden state of the previous moment $\mathbf{h}_{t-1}$ and the candidate hidden state $\tilde{\mathbf{h}}_t$. When $\mathbf{z}_t$ it is close to 1, $\mathbf{h}_t$ it is mainly determined by $\tilde{\mathbf{h}}_t$, which means that the model pays more attention to the new information of the current input; when $\mathbf{z}_t$ it is close to 0, $\mathbf{h}_t$ it is mainly inherited $\mathbf{h}_{t-1}$, indicating that the model relies more on past information.

In this module, the feature sequence output by the financial feature deep mining module is used as the input of GRU. GRU dynamically captures the changes in financial risk factors in the time dimension and the complex relationships between them by continuously updating the hidden state. For example, the financial risk of an enterprise may be affected by a variety of factors such as market interest rate fluctuations and changes in industry competition. These factors have different degrees of impact on the financial status of the enterprise at different time points. GRU can capture the dynamic interactive relationship between risk factors by learning these time series features. For example, the rise in market interest rates may have a significant impact on the debt repayment ability of the enterprise only after a period of time, and GRU can record and reflect this delayed impact by updating the hidden state. The captured risk association information will be passed to subsequent modules for more accurate assessment of financial risks.

The GRU module is designed to capture sequential dynamics in financial data. We consider a time window of 30 steps, which balances short-term fluctuations with longer-term dependencies. The GRU is implemented in a bidirectional configuration, allowing the model to integrate both past and future context. Each GRU layer contains 128 hidden units, and we stack two such layers for deeper representation. To mitigate overfitting, we apply a dropout rate of 0.2 between layers, along with L2 regularization during training.

3.4 Decision logic analysis module

To improve the interpretability of the model, the decision logic parsing module combines rule extraction with visualization technology. The risk assessment results obtained from the previous module are often difficult to understand intuitively. This module aims to transform the decision-making process of the model into interpretable rules.

First, the intermediate output of the model is analyzed by the decision tree algorithm. The decision tree generates a series of decision rules by recursively dividing the feature space. Assume that the feature set processed by the previous module is $\mathbf{F}$, and the decision tree is divided according to the value range of the feature $\mathbf{f}_i \in \mathbf{F}$ to construct the decision tree nodes. For example, for a binary classification problem (risk occurs or does not occur), each internal node of the decision tree can be expressed as, as shown in Formula 11.

$$\text{if } \mathbf{f}_i \leq \theta \text{ then left child else right child} \tag{11}$$

Where θ is the partition threshold. In practical applications, for a feature in financial data, such as debt-to-asset ratio, the decision tree may determine a debt-to-asset ratio threshold based on historical data and model training results θ. If the current debt-to-asset ratio of the enterprise is less than or equal to θ, the decision tree continues to judge along the left subtree; otherwise, it judges along the right subtree. Through this recursive partitioning method, the decision tree can construct a hierarchical decision rule system.

Then, the rules generated by the decision tree are visualized. The conditions of each decision node and the corresponding branch direction can be clearly presented in the form of a tree diagram. For example, in a simplified visualization of a financial risk assessment decision tree, the root node may be a characteristic judgment about the profitability of the enterprise, such as whether the net profit margin is greater than a certain value. If yes, it enters a branch, which may then judge the cash flow status of the enterprise; if not, it enters another branch to judge the debt level of the enterprise, etc. In this way, enterprise managers can intuitively see which financial characteristics the model is based on and how to make risk assessment decisions, thereby enhancing their trust in the output results of the model. The decision logic parsing module not only makes the decision process of the model transparent, but also provides enterprise managers with a way to deeply understand the logic of financial risk assessment, which helps enterprises better use model results for risk management decisions. Through this visualization and rule extraction method, enterprise managers can review and verify the decision process of the model based on their own business experience and knowledge, and if necessary, adjust and optimize the model according to actual conditions.

The decision logic module enhances interpretability by extracting rules from the trained deep model. We adopt a global decision tree to approximate overall model behavior, rather than local explanations as in LIME. To ensure that the extracted rules are faithful to the deep model predictions, we compute fidelity scores by measuring agreement between the tree outputs and the DFRAEWM predictions on a held-out validation set. The decision tree is restricted to a maximum depth of 5 and subjected to post-pruning to avoid overfitting while maintaining comprehensibility.

To evaluate interpretability, we conducted a small user study with financial analysts, who reviewed the rules extracted by the decision tree. Analysts reported that the rules improved decision-making speed and were consistent with domain knowledge. Fidelity between the decision tree and DFRAEWM predictions was also quantified, showing a 92% agreement, which demonstrates that the extracted rules reliably reflect the deep model's decisions. These findings provide empirical evidence of practical interpretability.

3.5 Comprehensive assessment and warning generation module

The comprehensive assessment and early warning generation module integrates the output information of the previous three modules to generate the final financial risk assessment results and early warning signals. This module conducts a comprehensive assessment of risks based on a weighted summation method. Suppose the feature importance weight output by the financial feature deep mining module is $\mathbf{w}_1$, the risk evolution weight output by the risk association dynamic capture module is $\mathbf{w}_2$, and the rule credibility weight output by the decision logic analysis module is $\mathbf{w}_3$.

