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RESEARCH ARTICLE

# Financial Risk Early Warning Model for Listed Companies Using BP Neural Network and Rough Set Theory

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**ABSTRACT** In current financial environment, listed companies are facing increasingly complex markets and ever-changing financial risks. The companies deeply recognize the crucial role of financial risk management in the sustainable development of enterprises. The challenge lies in rapidly changing market conditions, and traditional methods are difficult to predict risks in a timely and accurate manner. Therefore, improving the accuracy and timeliness of financial risk prediction has become an urgent need in the current field to reduce potential losses and maintain the financial health of enterprises. This work aims to enhance the accuracy and timeliness of predicting financial risks for listed companies and reduce potential losses caused by these risks. In the research process, a large volume of data is initially collected, including financial statements, market data, and financial risk event data. Subsequently, the Rough Set Theory (RST) is employed for feature selection to identify financial indicators and market factors highly relevant to financial risk. Finally, a financial risk early warning model on the basis of the Back Propagation Neural Network (BPNN) is built, and then trained and optimized using historical data. Cross-validation analysis is employed to assess the model's performance, and the model is compared with traditional financial risk early warning methods. The findings reveal that the financial risk early warning model based on RST and the BPNN demonstrates high accuracy and reliability in predicting financial risks for listed companies. The model exhibits excellent performance in terms of accuracy, recall, and F1 score, achieving rates of 96%, 95%, and 95.50%, respectively. These research findings are expected to positively impact the financial sector and provide financial decision-makers with more accurate risk early warning and decision support.

**INDEX TERMS** Rough set, back propagation neural network, financial risk, model prediction, cross-validation.

## I. INTRODUCTION

As global financial markets continue to evolve and grow in complexity, financial risk management for listed companies has become increasingly crucial [1]. Financial risk encompasses various uncertainties a company may face in its operations, such as market fluctuations, liquidity issues, economic cycle variations, and more. In this dynamic and complex environment, traditional methods of financial risk prediction encounter several challenges [2], [3], [4]. These conventional approaches often fail to comprehensively consider these factors, resulting in inadequate holistic predictions of financial risk. Furthermore, the growing uncertainty factors in financial markets, including policy changes, international relations tensions, natural disasters, and others, significantly impact a company's financial risk. Traditional methods often exhibit vulnerability in handling these uncertainty factors and struggle to adapt effectively to the dynamic changes in the market [5], [6].

Against this backdrop, researchers seek to introduce more advanced data mining and analysis techniques to enhance the efficacy of early warning for financial risk. Rough Set

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Theory (RST) is a potent data mining tool that can handle incomplete and uncertain information. It has been employed in market data analysis, investment risk assessment, and investment strategy development. It can aid financial analysts in identifying correlations between various financial assets, and uncovering potential opportunities and risks in the market. RST can also be used to construct predictive models to forecast stock price fluctuations or exchange rate changes [7]. However, despite the potential advantages of RST in financial risk management, its application in the financial risk early warning (FREW) field remains relatively limited. This limited application is partly due to the complexity of RST and issues related to its adaptability to large-scale data [8].

Therefore, to fully harness the potential of RST in FREW, this work integrates the strengths of RST and Back Propagation Neural Network (BPNN) to build a more robust and adaptable FREW model.

The primary research objectives are as follows.

1. The first is to build a thorough model for early detection of financial risks by utilizing attribute reduction in RST and fuzzy set theory, along with the deep learning features of the BPNN. This model is aimed at enhancing the accuracy of financial risk prediction.

2. The second is to identify the key financial indicators and market factors applicable to FREW, thus enhancing comprehension and response to financial risk.

