

Research on the financial risk measurement and prediction of small and medium-sized enterprises based on the artificial neural network under AHM-CRITIC coupling

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Abstract. Based on AHM-CRITIC coupling weights combined with an artificial neural network to measure and study the financial risk of SMEs, the financial index system of four primary indicators and ten secondary indicators is constructed by collecting the publicly available financial report information of SMEs. The AHP matrix is obtained by the expert scoring method to calculate the subjective weights, and CRITIC calculates the objective weights, and the weights of both are coupled. The coupled weights are combined with the financial report data of LPMC to build a financial risk index model, and ANN neural network is used to predict and study the financial risk of the enterprise. The backtest curve fits the realistic data well. It can better predict the dramatic fluctuation of financial risk caused by the change of financial environment during the COVID-19 epidemic. The model is useful for SMEs to measure their own financial risks and make reasonable business decisions for the future by combining financial indicators.

Keywords: AHM-CRITIC, coupling weights, SMEs, financial risk, ANN neural network.

1. Introduction

Small and medium-sized enterprises (SMEs) have an important position in economic development and are the backbone of the market. They are important in promoting economic growth, providing jobs, and contributing to fiscal revenue. However, due to their small production scale and financing difficulties, SMEs are exposed to potential financial risks and are more vulnerable to external influences. Once the risk occurs, it will generate negative problems such as unemployment, which is not conducive to stable economic and social development. Therefore, it is crucial to measure and predict the financial risks of SMEs. There is no shortage of studies in this field.

Zheng et al.[1] constructed a credit evaluation index system for SMEs from the perspective of big data technology development, and determined the weights by hierarchical analysis, which provides a reference for measuring the financial risk of SMEs. Lin Jiangpeng et al.[2] used factor analysis and ordered logit model to test the credit rating of SMEs in China. Hu Haiqing et al.[3] conducted a comparative study on the financial risk of SMEs from the perspective of supply chain finance using support vector machines and BP neural networks in machine learning methods. Xiao Binqing et al.[4] conducted a comparative study on credit rating models of micro and small enterprises, and evaluated and compared the rating effectiveness of different models by integrating mathematical and statistical methods and neural networks based on different algorithms. Wang Xin et al.[5] conducted an overview of the current status of research on credit evaluation of SMEs, compiled three research perspectives on evaluation index screening, index weighting and risk level evaluation. They also pointed out that each type of method currently has its advantages and disadvantages, and still needs to be studied in depth to solve and overcome the defects.

The existing studies mainly have the following shortcomings: firstly, the research on financial risk mainly focuses on the macro level, while there is a lack of in-depth research on SME financial risk

measurement in the enterprise dimension; secondly, the weighting methods of financial risk evaluation indicators lack uniformity and have their advantages and disadvantages. Therefore, from the perspective of SMEs, this paper selects four financial indicators of enterprises, determines the subjective weights of indicators by using attribute hierarchy model (AHM) and objective weights by using criteria importance through intercriteria correlation (CRITIC), and assigns weights to indicators by AHM-CRITIC coupling, so as to synthesize the risk index and realize the measurement of financial risks of SMEs. Next, an artificial neural network (ANN) is constructed to predict and analyze the financial risk of SMEs by using each financial indicator as to the input layer and the risk index as the output layer. The results show that the model in this paper can effectively measure the financial risk of SMEs, and it is effective in risk prediction. The research of this paper has some reference significance for the financial risk management of SMEs.

2. Indicator system construction

Corporate financial risk is closely related to a company's financial status. By reviewing the literature, this paper selects a total of 10 variables from four aspects: solvency, operating capacity, profitability and growth capacity, as indicators to measure the financial risk of SMEs.

2.1 Solvency (Y1)

Solvency refers to the ability of an enterprise to repay its debts with its assets and is an important indicator of its financial position. Commonly used indicators to measure solvency are asset-liability ratio, current ratio and quick ratio, etc.[6] The higher the asset-liability ratio, the more funds in the enterprise's assets originate from debt, and the weaker the debt-servicing ability. The higher the current ratio and current ratio, the stronger the liquidity of the enterprise and the stronger the debt servicing ability. According to the literature, this paper uses the asset-liability ratio (X1) and the average of current ratio and quick ratio (X2) as indicators to measure the solvency of enterprises.