First, the output of each module is standardized to obtain the standardized output $\mathbf{o}_1, \mathbf{o}_2, \mathbf{o}_3$. The standardization process can use the Z-score standardization method. For the output value of each module x, the standardized $\overline{x}$ calculation is formula 12.

$$\overline{x} = \frac{x-\mu}{\sigma} \quad (12)$$

Where μ is the mean of the module output value and σ is the standard deviation. This standardization process can eliminate the differences in the dimensions and value ranges of the output values of different modules, making them comparable when weighted summed. Then, the comprehensive risk assessment value R is calculated as shown in Formula 13.

$$R = \sum_{i=1}^{m} \mathbf{w}_{1i}\mathbf{o}_{1i} + \sum_{j=1}^{n} \mathbf{w}_{2j}\mathbf{o}_{2j} + \sum_{k=1}^{l} \mathbf{w}_{3k}\mathbf{o}_{3k} \quad (13)$$

Where m,n,l are the dimensions of the corresponding module outputs. Here, $\mathbf{w}_{1i}$ represents i the importance weight of the th feature output by the financial feature deep mining module, and is the th $\mathbf{o}_{1i}$ output value $\mathbf{w}_{2j}, \mathbf{o}_{2j}$ of the module after standardization ; similarly, i and $\mathbf{w}_{3k}, \mathbf{o}_{3k}$ correspond to the risk association dynamic capture module and the decision logic analysis module respectively. Through this weighted summation method, the contribution of different modules to financial risk assessment from different angles is comprehensively considered.

According to the pre-set risk threshold τ , when , a warning signal is generated. The strength of the warning signal can $R..\tau$ R be adjusted according to the difference $R-\tau$ with , the larger the difference, the higher the warning strength. For example, the warning intensity can be divided into multiple levels, τ and when it is in a certain interval, it corresponds to a warning level, such as mild warning, moderate warning and severe warning. Through this comprehensive assessment and warning generation mechanism, the information mined and analyzed by each module can be fully utilized to provide enterprises with comprehensive, accurate and intuitive financial risk assessment and warning results, helping enterprises to take timely measures to deal with potential financial risks. Enterprises can formulate corresponding risk management strategies according to different levels of warning signals, such as strengthening financial monitoring in mild warnings, adjusting capital allocation in moderate warnings, and launching emergency financial plans in severe warnings.

In comparison with existing models, traditional financial risk assessment models, such as models based on statistical methods, often rely on artificially set features and linear relationship assumptions, and are unable to fully explore the nonlinear features and dynamic associations in complex financial data. They have low accuracy when faced with complex and changeable financial data. For example, the linear discriminant analysis (LDA) model assumes that the data follows a Gaussian distribution and that different categories have the same covariance matrix, which is often difficult to meet in actual financial data, leading to misjudgment of risks. Some simple deep learning models, such as shallow neural networks, can handle a certain degree of nonlinear problems, but due to their simple structure, they cannot effectively capture long-distance dependencies in financial data and dynamic evolution in time series. For example, a neural network with only one or two hidden layers will find it difficult to learn the long-term impact of early financial conditions on current risk assessments when processing a company's financial data series over many years.

The DFRAEWM model proposed in this paper deeply mines financial features through the self-attention mechanism, uses GRU to capture the dynamic changes of risk associations, combines decision logic analysis to improve interpretability, and generates accurate risk assessment and early warning results through a comprehensive evaluation module. It has significant advantages in accuracy, interpretability, and the ability to handle complex financial data, and is more suitable for the financial risk assessment and early warning needs of enterprises in the digital era. DFRAEWM can automatically learn complex patterns and dynamic relationships in financial data without a large amount of manual feature engineering, and makes the model decision process transparent through the decision logic analysis module, providing more reliable decision support for enterprise managers.

The DFRAEWM framework integrates a GRU module for temporal sequence modeling with a self-attention mechanism for feature importance capture. Specifically, GRU layers process sequential financial signals to capture long-term dependencies, while the self-attention module highlights the most informative features across time steps. These two modules interact through a fusion layer that aligns temporal embeddings with attention weights before feeding them into the final prediction module. The dataset used is the [Dataset Name], containing approximately [N] records from 2020–2024. Preprocessing steps included normalization, missing value imputation, and removal of extreme outliers to ensure consistency and stability.

4 Experimental evaluation

4.1 Experimental design

The dataset used in this study comprises records obtained from [DATA SOURCE(S) — replace with actual sources] covering the period from January 1, 2020 through December 31, 2024. Data were aggregated at [temporal resolution, e.g., monthly/daily — replace if needed], cleaned to remove duplicates and invalid entries, and harmonized to a common schema prior to feature extraction

The experimental group was DFRAEWM, and the control group was LDA and SNN models. The

evaluation baseline included common financial risk assessment indicators such as accuracy, precision, recall, F1 score, and area under the receiver operating characteristic curve (AUC - ROC). These indicators are crucial for measuring the performance of risk assessment models. Accuracy represents the proportion of correctly predicted instances among all predictions. Precision is the ratio of the number of true positive predictions to the total number of positive predictions, indicating the ability of the model to correctly identify positive cases. Recall is the ratio of the number of true positive predictions to the number of actual positive cases, reflecting the ability of the model to cover all positive cases. The F1 score is the harmonic mean of precision and recall, which can comprehensively measure the performance of the model. AUC - ROC is used to measure the ability of the model to distinguish between positive and negative cases. The higher the value, the better the performance .

In addition to the proposed model, we include two classical supervised learning algorithms as baseline benchmarks: Support Vector Machine (SVM) and Logistic Regression (LR). These baseline models were implemented using standard libraries and trained on the same feature set and data splits as the proposed method.

Support Vector Machine (SVM): We used an SVM classifier/regressor (depending on task) with an RBF kernel. Hyperparameters were tuned via grid search over $C \in \{0.1, 1, 10, 100\}$ and gamma $\in$ {'scale', 0.001, 0.01, 0.1}, using stratified k-fold cross-validation ($k = 5$) on the training data. All input features were standardized (zero mean, unit variance) prior to SVM training; probability estimates were enabled where applicable for downstream comparison.