## II. LITERATURE REVIEW

FREW is one of the key tasks in the fields of financial management and regulation. Wang and Xie established an assessment index system for coastal financial risk using the Delphi method and conducted early warning analysis on the primary destinations of overseas mining investments using a BPNN model [9]. Cao et al. (2022) examined the development of an early warning system for financial risks within e-commerce businesses. They established a deep learning-based financial early warning model and analyzed and predicted financial risks for listed companies [10]. Metawa and Metawa utilized big data analysis techniques to construct an improved model based on the decision tree algorithm, achieving highly accurate risk early warning for China's internet finance sector [11]. The research findings indicated that the predicted data closely matched the actual circumstances, achieving an accuracy rate of 90%. Zhao et al. used macro indicators for local government implicit debt risk at the prefectural level and built a BPNN model with a training mean squared error of 0.00976 [12]. Regin et al. (2023) categorized all internet users as "sensors" and established an optimized model for measuring corporate financial risk through the utilization of big data mining and robust neural networks. They conducted big data mining and evaluated the results [13].

BPNN, as a powerful tool for pattern recognition and nonlinear modeling, has been widely applied in financial risk prediction. Song et al. (2023) utilized the K-means clustering algorithm to categorize a company's financial condition as either "healthy" or "early warning." They employed the BPNN algorithm to construct an early warning model, confirming that the model achieved accuracy, precision, recall, and specificity rates of 99.51%, 99.71%, 99.71%, and 98.30%, respectively [14]. Zhao created a financial risk evaluation model that relies on principal component analysis and RBF neural networks, effectively assessing financial risk for port enterprises [15]. Chen et al. (2023) constructed a financial risk prediction model using factor analysis - Particle Swarm Optimization - Long Short-Term Memory (FA-PSO-LSTM) deep learning. They introduced multiple benchmark models for comparative analysis of various evaluation indicators [16].

In the realm of RST application research, Liu et al. demonstrated that combining the Convolutional Neural Network (CNN) with fuzzy rough sets could effectively enhance the interpretability of deep neural networks [17]. Roma et al. conducted a consumer attitude analysis on the basis of the Dominance-based rough set approach, revealing the consumer characteristics that determined their specific categorization [18]. Gao et al. used RST to build a model and analyze the relationships between different supply chain risk occurrences, actively exploring the utilization of Internet of Things (IoT) data for supply chain risk management [19]. Xuan et al. constructed a model selection technique based on Rough Set and Approximate Ideal Solution Ranking, validating the model's scientific and effective application in ship cleanliness [20]. Li et al. (2023) employed a probability distribution-based rough set attribute reduction algorithm to reduce data redundancy. Cluster experimental results demonstrated that the improved K-prototype algorithm had superior clustering performance compared to the traditional K-prototype clustering algorithm, with a predictive accuracy rate of 87.9% [21].

The studies of the above scholars have provided valuable experience and methods for the field of financial risk warning. Studies have shown that various methods can be used for financial risk warning, including Delphi method, back-propagation neural network (BPNN), decision tree algorithm, deep learning, and Rough Set Theory (RST). The diversity of this method enables researchers to choose the most suitable method based on specific situations, improving the accuracy and interpretability of financial risk prediction. In addition, multiple studies have shown that BPNN, as a commonly used prediction tool, can improve performance through parameter optimization. This indicates the necessity of continuous improvement and optimization of neural network models. The application of RST in financial risk warning demonstrates its advantages in handling incomplete and uncertain information. This provides potential research opportunities for more rough set-based methods. Overall, these studies provide various methods and techniques for financial risk warning, which helps to improve the accuracy and efficiency of risk prediction. However, there are still areas that require further research and improvement, such

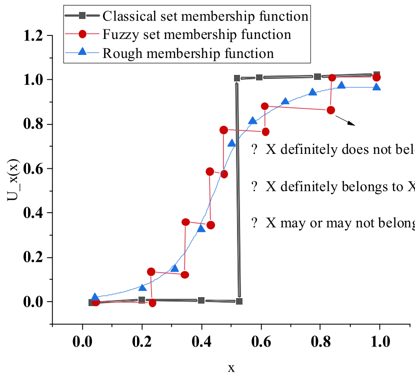


**FIGURE 1.** The membership function of rough sets.

as the interpretability of the model and its cross-industry applicability. Future research can continue to deepen these aspects to better address the constantly changing financial risk challenges.