2.2 Operating Capacity (Y2)

Operating capacity refers to the ability of a business to run its operations, i.e., the ability of a business to use its various assets to earn profits. Common indicators include current asset turnover ratio (X3), inventory turnover ratio (X4), accounts receivable turnover ratio (X5), etc.[7] Current asset turnover reflects the efficiency of current asset utilization, inventory turnover reflects the liquidity of inventory and the reasonableness of the number of funds occupied by inventory, and accounts receivable turnover reflects the liquidity of accounts receivable. Generally speaking, the higher the above-mentioned three indicators, the better the enterprise's operating ability, and the less likely the financial risks will occur. Therefore, this paper takes them as indicators to measure the operational capability of enterprises.

2.3 Profitability (Y3)

Profitability refers to the ability of a company to make profits and reflects the level of earnings of the company in a certain period. Common indicators include return on assets (X6), sales margin (X7), etc.[8] The return on assets reflects the efficiency of the enterprise's asset utilization, and the sales margin is used to measure the level of revenue of the enterprise's sales revenue. The higher the return on assets and sales margin, the more profitable the enterprise is and the lower the financial risk. In this paper, the above two indicators are selected to measure the profitability of enterprises.

2.4 Growth capacity (Y4)

Growth capacity refers to the ability of an enterprise to expand its business and reflects its future development trend. Commonly used indicators include total assets growth rate (X8), main business income growth rate (X9), net profit growth rate (X10), etc.[9] The growth rate of total assets reflects the enterprise's ability to expand and increase the value of assets, the growth rate of main business

income reflects the competitiveness of the enterprise's business, and the growth rate of net profit reflects the growth of the enterprise's profitability. The higher the above three indicators are, the better the expectation of enterprise growth and development, and the lower the probability of financial risk. Therefore, this paper uses them as indicators to measure the growth ability of enterprises.

Table 1 Financial risk measurement index system

Tier 1 Indicators	Secondary indicators	Code
Solvency Y1	Asset-liability ratio	X1
	Average of current ratio and a quick ratio	X2
Operating Capacity Y2	Current asset turnover ratio	X3
	Inventory turnover ratio	X4
	Accounts receivable turnover ratio	X5
Profitability Y3	Return on assets	X6
	Sales margin	X7
Growth capacity Y4	Total assets growth rate	X8
	Main business revenue growth rate	X9
	Net profit growth rate	X10

3. AHM-CRITIC Empowerment

3.1 AHM Empowerment

Attribute Hierarchy Model (AHM) is a subjective assignment method, an algorithm based on the hierarchical analysis method (AHP), which has not only the advantages of AHP, but also has the features of simplicity and speed, no need to calculate feature vectors and check the consistency.

The steps of AHM empowerment are as follows.

Step1 Determines the weights of assessment indexes. AHM determines the relative importance scales among the assessment indexes before establishing the attribute discriminant matrix.

The nine-level scale method was proposed by Satty based on Weber-Fechner's psychological theory. In this method, the relative degree of preference among indicators is quantified as the important factor of each indicator, which is divided into a total of nine levels, and an appropriate value is assigned to each level. The details are shown in the following table.

Table 2 9-level scale assignment

Relative Importance	Meaning
1	The effect of factor i is the same as that of factor j.
3	The effect of factor i is slightly stronger than that of factor j.
5	The effect of factor i is stronger than that of factor j.
7	The effect of factor i is significantly stronger than that of factor j.
9	The effect of factor i is definitely stronger than that of factor j.

In this paper, the nth-order AHP discriminant matrix $\mathbf{K} = (k_{ij})_{n \times n}$ is obtained by expert scoring method using 1~9 scales theory, where k_{ij} indicates the importance of element i compared with element j, and the AHP discriminant matrix $\mathbf{K} = (k_{ij})_{n \times n}$ has the following properties.

$$\begin{cases} k_{ij} > 0 \\ k_{ii} = 1 \\ k_{ji} = 1/k_{ij} \end{cases} \quad (1)$$

where $i \neq j$, $1 \leq i \leq n$, and $1 \leq j \leq n$.