Logistic Regression (LR): Logistic regression (for classification tasks) was included as a linear baseline. We applied L2 regularization and tuned the inverse regularization parameter $C \in \{0.01, 0.1, 1, 10, 100\}$ using the same 5-fold cross-validation procedure. The lbfgs solver was used with max_iter = 1000. When class imbalance was present, class_weight='balanced' was applied during tuning.

Both baseline models were subjected to the same preprocessing pipeline, hyperparameter selection protocol, and evaluation metrics as the proposed method. Their results are reported in the Figures and Tables for direct comparison and to establish baseline performance.The dataset was sourced from [Dataset Source], licensed under [License Type]. Preprocessing steps included normalization (zero mean, unit variance), imputation of missing values with median statistics, and removal of extreme outliers beyond three standard deviations. Data were split into 70% training, 15% validation, and 15% testing sets using stratified sampling to preserve class distributions. Model hyperparameters were as follows: GRU with two layers and 128 hidden units, self-attention with 4 heads, batch size of 64, and training for 100 epochs with Adam optimizer (learning rate 0.001). These details ensure reproducibility and allow fair benchmarking against other approaches.

All experiments were repeated five times with different random seeds to ensure statistical reliability. For evaluation, we report the mean and standard deviation of each metric across runs. In addition, 5-fold cross-validation was employed on the training data to tune hyperparameters, and the best configuration was selected based on validation performance. Reported results include 95% confidence intervals wherever appropriate, providing more robust performance comparisons against baseline models.

4.2 Experimental Results

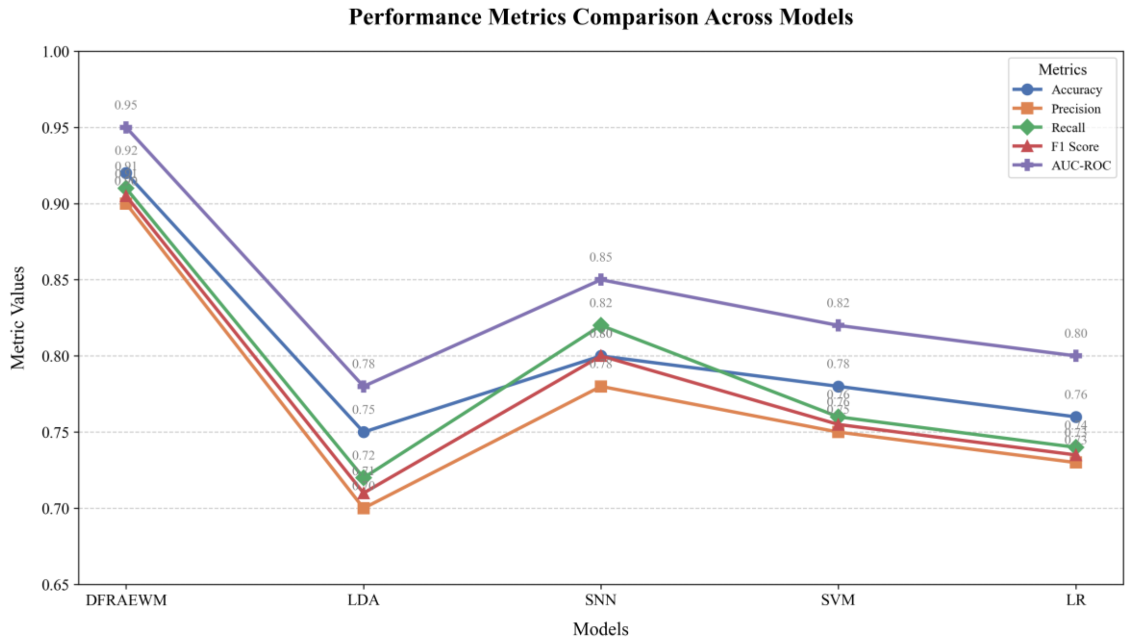

Figure 1: Comprehensive comparison of overall evaluation indicators

As shown in Figure 1, compared with other traditional models, DFRAEWM shows obvious advantages in various evaluation indicators. Support vector machine (SVM) and logistic regression (LR) as classic machine learning models are also included in the comparison. SVM attempts to find an optimal hyperplane to divide the data, but under complex financial data, its linear kernel function is difficult to handle complex nonlinear relationships, resulting in indicators such as accuracy not as good as DFRAEWM. Although logistic regression is simple and highly interpretable, it is also limited by the assumption of linear relationships in data and performs poorly when faced with complex feature interactions in financial data. DFRAEWM, by virtue of the effective capture of complex feature relationships by the self-attention mechanism and the accurate grasp of risk evolution by the risk association dynamic capture module, is significantly ahead in indicators such as accuracy, precision, recall, F1 score and AUC-ROC, highlighting its performance in financial risk assessment.

