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Article

Logistic Regression Analysis of Operational Risk and Financial Management in Cloud Accounting Model in Big Data Environment

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Abstract: In the production activities, from the financial risk can detect the risk of the enterprise's various business activities, the management of financial risk will also be for the enterprise's business management, capital utilization to improve the proposal. This paper constructs a logistic regression model, uses the great likelihood estimation method to solve the model, and derives the formula for calculating the parameter estimates according to the Logistic function. The sample of the tested enterprise is established, and the model of financial early warning index system is constructed by combining the reasons for the formation of enterprise financial risk and related research. The model is applied to the estimation of the financial risk level of enterprises after passing the test. During the period of 2020-2024, the financial risk warning value of the subject A enterprise is 73.6563, 55.877, 63.3313, 74.9454, 84.545, and the risk level is level 8 risk, level 6 risk, level 7 risk, level 8 risk, and level 9 risk, respectively, and the financial risk of this enterprise is increasing year by year. Analyzing the specific financial indicators of this enterprise, the cash ratio declined slightly from 0.9264 in 2020 to 0.8496 in 2021, and has been fluctuating during 2021-2024, with a value lower than 1, which indicates that the actual quality of profitability of this enterprise is not good, and it needs to draw the attention of the management. For the financial management problems of enterprise A, relevant countermeasures are proposed.

Keywords: logistic regression; great likelihood estimation; parameter estimates; financial management

1. Introduction

In the era of big data, the financial management challenges faced by enterprises and organizations are increasing. Traditional financial management methods can no longer meet the changing market demand and business development requirements, and need to be upgraded and transformed with the help of new technologies [1-4]. The emergence of big data technology has brought new opportunities and challenges for financial management, and the application of big data technology not only improves the efficiency and accuracy of financial management, but also broadens the content and methods of financial management. In this context, cloud accounting has emerged as an important part of financial management [5-8].

Cloud accounting refers to placing the accounting business in the cloud for processing, and realizing the informatization, networking and intelligence of enterprise financial management with the help of Internet technology. It is supported by cloud computing technology, which puts the enterprise's financial data storage, processing and analysis on cloud servers, realizing data sharing, collaboration and security [9-12]. Big data technology has brought revolutionary changes to accounting and promoted the digitalization, intelligence and cloudization of accounting, and cloud accounting, as a financial management method based on the background of big data, has gradually been recognized and

applied by enterprises and organizations for its high efficiency, security and convenience [13-16]. However, cloud accounting has some problems in actual operation, mainly including data privacy, service quality and operational risk. Since cloud accounting stores financial data in the cloud, its data security has also received much attention [17-20]. In addition, the service quality and operational stability of cloud accounting are also one of the important factors affecting enterprises to choose cloud accounting. Therefore, when choosing a cloud accounting service provider, enterprises need to fully consider these issues and select a trusted service provider for cooperation [21-24].

As an application field of cloud computing technology, cloud accounting has become the first choice of many enterprises. Cloud accounting offers many benefits, such as cost savings, data sharing, and increased flexibility. However, like any emerging technology, cloud accounting has some potential risks and security concerns. Literature [25] examines the risks of cloud-based accounting systems and services, points out that cloud accounting creates specific risks for the "accounting process", and describes measures such as vendor selection, policy development, and staff training that can help to reduce the risks of cloud accounting. Literature [26] explains the importance of utilizing cloud technology in the accounting field for enterprises, and emphasizes the risks associated with cloud technology, including data integrity, security, etc., and suggests that enterprises build the necessary technological facilities and models to achieve system operation and data security. Literature [27] describes that cloud accounting promotes the development of enterprise accounting informatization, but in the process of operating cloud accounting, it exposes the risks of information and data security, enterprise financial system, etc. Based on the characteristics of cloud accounting, it establishes the enterprise cloud accounting risk evaluation index system, and unfolds the analysis of the risk status of cloud accounting. Literature [28] emphasized the advantages of cloud accounting, which are of great significance for small and medium-sized enterprises, regardless of the size or activities of the enterprise, cloud accounting can have a significant positive impact on the business of the enterprise, and revealed some of the risks of cloud accounting. Literature [29] discusses the impact of network governance on reducing the risks of cloud accounting, gets a positive conclusion and that this impact is significant and makes a recommendation that network governance be adopted as a solution to the risks associated with the use of cloud accounting. Literature [30] systematically describes cloud accounting, the opportunities and risks it presents, and the impact it may have on the accounting industry, and the conclusions of the study are conducive to a better understanding of the use of cloud accounting by companies and provide a reference for accounting students to understand this industry. Literature [31] describes the importance of cloud accounting for enterprises in the context of the big data era, which improves the efficiency of enterprise accounting, improves the application mode of traditional accounting information, and examines the structure of the enterprise cloud accounting system, and puts forward the effective measures of risk management in cloud accounting.