Step2 Constructs the attribute discriminant matrix. In AHM, the relative attributes l_{ij} form an nth-order attribute discriminant matrix $\mathbf{L} = (l_{ij})_{n \times n}$, and the relative attributes l_{ij} have the following transformation relationship with the scale k_{ij}

$$l_{ij} = \begin{cases} 2q / (2q+1) & k_{ij} = q, i \neq j \\ 1 / (2q+1) & k_{ij} = 1/q, i \neq j \\ 0.5 & k_{ij} = 1, i \neq j \\ 0 & k_{ij} = 1, i = j \end{cases} \quad (2)$$

where q is a positive integer not less than 2.

Step3 Calculate the relative attribute weights of each indicator. According to the AHM algorithm flow, the relative attribute weights W_{AHM} of each indicator are calculated by the following equation.

$$W_{AHM} = \frac{2}{n(n-1)} \sum_{j=1}^n l_{ij} \quad (3)$$

where: $i = 1, 2, \dots, n$, and n is the number of indicators.

3.2 CRITIC Empowerment

CRITIC is an objective weighting method based on the comparative strength of evaluation indicators and the conflict between indicators to measure the objective weight of indicators. It considers the correlation between the indicators while considering the magnitude of variability of the indicators, not the larger the number means, the more important, and completely uses the objective properties of the data itself for scientific evaluation. The method uses standard deviation to indicate the size of the gap between the values taken by the evaluation scheme; the indicator correlation indicates the conflicting nature of the evaluation indicators, and is an effective method to study the determination of objective weights of indicators. The specific steps of the method are as follows.

Step1 Constructs the correlation coefficient matrix.

$$r_{ij} = \frac{\sum_{i=1}^n (x_i - \bar{x}_i)(x_j - \bar{x}_j)}{\sqrt{\sum_{i=1}^n (x_i - \bar{x}_i)^2 \sum_{j=1}^n (x_j - \bar{x}_j)^2}} \quad (4)$$

Where: $\bar{x}_i$ is the mean of all programs in X_i the indicator; $\bar{x}_j$ is the mean of all programs X_j in the indicator; r_{ij} is the correlation coefficient between the indicator X_i and the indicator X_j .

Step2 Finds the combined weight W_{CRI} of each indicator.

$$\begin{cases} W_{CRI} = \frac{C_j}{\sum_{i=1}^n C_j} \\ C_j = \sigma_j \sum_{j=1}^n (1 - r_{ij}) \end{cases} \quad (5)$$

3.3 Coupling Construction

After obtaining the subjective weights W_{AHM} and objective weights W_{CRI} , the multiplicative synthetic normalization method is used to find the coupling weights because it can effectively reflect the relative weight relationship of each index and its weight share in the whole.

$$W = \frac{W_{AHM} \quad W_{CRI}}{\sum_{j=1}^n W_{AHM} \quad W_{CRI}} \quad (6)$$

4. ANN construction

Artificial neural network (ANN) is a nonlinear dynamic system composed of a large number of

neurons, which abstracts the neuronal network of human brain from the perspective of information processing, builds some kind of simple model, and forms different networks according to different connections.

4.1 Artificial neuron model

Artificial neurons are simulations and abstractions of biological neurons, the basic processing units of neural networks. Most of the current artificial neural network models use the M-P model jointly proposed by psychologist W. McCulloch and mathematical logician W. H. Pitts. The following figure represents an artificial neuron model.