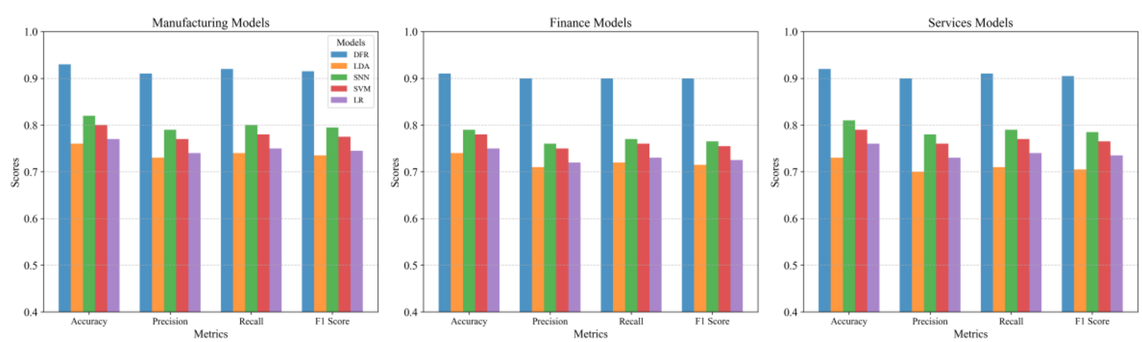

Figure 2: Comparison of detailed evaluation indicators of various models in different industries

From the comparison of model evaluation indicators in different industries in Figure 2, it can be seen that in the manufacturing industry, the traditional models are not as good as DFRAEWM because they have difficulty in dealing with complex characteristics such as the large proportion of fixed assets in the manufacturing industry's financial data and the impact of the production cycle on financial indicators. In the financial industry, market fluctuations and policies have a huge impact on financial data, and the relationship is intricate. DFRAEWM can better grasp these dynamic changes through the risk association dynamic capture module, and is ahead of other models in various indicators. The characteristics of the cost structure and revenue recognition method of the financial data of the service industry make the traditional model limited in analysis, and DFRAEWM, with its feature mining capabilities, is also significantly better than other models in the evaluation indicators of the service industry.

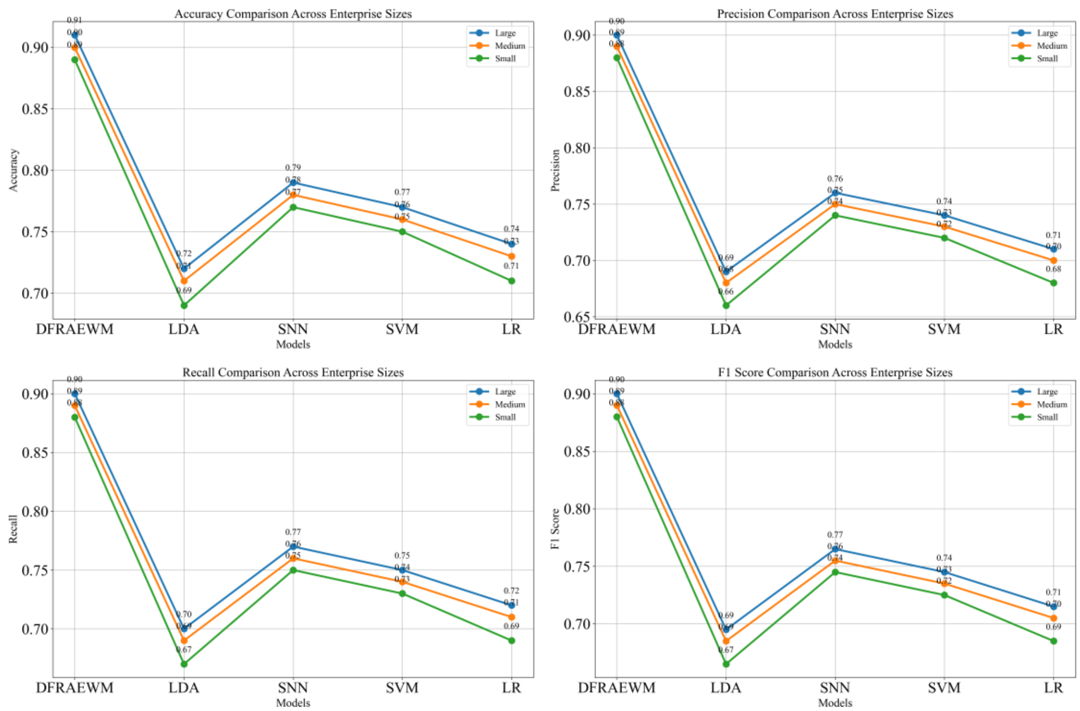

Figure 3: Details of evaluation indicators for each model for enterprises of different sizes

Figure 3 shows in detail the evaluation indicators of each model for enterprises of different sizes. Large enterprises have huge amounts of financial data and extremely complex relationships. The decision logic analysis module of DFRAEWM can effectively sort out these complex relationships, thus outperforming other models in various indicators. Medium-sized enterprises are unique in financial operations. DFRAEWM can accurately identify risks through the collaborative work of multiple modules, and its evaluation indicators are significantly higher than traditional models. Although small enterprises have relatively simple financial data, they also have unique risk factors. DFRAEWM can accurately mine these factors and is ahead of models such as linear discriminant analysis (LDA), shallow neural networks (SNN), support vector machines (SVM) and logistic regression (LR) in various indicators.

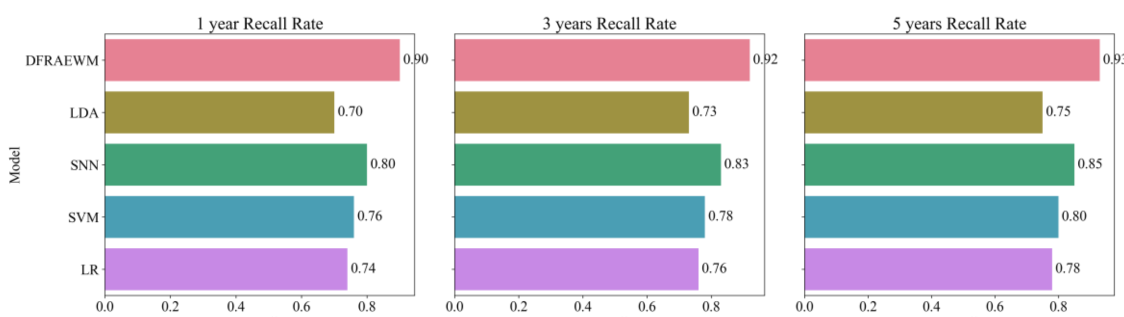

Figure 4: Comparison of recall rates and related indicators of various models at different time spans