## III. RESEARCH METHODOLOGY

### A. RST

RST is a mathematical method for handling imprecise, uncertain, and incomplete data. Rough sets introduce knowledge used for classification into sets and are primarily employed to reduce and classify information systems [22], [23], [24]. The membership function of rough sets is stepwise, and it provides a coarse description of uncertain information [25]. Figure 1 illustrates the membership function of rough sets.

Figure 1 reveals that the membership function of rough sets is computable. From a mathematical perspective, the concepts of equivalence relations on sets and the partition of sets are equivalent [26], [27]. A knowledge representation system is set to $S = \{U, R, V, f\}$. $U = \{x_1, x_2, \cdots, x_n\}$ is the set of all samples, $R = C \cup D$ is the attribute set, $C$ is the set of object attribute characteristics, and $D$ is the set of decision attribute categories. $V = \bigcup_{r \in R} V_r$ represents the set of attribute values, and $V_r$ is the range of values for attribute $r$. $f$ is the information function that determines the attribute values of $x$ in $U$, that is, $f(x_i, r) = V_r$. Moreover, for the knowledge $R$, the approximation accuracy of the uncertainty level of sample subset $X$ reads:

$$\alpha_R(X) = \frac{card(R_x)}{card(R(X))} \tag{1}$$

In (1), *card* represents the number of elements in a set, and $0 \leq \alpha \leq 1$. If $\alpha = 1$, the set $X$ is certain with respect to $R$. If $\alpha < 1$, the set $X$ is rough with respect to $R$, approximating the precision of set $X$ under the equivalence relation $R$. The approximation quality of $X$ with respect to $A$ reads:

$$r_A(X) = \frac{card(R_x)}{card(U)} = \frac{|R_x|}{|U|} \tag{2}$$

In (2), $2r_A(X)$ reflects the percentage of elements in $X$ that are definitely present in the existing knowledge base. Equation (3) represents the roughness measure of $X$ with respect to A:

$$\rho_A = 1 - \alpha_R(X) \tag{3}$$

In (3), $\rho_A \in [0, 1]$. The roughness measure reflects the incompleteness degree in the knowledge.

According to the principles of RST, in FREW, the indicators that influence the early warning of financial risks for listed companies are a comprehensive reflection of different elements. These factors include the company's financial structure, liquidity, profitability, management efficiency, and external market environment, among others. Investors and management should closely monitor these indicators to take necessary measures promptly for managing and reducing potential financial risks [28], [29], [30]. Figure 2 provides a detailed analysis of the FREW indicators for listed companies and the final indicators selected and optimized based on RST.

Figure 2 illustrates that, according to the RST, debt-paying capability is crucial in assessing whether a company can repay its debts on time. Profitability reflects the level of profit generated by the company's operations. Cash flow coverage capability is a key factor in evaluating whether the company can cover its debt with its own cash flow. Operational development indicators reflect the company's future growth potential. Asset operational capability affects the company's liquidity and operational efficiency. The company's expansion capability has a significant impact on future financial risk. The quality of corporate governance also plays a vital role in financial risk.

### B. KRUSKAL-WALLIS (K-W) TEST FOR FINANCIAL RISK WARNING INDICATORS OF LISTED COMPANIES

This work employs the K-W test for the early warning identification of the aforementioned financial risk warning indicators for listed companies [31]. Table 1 outlines the steps for the K-W test on financial risk warning indicators of listed companies.