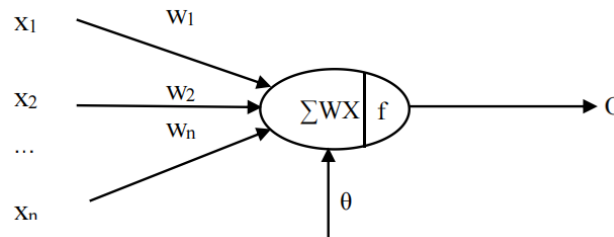


Figure 1 Artificial neuron model

In the figure $X = (x_1, x_2, \dots, x_n)$ is the n inputs of this neuron, the outputs from external or other neurons. $w = (w_1, w_2, \dots, w_n)$ denotes the strength of the connection between the n neurons connected to this neuron, called the weights; $\sum WX$ is called the activation value and denotes the sum of the inputs of this artificial neuron; O denotes the output of this neuron; and θ represents the threshold value of this artificial neuron. When the weighted sum of this input signal exceeds C , the artificial neuron is activated. In this way, the output of the artificial neuron can be described as

$$O = F(\sum WX - \theta) \quad (7)$$

which $f(\cdot)$ represents the neuron input-output relationship function, is called the activation function or output function. The threshold value is θ generally not a constant; it varies with the excitation level of the neuron.

Figure 2 shows a classical 3-layer neural network structure, including input, hidden and output layers. In the structure figure 2, each small circle represents a neuron, and each connection represents a different weight (weight), which can be obtained by training. The neurons are interconnected to form a network topology.

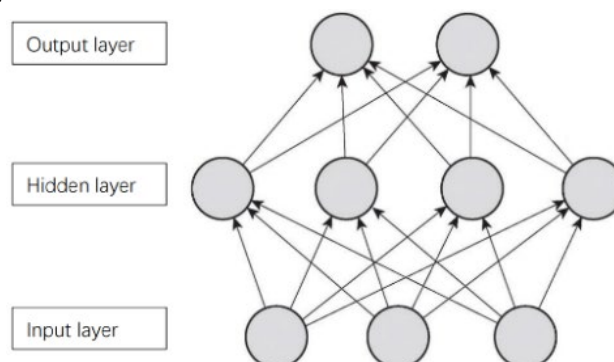


Figure 2 Neural network structure diagram

In this paper, the input layer of the ANN is the coupled weights obtained by AHM-CRITIC for the leading risk indicators of a specific firm, and the output layer is the corresponding risk prediction value. That is, the risks of SMEs are quantified using artificial neural networks.

4.2 activation function

In neural networks, the ability and efficiency of the network to solve problems depend largely on the activation function used by the network and the network structure. The choice of the activation function has a large impact on the convergence speed of the network, and the choice of the activation

function should be different for different practical problems. The function used in this case is the S-shaped function (Sigmoid). Its expression is.

$$f(x) = \frac{1}{1 + \exp(-x)} \quad (8)$$

The output of this function lies between 0 and 1, and it is the most widely used activation function in neurons.

5. Empirical Analysis

5.1 Research Subject Identification and Data Collection

In the study of small and medium-sized enterprises, in order to select representative enterprises, the sample of research companies is set in the GEM50 index where small and medium-sized enterprises are concentrated, of which LP Medical is a sample stock or a more prominent pharmaceutical concept in the capital market in recent years, which is suitable as a research object company. In this paper, we select the public financial data of LOPE Medical in recent nine years, and select ten a combination of secondary indicators to become four a primary indicator for analysis. The data was collected and processed through the public channel NetEase Finance.

5.2 Index Synthesis

In studying the financial risk measurement of SMEs, the company's financial risk is usually examined from four primary indicators, which can be subdivided into several secondary indicators. We invited several relevant experts to score and construct the AHP discriminant matrix of each index, and then converted it into the attribute discriminant matrix by the formula, based on which the attribute weights of each evaluation indicator are calculated.