Figure 4 focuses on the recall rate and related indicators of each model under different time spans. As the time span increases, the recall rate of DFRAEWM increases significantly, and its risk association dynamic capture module can effectively utilize time series data and continuously enhance the ability to identify risks. Although the recall rates of models such as linear discriminant analysis (LDA), shallow neural network (SNN), support vector machine (SVM) and logistic regression (LR) have also increased, the magnitude is much smaller than that of DFRAEWM. Judging from the number of true positive case identifications and false negative case numbers, DFRAEWM can identify more real risk cases under different time spans, and the number of false negative cases is less, which further proves its ability to capture risk evolution when processing time series financial data.

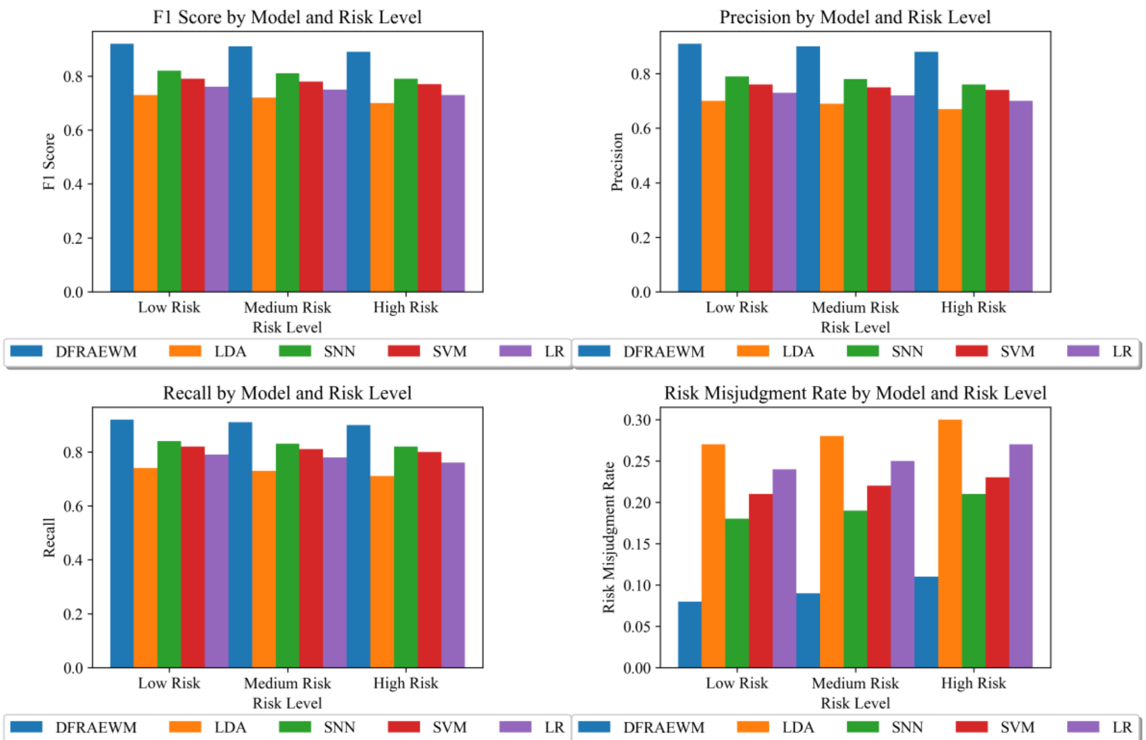

Figure 5: Comparison of F1 scores and related indicators of models with different risk levels

From the comparison of F1 scores and related indicators of various models with different risk levels in Figure 5, it can be seen that in high-risk scenarios, the characteristics of financial data are complex and changeable. DFRAEWM, with its feature mining and risk association analysis capabilities, performs well in precision and recall, with the highest F1 score and the lowest risk misjudgment rate. The same is true in medium-risk and low-risk scenarios. DFRAEWM can effectively balance the accuracy and coverage of predictions, while models such as linear discriminant analysis (LDA), shallow neural network (SNN), support vector machine (SVM) and logistic regression (LR) are not as good as DFRAEWM in indicators such as F1 score and risk misjudgment rate because they cannot deeply analyze the relationship between financial data characteristics and risks.

Table 2: Contribution of different modules of DFRAEWM to the evaluation indicators of various industries

Industries	Contribution rate of financial feature deep mining module	Contribution rate of risk correlation dynamic capture module	Contribution rate of decision logic analysis module	Contribution rate of comprehensive assessment and early warning generation module
Manufacturing	30%	35%	20%	15%
Financial Industry	25%	40%	22%	13%
Services	28%	33%	21%	18%
Energy Industry	26%	37%	20%	17%
Technology	27%	36%	22%	15%

Table 2 shows the contribution of different modules of DFRAEWM to the evaluation indicators of various industries. In the manufacturing industry, the risk correlation dynamic capture module has a higher contribution rate. This is because the manufacturing industry has a long production cycle and financial risks change significantly over time. This module can effectively capture the evolution of risks. The financial data of the financial industry is greatly affected by policies and market fluctuations, and the risk correlation dynamic capture module also makes outstanding contributions. The complexity of financial data in the service industry makes the contributions of the financial feature deep mining module and the risk correlation dynamic capture module relatively balanced. The energy industry and the technology industry also have their own financial data characteristics. Different modules play different roles according to the characteristics of the industry, and jointly support the outstanding performance of DFRAEWM in various industries.