Financial management plays an important role in enterprise operation and development. For enterprise financial management, the use of cloud accounting model is a new challenge, and at the same time, it is also an important way to improve the level of financial management, which provides new possibilities for the development of enterprise financial management. Literature [32] emphasizes that the big data era has brought unprecedented cloud accounting mode for all enterprises, and enterprises realize financial management analysis by relying on data platforms and cloud computing platforms, so as to effectively cope with the shortcomings of economic development and enhance market competitiveness. Literature [33] analyzes the financial management informatization model of small and medium-sized enterprises, outlines the financial management of small and medium-sized enterprises in the context of cloud computing, explores the effective implementation strategy of the enterprise financial management informatization model, and points out the precautions for constructing the cloud computing financial management informatization model. Literature [34] explored the impact of cloud accounting on enterprise financial transparency and decision-making, showing that cloud accounting not only improves financial transparency, but also enhances decision-making by providing accurate financial information, but there are problems such as difficulties in system integration, and it is suggested to solve these problems by training and formulating policies to accelerate the adoption of cloud accounting. Literature [35] examined the relationship between the financial performance of manufacturing firms and the costs associated with cloud accounting, revealing that an effective cost management system is important for manufacturing firms to achieve sustained profitability and emphasizing the need for prudent financial strategies in the face of evolving technologies in accounting. Literature [36] built a cloud accounting IT audit model based on big data technology and constructed an evaluation index system to verify the effectiveness of the model, which can provide more accurate data analysis results for enterprise financial decision-making and contribute to the sustainable development of enterprises.

This paper explores the Logistic basic principle, assumes that the dependent variable of enterprise

financial operation risk is a dichotomous variable, makes Logit transformation of the target probability to get the whole set of real numbers, and analyzes the level of enterprise financial risk through Logistic regression. The Forward method is chosen as the covariate selection method, and the financial early warning indicator system is constructed from the aspects of solvency, operating ability and profitability. Logistic regression is done on the indicator system to get the Logistic financial early warning model, and the testing effect of the model is verified through the analysis of goodness-of-fit and prediction accuracy. The model is applied to the financial operation risk assessment of an enterprise, evaluating its financial risk level, specifically analyzing the level of financial risk indicators of the tested enterprise, and proposing corresponding management strategies for the existing financial operation risk problems.

2. Construction of an early warning model for corporate financial risk based on logistic regression modeling

2.1. Logistic regression fundamentals

2.1.1. Fundamentals of Logistic

Logistic regression analysis, which is regression when the dependent variable is a categorical variable, is mainly used to find risk factors (e.g., to find risk factors for a particular disease) or for prediction, which can be based on a regression model that predicts what the probability of a certain situation will occur under different conditions of the independent variable [37]. Since the target probability takes values between 0 and 1, it is necessary to do a Logit transformation of the target probability to transform the interval of values into the whole set of real numbers, and the regression analysis treated in this way is Logistic regression.

Logistic regression independent variables can be either continuous or categorical, and the dependent variable can be binary or multicategorical, but binary is more commonly used and easier to interpret, so the most commonly used in practice is binary logistic regression.

Logistic regression usually assumes the premise that the dependent variable is a dichotomous variable, the dependent variable is assumed to be a function of the K independent variables, the relationship between the dependent variable and the independent variables is nonlinear, and there is no multicollinearity between the independent variables.Logistic regression does not impose strict restrictions on whether the independent variables follow a normal distribution.