Based on Table 1, the K-W statistic can be calculated using equation (4).

$$H = \frac{12}{N(N+1)} \sum_{i=1}^{k} \frac{R_i^2}{n_i} - 3(N+1) \tag{4}$$

In (4), $k$ represents the number of groups, $N$ is the total sample size, $R_i$ is the sum of ranks for the $i$-th group, and $n_i$ is the sample size of the $i$-th group. The K-W test can help determine which financial indicators have a higher level of recognition for financial risk in listed companies. This, in turn, can optimize the risk warning model and enhance the ability to identify potential risk signals more accurately. It contributes to improving the efficiency and decision-making accuracy of financial risk management [32], [33], [34].

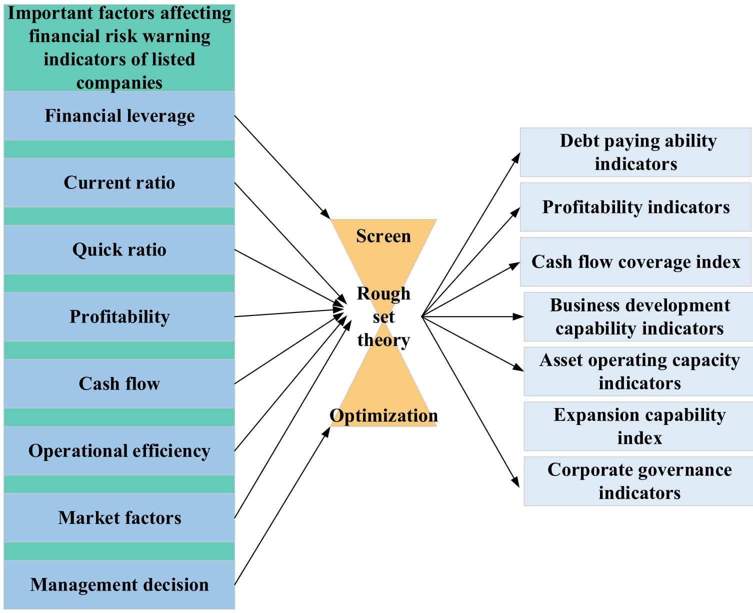


**FIGURE 2.** Financial risk warning indicators for listed companies.

### C. CONSTRUCTION OF A FREW MODEL FOR LISTED COMPANIES BASED ON BPNN

BPNN is a type of multilayer feedforward neural network that utilizes an error backpropagation mechanism. It consists of an input layer, a hidden layer, and an output layer, with data flowing from the input layer through the hidden layer and ultimately to the output layer. If errors occur in the intermediate steps, the network automatically modifies the weights as well as thresholds until the output results reach the desired level of accuracy. This iterative process allows prediction results to gradually approach the target values [35], [36], [37]. Figure 3 represents the structure of the BPNN.

Figure 3 suggests the structure of the BPNN, which can be regarded as a nonlinear function. It uses $X1$, $X2$, …, $X7$ to represent input values and $Y1$, $Y2$ to represent output values. Weight parameters between the input layer and the hidden layer are denoted as the vector $o_{ij}$, and between the hidden and output layers, they are represented as $o_{jk}$. When a BPNN has $n$ input nodes and $m$ outputs, the network can represent a mapping relationship from $n$ to $m$ [38], [39].

In order to ascertain the quantity of nodes in the input layer, it is essential to consider the required quantity of financial risk warning indicators. Here, 7 financial risk warning indicators have been selected, so the BPNN model's input layer contains 7 nodes. The node quantity in the output layer represents the objective quantity in the system. When dealing with the problem, the model first outputs a possible result matrix and then processes the output values into four categories using rounding: high, medium, and low [40], [41]. This corresponds to a three-dimensional matrix, as shown in equation (5).