Table 3: AHP discriminant matrix and weights of primary indicators

	Y1	Y2	Y3	Y4	WA
Y1	0	1/2	1/9	1/3	0.157
Y2	1/2	0	1/15	1/9	0.113
Y3	8/9	14/15	0	1/2	0.387
Y4	6/7	8/9	1/2	0	0.374

Table 4: AHP discriminant matrix and weights of Y2 secondary indicators

	X3	X4	X5	WC
X3	0	1/5	2/7	0.162
X4	4/5	0	2/5	0.400
X5	5/7	3/5	0	0.438

Table 5: AHP discriminant matrix and weights of Y1 secondary indicators

	X1	X2	WB
X1	0	1/5	0.200
X2	4/5	0	0.800

Table 6: AHP discriminant matrix and weights of Y3 secondary indicators

	X6	X7	WD
X6	0	1/3	0.333
X7	2/3	0	0.667

Table 7: Y4 AHP discriminant matrix and weights of secondary indicators

	X8	X9	X10	WE
X8	0	1/5	7/8	0.358
X9	4/5	0	1/3	0.378
X10	1/7	2/3	0	0.270

The subjective weights and objective weights are obtained from the above judgment matrix and CRITIC assignment method and coupled by the formula (6). Finally, the coupling weights of AHM-CRITIC are obtained, and the results are shown in graph 2.

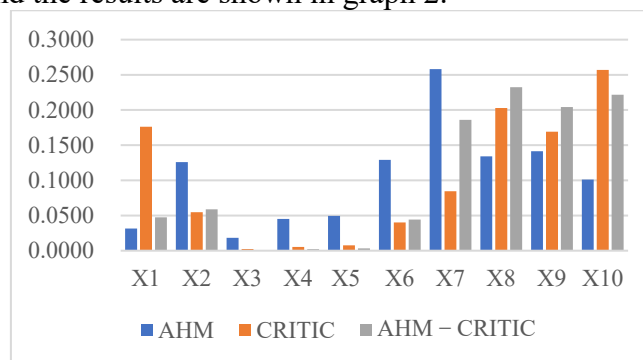


Figure 3: Evaluation results of different empowerment methods

Combined with the graph 2, the analysis of different assignment methods, we can see that the three indicators for X1 (gearing) AHM assignment result is 0.0315, CRITIC assignment result is 0.1763. However, after coupling the two weights is 0.0474, closer to the AHM assignment, a good balance between the subjective and objective difference how much imbalance.

In business operations, the gearing ratio is an indicator that measures the ability of the enterprise to use creditors to provide funds for business activities and reflect the security of creditors to issue loans. Subjective scoring is relatively low weight for the analysis of financial risk with this indicator. However, objectively higher liabilities of assets are a financial risk, so there will be a large difference.

For X6 (return on assets), the same, return on assets is to evaluate the ability of managers to use various sources of funds to earn compensation. The better the subjective scoring of this indicator in business operations, it naturally means that the company's profitability is stable and financial risk is small, so the weight is significant. The weight of AHM is 0.1290, nearly three times 0.0401 the objective weight, but the weight after coupling for the deviation of the higher subjective scoring is well corrected. The AHM -CRITIC is 0.0442, precisely illustrates that the coupled weights are more comprehensive and stable than the general weights when used in combination with an assignment method like AHM, which makes use of the relativity of the size of numbers, and CRITIC, which analyzes indicators or factors that have a certain correlation between them.

In the processing of the data afterward, the data are normalized to the maximum and minimum values and then combined with the calculation method: $\text{Risk_Index} = \sum (\text{secondary indicator data} * \text{weight})$ to obtain the Risk_Index for each reporting period (Risk_Index).

5.3 Prediction and Analysis

In this prediction and analysis, the data is firstly preprocessed, the normalization method is chosen as maximum-minimum normalization method, the Tanh function is used as activation function, the ratio of training set and validation set is divided into 7:3, the number of hidden layers of the neural network is one layer, the number of nodes in the layer is 4, the value of MSE is obtained by calculation 0.000274445, the MSE calculation formula is shown in (9), the training accuracy is shown in Fig.3, the lag time series is predicted with a step size of 3, and reasonable analysis is made based on the predicted and measured charts, the predicted value and measured value fit well along $Y = X$, and the prediction result is shown after training is displayed in Fig.4