The Logistic model assumes that the probability of an event occurring obeys the cumulative probability distribution function of the standard Logistic.

Logistic distribution function:

$$Y_i^* = \frac{1}{1+e^{-X_i B}} = \frac{1}{1+e^{-Z_i}} = \frac{e^{Z_i}}{1+e^{Z_i}} \tag{1}$$

Let the dependent variable be Y, whose value 1 means that the event occurred and 0 means that the event did not occur, the m independent variable affecting Y is denoted as $X_1, X_2 ... X_m$, and the conditional probability of the event occurring is denoted as $P(Y=1/X_i)=P_i$. If Y_i^* is an unobservable hidden variable, but it can be corresponded to an observable variable Y_i, and Y_i dichotomous variables (if $Y_i^* > 0$, $Y_i = 1$, and if $Y_i^* < 0$, $Y_i = 0$), the above equation can be expressed as:

$$\begin{aligned} P_i = E(Y_i / X_i) &= \frac{1}{1+e^{-X_i B}} = \frac{1}{1+e^{-Z_i}} \\ 1-\mathrm{P}_i &= 1-\frac{1}{1+e^{-Z_i}} = \frac{e^{-Z_i}}{1+e^{-Z_i}} \end{aligned} \tag{2}$$

where P_i represents the probability that the event occurs in the i nd observation and $1-P_i$ represents the probability that it does not occur in the i th observation, both of which are nonlinear functions consisting of independent variables X_i.

The ratio of the probability of an event occurring to the probability of it not occurring $P_i/(1-P_i)$ is known as the incidence ratio of the respectable piece, denoted Odds, which is positive and has no upper bound, and a logarithmic transformation of which enables the linear pattern of the logistic regression model to be obtained:

$$In(P_i/(1-P_i)) = a + \sum b_i X_i \tag{3}$$

It is generally common to encounter Logistic models based on non-cluster or individual data where a good estimate of the probability of an event occurring (i.e., P_i) cannot be obtained, in which case both OLS and weighted least squares are not helpful. For such Logistic models for non-cluster or individual data, they need to be solved using great likelihood estimation.

Let n cases $Y_1, Y_2, ..., Y_n$ be randomly selected as samples from the population, and let $P_i = P(Y_i = 1/X_i)$ be the probability of $Y_i = 1$ under the given X_i conditions. Similarly, the probability of $Y_i = 0$ can be expressed as $P(Y_i = 0/X_i) = 1 - P_i$. The probability of both can be expressed as $P(Y_i) = P_i^{Y_i}(1-P_i)^{1-Y_i}$, where $Y_i = 1$ or $Y_i = 0 (i = 1, 2, ..., n)$. Since the observations are independent of each other, a sufficiently necessary condition is that their joint probability distribution (set to $L = (\theta)$) is equal to the product of the marginal distributions:

$L(\theta) = \prod_{i=1}^{n} P_i^{Y_i}(1-P_i)^{1-Y_i}, L = (\theta)$ is the likelihood function of the n observations.

For a deterministic Y_i it is a function of β_0 and $\beta_i (i = 1, 2, \ldots, P)$, i.e:

$$P_i = \frac{e^{\beta_0 + \beta_1 X_{i1} + \beta_2 X_{i2} + \cdots + \beta_\rho X_{i\rho}}}{1 + e^{\beta_0 + \beta_1 X_{i1} + \beta_2 X_{i2} + \cdots + \beta_\rho X_{i\rho}}} \tag{4}$$

The objective is to find the parameter estimates that maximize $\ln[L(\theta)]$. Based on the Logistic function, the formula can be obtained:

$$P_i = P(Y_i = 1/X_i) = \frac{e^{\beta_0 + \beta_1 X_{i1} + \beta_2 X_{i2} + \cdots + \beta_p X_{i\rho}}}{1 + e^{\beta_0 + \beta_1 X_{i1} + \beta_2 X_{i2} + \cdots + \beta_p X_{i\rho}}} \tag{5}$$