$$t = \begin{pmatrix} 1\ 0\ 0 \\ 0\ 1\ 0 \\ 0\ 0\ 1 \end{pmatrix} \tag{5}$$

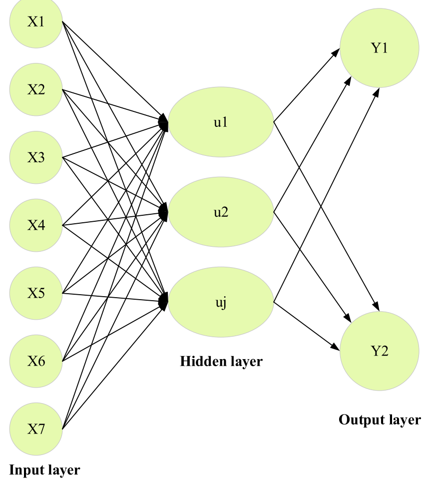


**FIGURE 3.** BPNN structure.

High risk is represented as the vector (1,0,0), medium risk as the vector (0,1,0), and low risk as the vector (0,0,1). Determining the node quantity in the hidden layer requires balancing accuracy and training time. Increasing the node quantity in the hidden layer can enhance network accuracy, but it leads to longer training time [42]. Equation (6) is applied to determine the number of nodes in the hidden layer.

$$l = \sqrt{n+m} + \propto \tag{6}$$

In equation (6), $l$ refers to the node quantity in the hidden layer, $n$ suggests the node quantity in the input layer, $m$ indicates node quantity in the output layer, and ∝' is a constant [43]. Among many activation functions, this work has chosen the tansig function. This function allows for any input values and restricts the output values within

**TABLE 1. Steps for the K-W test on financial risk warning indicators of listed companies.**

| Steps | Illustration |
|---|---|
| *Step 1:* | 1. Null Hypothesis (H0): There is no significant difference in risk identification among different financial indicators, meaning their medians are equal.<br>2. Alternative Hypothesis (H1): At least one financial indicator significantly differs in risk identification, meaning their medians are not all equal. |
| *Step 2:* | Group the data of listed companies based on various financial indicators, with each group representing different values or ranges of a specific indicator. |
| *Step 3:* | Rank the company's data in each group to determine their relative positions within their respective groups. Ranking is the process of assigning positions to companies within each group based on the ascending order of their financial indicator values. |
| *Step 4:* | Calculate the K-W statistic. This statistic is computed based on ranked data and is used to compare the differences in medians among different groups. |
| *Step 5:* | Look up the critical value of the K-W distribution based on the selected significance level (0.05) to determine whether to reject the null hypothesis. If the calculated K-W statistic exceeds the critical value, the null hypothesis is rejected, indicating that at least one financial indicator significantly differs in risk identification. |
| *Step 6:* | If the null hypothesis is rejected, meaning there is a significant difference, further analysis is conducted to determine which financial indicators exhibit significance in identifying risk. |

the range of $[-1, 1]$, considering the data type and precision requirements [44]. BPNN can use different training functions, including trainlm, traingc, and traingd [45]. Due to the moderate model size, comparative analysis is conducted and the trainlm function is selected to improve the algorithm's efficiency [46], [47]. In conclusion, Figure 4 illustrates the algorithm flow of BPNN in FREW for listed companies.

## IV. EXPERIMENTAL DESIGN AND PERFORMANCE EVALUATION

### A. DATASETS COLLECTION

This work chooses financial sector companies from the Shanghai and Shenzhen stock markets in the third quarter of 2022 as research samples, including a total of 88 companies. There are 55 samples used for training and 33 samples for testing. In order to establish this model, financial data for these companies from 2012 to 2022 are used.