$$MSE = \frac{1}{n} \sum_{i=1}^m w_i (y_i - \hat{y}_i)^2 \quad (9)$$

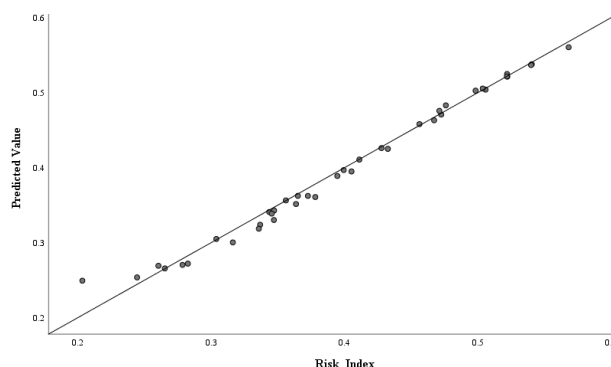


Figure 4: Predicted - measured graph

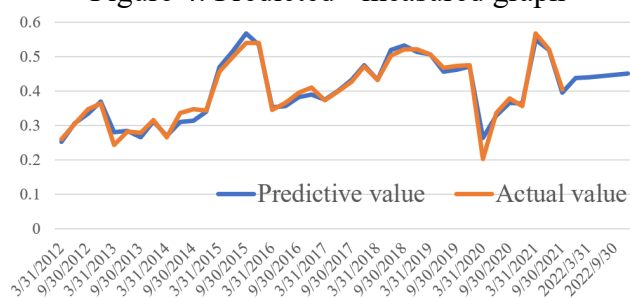


Figure 5: Predicted and measured fit

It can be seen from the comparative analysis of Figure 3 that the values of the predicted risk index and the actual risk index are mostly on both sides of the straight line $y=x$, with a low degree of dispersion, no excessive deviation, and a high degree of prediction fit.

Combined with the analysis in Figure 4, it can be seen intuitively that the current model fits well, and there is no significant deviation, especially in the reporting period from September 2019 to July 2020, from the drastic changes in its financial risk index. Obviously, this period coincides with the epidemic period of COVID-19. Due to the impact of the epidemic and the downward pressure on the economy during this period, financial risks fluctuated wildly. Combined with the principle of time lag, it is predicted that the overall financial risk will rise in 2022 with a 4-digit step size.

The analysis of the financial indicators in the model can be seen in the figure5, which can be learned from the composition of the risk index in the degree of importance of its secondary indicators are as follows: $X_{10} > X_1 > X_2 > X_8 > X_5 > X_9 > X_3 > X_4 > X_7 > X_6$. It can be seen that the importance of X_{10} (net profit growth rate) is the highest proportion. Combined with the actual situation, the higher the growth rate of net profit, the stronger the company's ability to create value. Moreover, the increase in cash flow brought by the increase in corporate profit is conducive to resist financial risks in a complex environment and help the company grow better. Hence, the corporate strategy can be shifted to progressive expansion when the growth rate of net profit is high, and vice versa to conservative management to prevent possible financial risks.

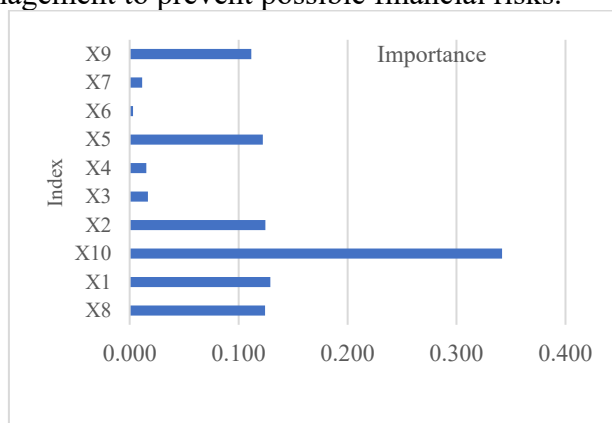


Figure 6: Normalized importance of each indicator

The importance of the first-level indicators can be derived from the product of the importance of the second-level indicators and the coupling weights. The importance of the first-level indicators is six ranked as follows: $Y4 > Y3 > Y1 > Y2$.