$$\begin{aligned}
\ln[L(\theta)] &= \ln\left[\prod_{i=1}^{n} P_i^{Y_i}(1-p_i)^{1-Y_i}\right] \\
&= \sum_{i=1}^{n}\left[Y_i \ln(P_i) + (1-Y_i)\ln(1-P_i)\right] \\
&= \sum_{i=1}^{n}\left[Y_i \ln(\frac{P_i}{1-P_i}) + \ln(1-P_i)\right] \\
&= \sum_{i=1}^{n}\left[Y_i(\beta_0 + \sum_{j=1}^{p}\beta_j X_{ij}) + \ln(1 - \frac{\exp(\beta_0 + \sum_{j=1}^{p}\beta_j X_{ij})}{1 + \exp(\beta_0 + \sum_{j=1}^{p}\beta_j X_{ij})})\right] \\
&= \sum_{i=1}^{n}\left[Y_i(\beta_0 + \sum_{j=1}^{p}\beta_j X_{ij}) - \ln(1 + \exp(\beta_0 + \sum_{j=1}^{p}\beta_j X_{ij}))\right]
\end{aligned} \tag{6}$$

The above equation becomes the likelihood logarithmic function [38]. In order to find the coefficients to maximize $L = (\theta)$, take the partial derivatives of $\beta_j (j = 1, 2, \ldots P)$ separately and make them zero, as:

$$\frac{\partial \ln[L(\theta)]}{\partial \beta_0} = \sum_{i=1}^{n}(Y_i - \frac{\exp(\beta_0 + \sum_{j=1}^{p}\beta_j X_{ij})}{1 + \exp(\beta_0 + \sum_{j=1}^{p}\beta_j X_{ij})}) = 0 \tag{7}$$

$$\frac{\partial \ln[L(\theta)]}{\partial \beta_j} = \sum_{i=1}^{n}(Y_i - \frac{\exp(\beta_0 + \sum_{j=1}^{p}\beta_j X_{ij})}{1 + \exp(\beta_0 + \sum_{j=1}^{p}\beta_j X_{ij})})X_{ij} = 0 \tag{8}$$

$$j = 1, 2, \ldots P$$

$\hat{\beta}$ from the above equation, is the great likelihood estimate, while the corresponding estimate of the conditional probability is $\hat{\beta}_i$. This value is the probability estimate of $Y_i = 1$ given X_i, which represents the fitted or predicted value of the logistic regression model. I.e:

$$P_i = \frac{e^{\beta_0 + \beta_1 X_{i1} + \beta_2 X_{i2} + \cdots + \beta_p X_{ip}}}{1 + e^{\beta_0 + \beta_1 X_{i1} + \beta_2 X_{i2} + \cdots + \beta_p X_{ip}}} \tag{9}$$

2.1.2. Logistic regression process

This paper takes 310 enterprises as samples, defines 2020 as year t-0, and selects the cross-section data of year t-1, year t-2 and year t-3 before the occurrence of distress as samples to build the model respectively. At year t-4, the difference between financial risky enterprises and normal enterprises is not obvious, and the effective prediction period of financial risk often starts at year t-3. The results of financial risk discrimination based on operational risk are taken as the explanatory variables, i.e., the categorical variable Type(1,0), the highest risk level (red) is defined as financial risk, denoted as 1, and the other categories are uniformly defined as non-distressed, denoted as 0. 25 early warning indicators (X1 to X25) constructed based on the logistic regression system are taken as the explanatory variables X, i.e., the regression dependent variables. The statistical software used in this paper is Spss16.0, and the logistic regression analysis process was executed through the Analysis-Regression-Binary Logistic command. Variable screening for logistic stepwise regression uses a test statistic, such as the likelihood ratio statistic $G = 2(InL^{(1)}_1 - InL^{(1)}_0)$ as a variable screening criterion, to decide whether X_j is introduced into the model by comparing the models with and without X_j and X_j when proceeding to step 1. Parameter estimation for Logistic regression model can be done by maximum likelihood method or iterative method. The tests in this paper are likelihood ratio test and Wald test.

The methods used to specify the covariates to enter the model are given as kind of options, and the methods chosen in this paper based on the prediction accuracy and the efficiency of the model implementation include three main ones.