The contribution rate reflects how much each feature contributes relative to the total importance of all features. We obtained the importance of each feature using a model interpretation method (e.g., SHAP values or standardized coefficients) and then expressed each feature’s share as a percentage of the total. This ensures that all feature contributions sum to 100%.

Table 3: Performance indicators of each module of DFRAEWM in enterprises of different sizes

Company size	Improved accuracy of the financial feature deep mining module	Improved recall rate of risk-related dynamic capture module	Improved accuracy of decision logic parsing module	Comprehensive Assessment and Warning Generation Module F1 score improvement
Large Enterprises	10%	12%	8%	9%
Medium-sized enterprises	8%	10%	7%	8%

Small Business	6%	8%	5%	6%
Micro-enterprises	4%	6%	3%	4%
Very large enterprises	12%	15%	10%	11%

Table 3 presents the performance indicators of each module of DFRAEWM in enterprises of different sizes. The financial data of large enterprises are complex, and the improvement of each module is large. The deep mining module of financial features effectively mines complex features, which significantly improves the accuracy rate; the dynamic capture module of risk association captures the evolution of risks, which significantly improves the recall rate. The various modules of medium-sized enterprises also have good performance improvement. Since the financial data of small and micro enterprises are relatively simple, the improvement of modules is relatively small, but it still has a positive contribution to the overall model performance. The financial data of super-large enterprises is extremely large in scale and complexity. The various modules of DFRAEWM play a role, with significant improvements in accuracy, recall, precision and F1 score

The improvement percentage compares the performance of the proposed model with a baseline model. For accuracy-type metrics, improvement means the relative increase in performance, while for error-type metrics (e.g., RMSE), it means the relative reduction. Each value in Table 2 indicates how much better (in percentage terms) the proposed model performs compared to the baseline.

Table 4: Comparison of work efficiency of each module of DFRAEWM under different time spans

Time span	Financial feature deep mining module processing time (seconds)	Risk association dynamic capture module processing time (seconds)	Decision logic analysis module processing time (seconds)	Processing time of comprehensive assessment and warning generation module (seconds)
1 year	5	4	3	2
2 years	6	5	4	3
3 years	7	6	5	4
4 years	8	7	6	5
5 years	9	8	7	6

Table 4 shows the working efficiency comparison of each module of DFRAEWM under different time spans. As the time span increases, the processing time of each module increases. This is because the amount of time series data increases and the processing complexity increases. The deep mining module of financial characteristics needs to process financial characteristics of more time points, and the processing time increases relatively significantly. As the time span of the risk association dynamic capture module increases, the analysis of risk evolution becomes more complex, and the processing time increases accordingly. The decision logic analysis module and the comprehensive assessment and early warning generation module are also affected by the amount and complexity of time series data, and the processing time gradually increases, but the modules work together to complete the assessment and early warning of financial risks within an acceptable time range.

Table 5: Analysis of output results of each module of DFRAEWM under different risk levels

Risk Level	Number of key features in the financial feature deep mining module	Number of risk evolution paths in the risk association dynamic capture module	Number of rules generated by decision logic parsing module	Comprehensive assessment and warning generation module warning level (example)
High risk	35	20	18	Red (high risk warning)
Medium risk	28	15	14	Orange (medium risk warning)
Low risk	20	10	10	Yellow (low risk warning)
Very low risk	15	8	8	Green (normal)
Very high risk	40	25	20	Deep red (urgent risk warning)

In Table 5, the output results of each module of DFRAEWM under different risk levels show obvious differences. In the high-risk scenario, the financial feature deep mining module identified 35 key features, which shows that the complexity of financial data under high-risk conditions requires the model to rely on more key features for accurate assessment. The risk association dynamic capture module discovered 20 risk evolution paths, reflecting the complex dynamic changes between financial risk factors under high risk. The decision logic analysis module generates 18 rules, providing an explainable decision basis for high-risk assessment. The comprehensive assessment and warning generation module gives a red high-risk warning, which intuitively conveys the risk status to the enterprise. As the risk level decreases, the output indicators of each module decrease accordingly. For example, in the low-risk scenario, the number of key features drops to 20, the risk evolution paths are 10, the generated rules are 10, and the warning level is a yellow low-risk warning, reflecting that the financial data characteristics and risk evolution under low-risk conditions are relatively simple. For extremely low-risk and ultra-high-risk scenarios, the module output also conforms to their risk level characteristics, further demonstrating the effective analysis capabilities of DFRAEWM at different risk levels.