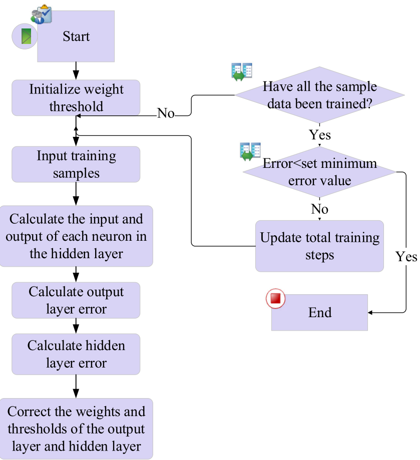


**FIGURE 4. The algorithm flow of BPNN in FREW for listed companies.**

This work aims to implement an effective financial risk warning model to improve the accuracy of risk prediction for listed companies. In the research process, a large amount of data is used, including financial statements, market data, and financial risk event data. However, it should be noted that the dataset used in this work has certain limitations, mainly reflected in terms of time and industry. The time constraints of the dataset may affect the generalization ability of the model, as the rapid changes in financial markets may limit the applicability of the model in different time periods. In addition, due to industry differences, the applicability of the model in specific industries may also be affected to some extent. To overcome these limitations, this work further expands its scope by collecting data from listed companies in different industries and countries for simulation, and constructing a more widely applicable financial risk warning model. This work not only considers traditional industries such as manufacturing and finance, but also introduces emerging industries such as technology and biopharmaceuticals. Moreover, this work incorporates company data from multiple regions such as Asia, Europe, and North America to ensure the applicability of the model in different countries and regions. Specifically, the work collects detailed financial statements, market data, and financial risk event data from companies in countries such as China, Germany, and the United States. This multi-country and multi-industry data collection method helps to comprehensively consider the impact of different market environments and financial systems, and improve the predictive ability of the model for global financial risks. By introducing these more specific and diverse data, it is expected that the work can have a more comprehensive and in-depth understanding of the characteristics of financial risks in different contexts, thereby providing more specific directions for model optimization and improvement.

**TABLE 2. Experimental parameter settings for the FREW model for listed companies based on BPNN.**

| Experimental parameters | Setting |
|---|---|
| *Node quantity in the input layer* | 7 (The number of corresponding financial risk warning indicators) |
| *Node quantity in the hidden layer* | 10 |
| *Node quantity in the output layer* | 3 |
| *Learning rate initialization* | 0.001 |
| *Learning rate decay strategy* | If the validation set loss does not significantly improve for five consecutive epochs, the learning rate is reduced to one-tenth of its original value. |
| *Batch size* | 64 |
| *Dropout adaptive regularization* | 0.2 |
| *Early Stopping Training Strategy.* | Training is stopped if the validation set loss does not improve for three consecutive epochs. |

## B. EXPERIMENTAL ENVIRONMENT

Hardware Configuration: Intel(R)Core(TM)i7 9750H CPU@2.60Ghz 2.59GHz, 16GB of memory.

Software Environment: Operating system: Windows 10; Graphics card: RTX2080Ti(CPU); Data analysis tool: Matplotlib.

## C. PARAMETERS SETTING

Table 2 shows the experimental parameter settings for the FREW model for listed companies based on BPNN.

## D. PERFORMANCE EVALUATION

Figure 5 displays the factor analysis results of FREW indicators for listed companies using the K-W test. According to the factor analysis in Figure 5, the expansion capability indicator (KMO = 0.781) exhibits high usability. Debt-paying capacity indicator (KMO = 0.725) and corporate governance quality indicator (KMO = 0.673) also demonstrate high usability. Profitability indicator (KMO = 0.717) and operational development capability indicator (KMO = 0.54) have moderate usability. On the other hand, the cash flow coverage capability indicator (KMO = 0.5) and asset operational capability indicator (KMO = 0.562) show relatively lower usability. Among these, the expansion capability, cash flow coverage capability, debt-paying capacity, profitability, corporate governance quality, asset operational capability, and operational development capability are financial risk warning indicators with a higher recognition level and significance in factor analysis.