Forward: forward stepwise method (likelihood ratio), variables are introduced based on the significance level of the score statistic, and variables are excluded based on the probability value of the likelihood ratio statistic obtained from maximum partial likelihood estimation.

Forward: Wald's forward stepwise method (Wald's method), where the variable is introduced based on the significance level of the score statistic and the variable is dropped based on the probability value of the statistic.

Backward: the LR backward stepwise method (Likelihood Ratio), where variables are excluded from the model on the basis of the probability value of the likelihood ratio statistic obtained from the maximum partial likelihood estimation.

Since 25 variables is too many relative to a sample of 310, the Forward method is the most applicable, and this paper found no difference in results when each method was tested separately.

2.2. Enterprise operation risk early warning system construction

2.2.1. Sample Selection and Data Sources

This paper screens the enterprises whose main business is in the five major fields of manufacturing in the listed enterprises, and considers the leading enterprises of traditional industries and the concept stocks of manufacturing industry recognized by major financial institutions when choosing the samples, and excludes the listed companies that have been ST in the last three years and those whose data are incomplete, and establishes 310 enterprises of high-end manufacturing industry, and the scope of the samples chosen in this paper is 2020- 2024 continuous operation of A-share listed companies in Shanghai, Shenzhen and Anhui. The sample scope selected in this paper is the high-end manufacturing companies listed on the A-share market in Shanghai and Shenzhen that will continue to operate from 2020 to 2024, and the relevant financial data of the listed companies come from the WIND database, the GuotaiAn database, and the annual reports released by the listed companies.

2.2.2. Construction of financial early warning indicator system

Combined with the analysis of the reasons for the formation of enterprise financial risk and the previous research related to enterprise financial early warning, this paper mainly selects the corresponding indicators from the aspects of solvency, operating ability, profitability, cost control

ability, growth ability, cash flow management ability, research and development ability, and non-financial indicators to establish the financial risk early warning indicator system of high-end manufacturing enterprises. Specific indicators are shown in Table 1.

Table 1. Corporate financial warning indicators

Solvency	X1	Current ratio
	X2	Quick ratio
	X3	Asset-liability ratio (%)
Operational capacity	X4	Inventory turnover(times)
	X5	Total assets turnover(times)
	X6	Accounts receivable turnover ratio (times)
	X7	Turnover of fixed assets(times)
Profitability	X8	Return on equity (%)
	X9	Earnings per share (Yuan)
	X10	Return on total assets (%)
	X11	Net profit margin on sales (%)
Cost control capability	**X12**	Period expense rate (%)
	X13	Operating cost/Revenue (%)
	X14	Overhead rate (%)
Growth ability	X15	Total assets Growth rate (%)
	X16	Net profit Growth rate (%)
	X17	Operating income growth rate (%)
	X18	Net asset Growth rate (%)
Cash flow management capability	X19	Cash ratio (%)
	X20	Net cash flow from operations/liabilities (%)
	X21	Operating net cash flow/Sales income (%)
R&D ability	**X22**	Research and development expenses as a percentage of sales revenue
	X23	Research and development expenses as a percentage of sales revenue
Non-financial indicators	X24	Government subsidies as a percentage of sales revenue
	X25	Equity nature (state-owned enterprises 1, non-state-owned enterprises 0)

2.3. Enterprise financial risk early warning model construction and test

2.3.1. Financial risk early warning modeling

(1) Logistic regression results

Table 2 shows the results of logistic regression of corporate financial risk, after principal component analysis, it can be seen that the principal component factor F_1 has a high correlation with X_1, X_2 and X_3, and these indicators are related to the company's solvency, so F_1 is the principal component reflecting the solvency of the enterprise [39]. By analogy, principal component factors F_2 to F_8 reflect the operating ability, profitability, cost control ability, growth ability, cash flow management ability, research and development ability, and non-financial indicators, respectively.