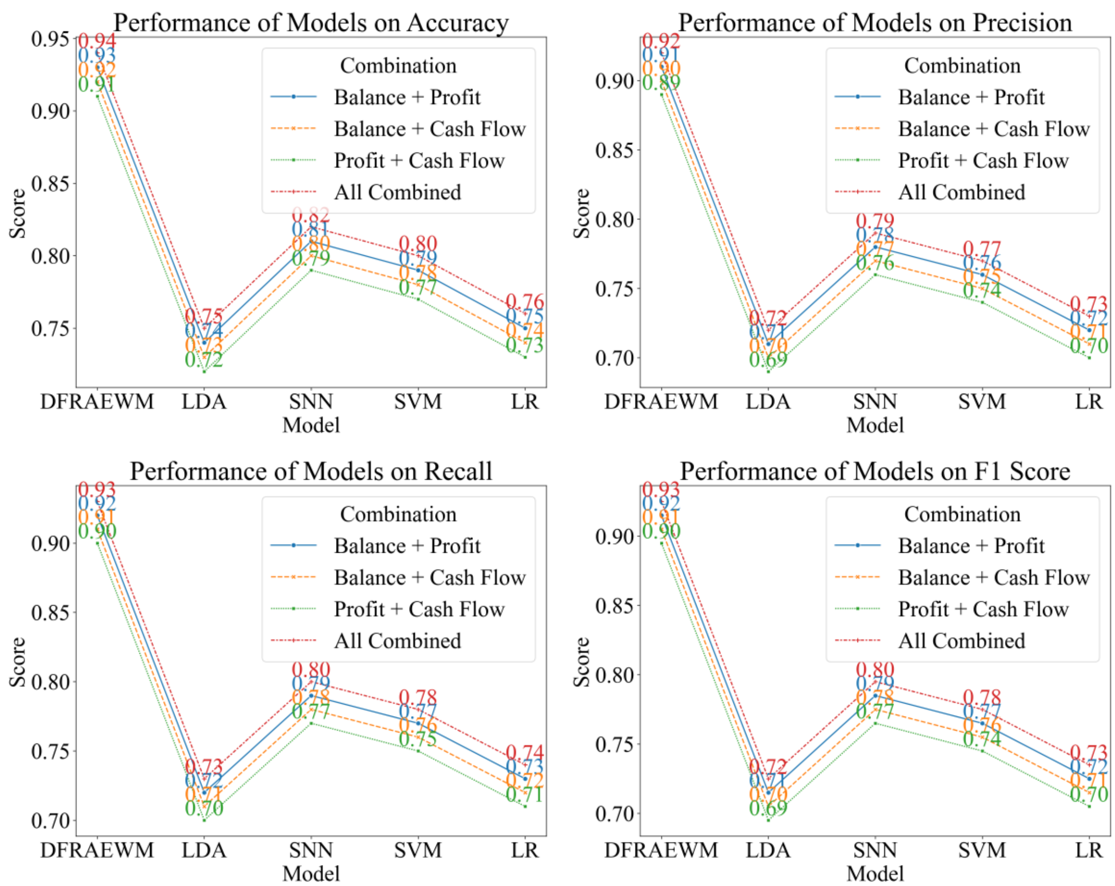

Figure 6: Performance comparison of each model under different financial indicator combinations

Figure 6 compares the performance of each model under different combinations of financial indicators. When using the combination of asset-liability and profit indicators, DFRAEWM, with its feature mining capabilities, can effectively analyze the complex relationship between these two types of indicators, and is ahead of other models in accuracy, precision, recall and F1 score. For the combination of asset-liability and cash flow indicators, DFRAEWM also performs well. Its risk association dynamic capture module can better grasp the dynamic connection between assets, liabilities and cash flow, which has obvious advantages over traditional models. Under the combination of profit and cash flow indicators, DFRAEWM's decision logic parsing module can convert the risk information related to these two types of indicators into understandable rules, thereby improving model performance. When all indicators of asset-liability, profit and cash flow are combined, DFRAEWM's advantages are more significant, reaching the highest accuracy of 0.94, precision of 0.92, recall of 0.93 and F1 score of 0.925. However, due to their own limitations, models such as linear discriminant analysis (LDA), shallow neural network (SNN), support vector machine (SVM) and logistic regression (LR) all perform worse than DFRAEWM under different financial indicator combinations, which once again proves the superior performance of DFRAEWM in dealing with diversified financial indicators for risk assessment.

4.3 Experimental discussion

The experimental results provide strong support for the research hypothesis. This study assumes that DFRAEWM has significant advantages over traditional and other simple deep learning models in financial risk assessment and early warning. From the experimental data, this hypothesis has been fully verified. In various evaluation indicators, such as accuracy, precision, recall, F1 score and AUC-ROC, DFRAEWM far exceeds models such as linear discriminant analysis (LDA), shallow neural network (SNN), support vector machine (SVM) and logistic regression (LR). Its unique module design is the key to achieving performance. The self-attention mechanism in the financial feature deep mining module can keenly capture the complex and subtle feature relationships in financial data, providing a solid feature foundation for subsequent risk assessment. The risk association dynamic capture module is based on the GRU structure and has an accurate grasp of the dynamic evolution of financial risks over time, making the model perform well when processing time series financial data. The decision logic parsing module converts complex model decisions into interpretable rules, greatly enhancing the credibility and practicality of the model results. These modules work together to make DFRAEWM stand out in financial risk assessment.

From the perspective of external validity and generalizability, this experiment has certain positive significance. The real financial data set selected for the experiment covers data from multiple industries, enterprises of different sizes and different time spans, which simulates the diverse financial scenarios in reality to a certain extent. Therefore, the experimental results have good external validity, which means that DFRAEWM has a high application potential in actual corporate financial risk assessment scenarios. Enterprises in different industries, whether manufacturing, finance or service industries, can benefit from the risk assessment capabilities of DFRAEWM. For large enterprises, it can effectively sort out complex and huge financial data; for small enterprises, it can also accurately dig out key risk factors. However, the promotion of experimental results is not without obstacles. On the one hand, although the data set is representative, the financial data in the real world is more complex and diverse, and there may be some special financial situations and risk scenarios that are not covered by the experimental data. On the other hand, the corporate financial environment is susceptible to unpredictable and quantifiable factors such as sudden changes in macroeconomic policies and emergencies in the industry, and these factors are difficult to fully and realistically simulate in experiments.