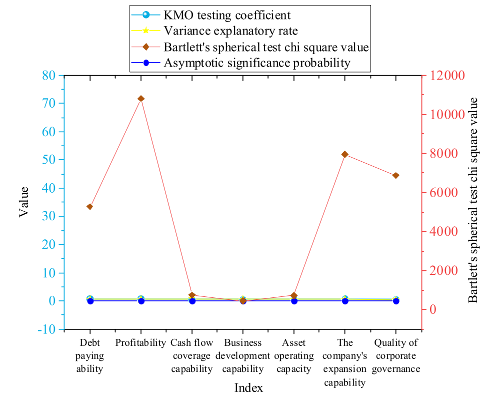


**FIGURE 5. Factor analysis results of financial risk warning indicators for listed companies using the K-W Test.**

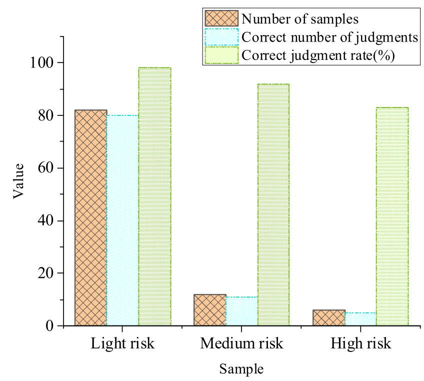


**FIGURE 6. Experimental results of the BPNN model.**

Figure 6 presents the experimental results of the BPNN model. It reveals that for the predictions made by the BPNN model, there are 82 samples in the low-risk category, with 80 of them correctly predicted, resulting in an accuracy of 98%. In the medium-risk category, there are 12 samples, with 11 of them correctly predicted, yielding an accuracy of 92%. In the high-risk category, there are 6 samples, with 5 of them correctly predicted, resulting in an accuracy of 83%. Overall, the BPNN-based FREW model for listed companies demonstrates a high level of accuracy in most cases, particularly in the low and medium-risk categories. This indicates the model's potential to assist with the prediction of financial risks for listed companies and its utility as a valuable tool for financial management and regulation.

Figure 7 presents the cross-validation results of different financial risk warning models and the model presented. It reveals that the model exhibits very high performance in terms of accuracy, recall, and F1 score, reaching 96%, 95%, and 95.50%, respectively. Compared to other models, the model presented has a significant advantage in these key performance indicators, especially in terms of accuracy and F1 score.

Bias-weight trade-off is an important concept used in machine learning to adjust model complexity. It involves the degree of fitting of the model on training data and the impact of weight size on model performance. Bias refers to

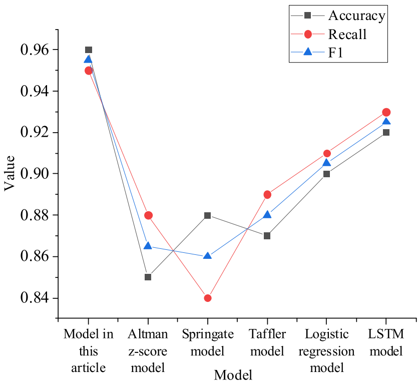


**FIGURE 7.** Cross-validation results of different FREW models and the model proposed.

**TABLE 3.** Bias-weight trade-off results.

| Regularization parameter | Optimization algorithms | Training set accuracy | Verification set accuracy |
|---|---|---|---|
| 0.01 | Adam | 0.95 | 0.92 |
| 0.1 | SGD | 0.92 | 0.90 |
| 0.001 | RMSprop | 0.97 | 0.94 |

the degree of fit of the model to the training data, and a higher bias indicates a lower degree of fit of the model to the data, that is, underfitting of the model. Weight refers to the importance of the features learned by the model, and larger weights may lead to overfitting on the training set and loss of generalization ability for new data. In this work, a bias weight balance was achieved by adjusting regularization parameters and optimizing algorithms. The adjustment of regularization parameters can affect the model's penalty for weights and prevent overfitting on the training set. By optimizing the selection of algorithms, the updating method of weights can be more finely adjusted to find an appropriate balance point, neither overfitting nor underfitting. The results of the deviation weight balance are shown in Table 3:

Table 3 shows the model performance under different regularization parameters and optimization algorithms. When the regularization parameters are moderate, the model achieves good accuracy on both the training and validation sets, exhibiting lower bias and variance. This indicates that the proposed model has found a suitable balance point in the bias-weight trade-off, neither overfitting the training data nor underfitting. This indicates that the proposed model has achieved good results in trade-offs and has strong generalization ability.