Table 2. Refactored the logical regression of the report

Constituent	B	S.E.	Z value	Wals	OR value
F_1	-2.0348	0.3915	-5.1933	27.0552	0.1358
F_2	-0.6158	0.2065	-3.2158	10.5233	0.5135
F_3	-0.5836	0.2369	-2.4352	6.0125	0.5533
F_4	-1.7652	0.3248	-5.4625	29.8622	0.1768
F_5	-0.6582	0.1925	-3.3856	11.1352	0.5135
F_6	-0.7468	0.6036	-1.1985	1.3885	0.4955
F_7	1.1368	0.2348	4.8685	23.7966	3.1056
F_8	-0.7988	0.2678	-3.0548	9.3456	0.4536
Intercept	-2.5698	0.3452	-7.3088	53.3154	0.0835

Based on the coefficients in the above table, the Logistic Financial Early Warning Model can be obtained [40].

$$\ln(\frac{p}{1-p}) = -2.5698 - 2.0348F_1 - 0.6158F_2 - 0.5836F_3 \\ -1.7652F_4 - 0.6582F_5 - 0.7468F_6 + 1.1368F_7 - 0.7988F_8 \quad (10)$$

(where P represents the probability of whether the crisis is 1, and 1-P represents the probability of whether the crisis is 0).

(2) Analysis of model fitting goodness and prediction accuracy

Table 3 shows the analysis of model fit goodness of fit and prediction accuracy. First, in Logistic regression analysis, the Nagelkerke R-square is usually used to measure the fit of the regression model built based on the sample. The Nagelkerke R-square of the financial risk early warning model is 0.5895 indicating that the financial risk early warning model has a very good fitting effect, and secondly, the smaller the -2 log-likelihood value is, the better the fit of the model is, and the -2 log-likelihood value of the financial risk early warning model is 185.8165, which side by side proves that the early warning model constructed on the basis of logistic has a better fitting effect. The logistic-based early warning model has a better fitting effect.

Hosmer-Lemeshow test (HL test) for the model fitting indicators, the principle is to determine the gap between the predicted value and the true value of the situation, the larger the P-value indicates that there is no obvious difference between the predicted value and the true value of the [41]. The P-value of the financial risk early warning model constructed in this paper is 0.8752, and the early warning model constructed based on Logistic has a better fitting effect.

Table 3. Analysis of the fitting of the model and the prediction accuracy

Model goodness of fit				
-2 Likelihood log	Cox&snell R square	Nagelkerke R square		
185.8165	0.3984	0.5895		/
Chi-square	Degree of freedom	P value		
3.9152	8	0.8752		
Model prediction accuracy				
Actual type	Normal company	ST company	Total	Prediction accuracy
Normal company	210	20	230	0.91304348
ST company	24	56	80	0.7
Overall accuracy				0.80652174

2.3.2. Testing the effectiveness of financial risk early warning models

Figure 1 shows the logistic regression model evaluation, according to the above Table 3 it can be concluded that since 56 samples out of 80 actual non-financial risks were predicted to be non-financial risks, a specificity of 0.7 was obtained, 210 samples of financial risks out of 230 samples of actual financial risks existed to be predicted correctly, thus a recall of 0.913 was obtained, and the validation set's accuracy was 0.8, and the model's overall prediction accuracy is good.

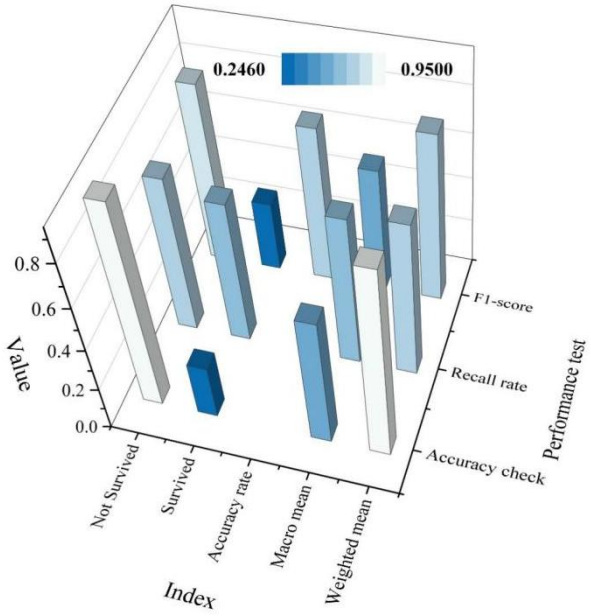

Figure 1. Logistic regression model evaluation

2.3.3. Causes of financial risk

The above steps show that the Logistic model proposed in this paper can effectively identify and predict the financial risk situation of enterprises accurately, and then use SHAP interpretable method for the financial risk warning model obtained from the training, and output the model's characteristic importance index ordering through the SHAP value, as shown in Figure 2. The results show that the top five indicators in the enterprise that have the highest degree of influence on the financial risk of listed companies are total asset turnover (X5), net sales margin (X11), R&D expenses as a percentage of sales revenue (X22), period expense ratio (X12), and accounts payable turnover (X6), respectively.