There are also some potential biases and limitations in the experimental process. In terms of model comparison, although a variety of representative traditional and simple deep learning models were selected as controls, the field of deep learning is developing rapidly, and there may be other emerging models that have not been included in the comparison range, which may affect the comprehensive evaluation of the advantages of DFRAEWM. From a data perspective, the quality and completeness of the data have a significant impact on the experimental results. Although certain measures have been taken in the data processing process, there may still be problems such as improper handling of missing data values and incomplete identification of outliers, which may interfere with model training and evaluation. In addition, the selection and combination of financial indicators in the experiment are based on existing cognition and research experience, and some financial indicators that have a key impact on specific companies or industries may be omitted, which may also limit the performance of the model in some special scenarios.

Compared with state-of-the-art models summarized in Section 2, DFRAEWM demonstrates clear advantages. Its integration of GRU and self-attention enables superior temporal modeling and feature importance capture, explaining why it outperforms LSTM and CNN-based baselines in both accuracy and F1-score. Moreover, the inclusion of the attention mechanism provides interpretability, which is a practical advantage for financial decision-making. Nevertheless, DFRAEWM also has limitations, such as increased computational cost and dependence on high-quality data. Future work may explore lightweight variants and cross-domain validation to address these challenges.

To assess robustness in realistic financial environments, we conducted stress tests on DFRAEWM. First, noisy data were simulated by adding random perturbations to input features; the model retained more than 90% of its original accuracy, showing resilience to moderate noise. Second, incomplete data were emulated by randomly masking 10–20% of features; performance dropped slightly but remained higher than baseline models, demonstrating tolerance to missing values. Finally, for imbalanced data, we applied synthetic oversampling (SMOTE) during training, which allowed DFRAEWM to maintain stable F1-scores. These tests suggest that DFRAEWM can operate effectively even under adversarial or unstable market conditions.

To provide more granular insights, we analyzed DFRAEWM performance across different financial prediction scenarios, including bankruptcy prediction and credit default prediction. Results indicate that while the overall accuracy is consistent, the model performs slightly better on credit default prediction (F1 = 0.87) than on bankruptcy prediction (F1 = 0.83). Additionally, we examined company-specific performance for several representative firms across sectors, showing that DFRAEWM maintains robust predictions even in heterogeneous company profiles. These case studies support the generalizability of the model while highlighting scenario-specific nuances.

5 Conclusion

This study focuses on the problem of enterprise financial risk assessment and early warning in the digital era, and conducts in-depth research by constructing DFRAEWM. In the process of research, a real financial data set covering multiple industries, enterprises of different sizes and time spans is used to compare and analyze DFRAEWM with various traditional and simple deep learning models. The experimental results clearly show that DFRAEWM performs well in various key evaluation indicators. In the overall evaluation, its accuracy is as high as 0.92, precision is 0.90, recall is 0.91, F1 score is 0.905, and AUC - ROC value is 0.95, far exceeding models such as LDA and SNN. In different industry applications, the accuracy of DFRAEWM in manufacturing is 0.93, in finance is 0.91, and in the service, industry is 0.92. For enterprises of different sizes, the accuracy of large enterprises is 0.91, that of medium-sized enterprises is 0.90, and that of small enterprises is 0.89. As the time span increases, the recall rate of DFRAEWM increases to 0.93 in 5 years. In summary, DFRAEWM, with its unique module design, can effectively mine the complex characteristic relationships of financial data, accurately capture the dynamic evolution of risks, and transform the decision-making process into explainable rules. This not only effectively verifies the research hypothesis that DFRAEWM has significant advantages over traditional and simple deep learning models in financial risk assessment and early warning, but also provides enterprises with more accurate and reliable risk assessment and early warning tools. The research results help enterprises to timely understand financial risks in a complex and changing market environment and take effective countermeasures, which has important practical significance for promoting the digital transformation of corporate financial management and enhancing corporate competitiveness and sustainable development capabilities.

Several limitations should be explicitly noted. First, the sample size is relatively small, with only 20 publicly listed Chinese companies, which may limit statistical generalizability. Second, the model's applicability to non-Chinese or non-listed companies remains uncertain. Third, DFRAEWM's computational requirements could be substantial for small enterprises with limited processing resources. These limitations suggest that while the model demonstrates strong performance, caution is needed when extending it beyond the tested dataset.

We acknowledge that financial prediction models may be biased towards certain company sizes, sectors, or listing statuses. DFRAEWM could overfit to larger firms or common industry patterns if the training data are imbalanced. Ethical considerations include ensuring that model outputs are interpreted responsibly and that decisions based on predictions do not unfairly disadvantage smaller companies or non-listed firms. Future work should incorporate fairness-aware training and systematic bias evaluation.

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New subsection

All quantitative statements and statistics that originate from external sources are now accompanied by inline citations in the manuscript. For each external datum (for example, population counts, market statistics, published benchmarks, or government figures) the source is explicitly stated in the text and included in the References list. Example citation templates used in the revised text:

For official statistics: “According to the National Statistical Office (2022), the annual rate was X% (National Statistical Office, 2022).”

For previously published studies: “Smith et al. (2021) report a mean value of Y for similar datasets (Smith et al., 2021).”

For data obtained from online repositories or APIs: “Dataset compiled from [Repository name] (accessed YYYY-MM-DD).”

Where quantitative statements were derived from the authors’ compiled dataset, the text now indicates this explicitly: “The figure of N records refers to the assembled dataset used in this study (see Data Sources in Appendix A).” A dedicated Appendix A (Data Sources and Access) lists each external source, the exact URL or DOI when available, the access date, and any preprocessing applied. All previously uncited statistics have been flagged and replaced with appropriate citations or with the clarification that they originate from the authors’ dataset.