### E. DISCUSSION

The BPNN-based FREW model for listed companies is constructed and experimental validation is conducted. The experimental results reveal that the model demonstrates high accuracy in predicting low-risk and medium-risk categories, achieving 98% and 92% accuracy rates, respectively. Compared with existing research, the research results of this work present a series of prominent characteristics. Firstly, compared with the optimized BPNN model proposed by Li et al., the BPNN proposed here shows higher accuracy in predicting financial risks of listed companies [48]. Li et al.'s model achieved an accuracy rate of over 80% in predicting the financial distress of normal companies, while the proposed model demonstrated accuracy rates of 98% and 92% in light and medium risk categories, significantly exceeding their results. Secondly, compared with Liu et al.'s discussion on the positive impact of BPNN-based models on internet financial risk warning, the experimental results of this work emphasize the efficiency of the BPNN model in predicting financial risks of listed companies [49]. In this work, the BPNN model achieves an accuracy of 98% and 92% in light risk and medium risk categories, respectively, further demonstrating the strong effectiveness of the model in financial risk warning. Finally, compared with Li and Quan study on optimizing BPNN parameters through IPSO to construct a financial risk warning model, the proposed model has achieved a more significant advantage in accuracy [50]. The prediction accuracy of Li et al.'s model is 88%, while the proposed model achieves 96%, 95%, and 95.50% accuracy, recall, and F1 score, demonstrating better performance. Overall, the research findings surpass existing research in terms of accuracy and comprehensiveness. This indicates that the proposed financial risk warning model has significant advantages in addressing the financial risks of listed companies, providing more reliable and accurate support for financial decision-making.

## V. CONCLUSION

### A. RESEARCH CONTRIBUTION

This work has made significant contributions in the field of FREW. First, it develops a FREW model for listed companies based on BPNN. This model utilizes rich financial data, accurately identifying companies with different risk levels and demonstrating high accuracy in most cases, particularly in the low-risk and medium-risk categories. Next, this work employs factor analysis and K-W test methods to identify which financial indicators have a high level of recognition and significance in the risk warning model. This helps financial managers to monitor and assess a company's financial health in a more targeted manner. Lastly, through performance comparisons with other financial risk warning models, the work confirms the significant advantages of the model in key performance indicators such as accuracy, recall, and F1 score. It provides robust decision-support tools for financial management and regulation.

### B. FUTURE WORKS AND RESEARCH LIMITATIONS

Although this work has achieved significant results in the field of financial risk warning, there are also some limitations that need to be noted. Firstly, the dataset used may be limited by time and industry, resulting in certain limitations on the model's generalization ability. The rapid changes in the financial market and the differences between different industries may have a certain impact on the applicability of the model. Secondly, although the financial indicators and market data used here are comprehensive, they cannot exhaust all potential influencing factors. Some risk factors in special environments may not be fully considered, which may limit the comprehensiveness of the model. Additionally, although the methods such as K-W test and factor analysis are used in model construction, the interpretability of the model may still be challenged in practical applications. Finally, this work is limited to using BPNN and RST to construct financial risk warning models, and the application of other advanced algorithms may further expand the depth and breadth of the research. Thus, when applying the results of this work to practical decision-making, these limitations should be carefully considered to ensure the effectiveness and reliability of the model. Future research can expand the coverage of research samples to include more industries and market situations to enhance the model's generalization performance. Additionally, further exploration of the application of deep learning techniques can help capture the temporal and nonlinear characteristics of financial risk more effectively.

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