The graph analysis shows that for SMEs, Y4 (growth capacity) is the top priority for financial risk prevention, and companies with stronger growth capacity can resist financial risks through continuous growth. It is recommended that SMEs strengthen their financial risk prevention capability by starting from their growth capability, increasing the net profit growth rate, and strategically orienting towards their main business to increase the growth of their main business and further drive the growth of their total assets.

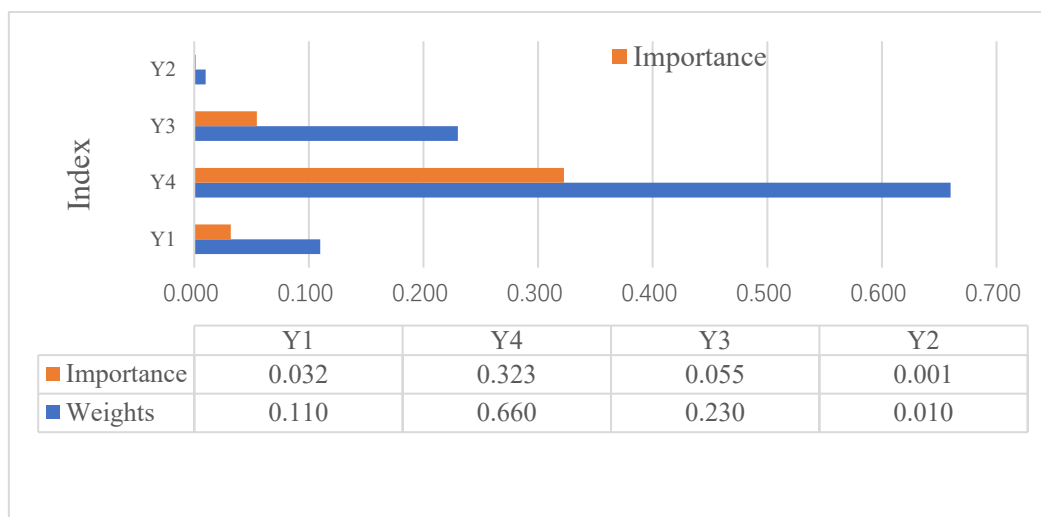


Figure 7: Importance and weighting of primary indicators

The significance of this research is that through the research of artificial neural network based on AHM-CRITIC coupling in the financial risk measurement and prediction of SMEs government banks and other service institutions can make accurate control of the financial risk of enterprises. In addition, the artificial neural network can help predict the small and medium-sized enterprises with significant financial risks and use the internal financial data of the enterprise for statistical sorting to diagnose the possible short-term financial risks of the enterprise and find problems in time and improve solutions.

6. Conclusion

This paper focuses on analyzing and predicting financial risk measures for SMEs based on AHM-CRITIC coupling weights. The enterprise is selected as the underlying based on the medical sector, which has received a lot of capital attention in the capital market in recent years.

The AHP index matrix is constructed, and the subjective weights are calculated by taking the financial report data of the company in recent years. Then the objective weights are solved by the CRITIC assignment method, and the two are coupled to obtain the AHP-CRITIC coupling weights.

The data are normalized and combined with the weights to obtain the risk index (Risk_Index) for each reporting period. The data are trained to predict based on ANN neural network.

Two final conclusions can be drawn.

(1) This paper combines the subjective weights of AHM with the objective weights of CRITIC to make up for the shortcomings of a single assignment and construct a coupled AHM-CRITIC assignment mechanism; quantifies the relative relationship between samples and criteria, and establishes a financial risk measurement model based on the AHM-CRITIC assignment.

(2) Applying the model to the prediction and analysis of financial risk metrics with LOPE Medical as the sample, the predicted financial risk index obtained is in line with the actual expectation. Due to the limitation of the information in this study, the sampling of individual SME financial data cannot

reflect the overall financial risk degree of SMEs, and the sampling scope can be expanded to carry out a larger scale of prediction and analysis research in the later stage.

Through the above construction and analysis, it can be concluded that the MLP prediction model constructed in this paper can better predict the risk index, thus facilitating the construction of later prediction and analysis models for SME financial risk metrics.

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