Total Asset Turnover (X5), Net Sales Margin (X11), R&D Expenses to Sales Revenue (X22), Period Expense Ratio (X12), and Accounts Payable Turnover (X6) are the key indicators for predicting the existence of financial risk in a firm, and the mean values of these importance indicators in SHAP are 0.155, 0.113, 0.083, 0.082, and 0.078 respectively. The above indicators require extra attention in the process of business management in the same type or even in each previous period of the company.

In summary, this paper analyzes the logistic regression model combined with the SHAP value of the enterprise, which can achieve the purpose of predicting the financial risk situation of the enterprise, and at the same time, it can form the order of importance of the indicators affecting the financial crisis of the enterprise, which shows that the model is reliable in analyzing the degree of importance of the enterprise's financial warning indicators.

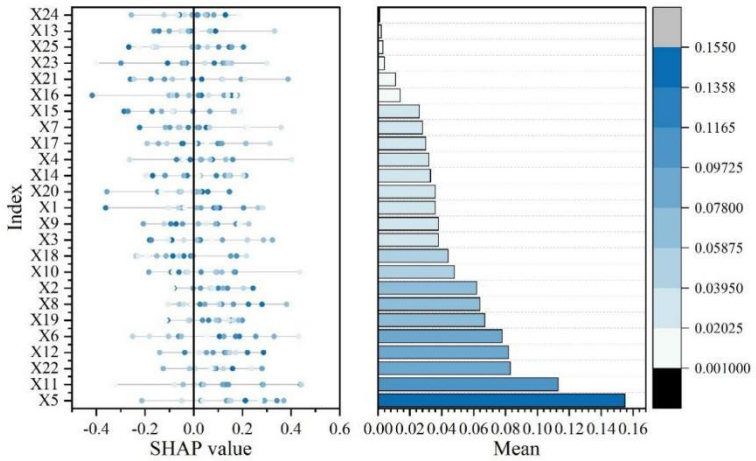

Figure 2. Enterprise SHAP analysis

3. Early warning analysis of financial risk of enterprise A based on logistic regression models

3.1. Application of financial risk early warning system of enterprise A and analysis of results

3.1.1. Financial risk early warning system application

According to the importance of the 25 financial risk indicators collated in 2.3.3, the actual raw data of their financial risk indicators are statistically collated in this section, as shown in Table 4, the financial risk indicators show different degrees of fluctuation in five years, of which indicator X11 is more prominent, dropping from 6.0245 to 3.7453 in 2020, then rising to 5.0485, and stabilizing at 4.5 afterwards around.

Table 4. Actual value of Company A's financial risk index from 2020 to 2024

Categories	Pointer code	2020	2021	2022	2023	2024
Financial index	X5	1.1263	0.9485	1.0485	0.9456	1.0945
	X11	6.0245	3.7453	5.0485	4.5485	4.5152
	X22	0.4623	0.5162	0.5126	0.5045	0.4265
	X12	0.3525	0.4685	0.4158	0.3652	0.2875
	X6	5.1896	3.8562	3.5487	4.1652	5.8153
	X19	0.5733	0.5152	0.5612	0.5125	0.5753
	X8	0.2985	0.3485	0.4875	0.4185	0.4232
	X2	0.6123	0.2486	0.2836	0.1258	0.3185
	X10	0.6928	0.1384	0.0918	0.0345	0.4985
	X18	0.2863	0.0982	0.0755	0.1685	0.1832
	X3	0.2198	0.0948	0.0786	0.1453	0.1385
	X9	1.3152	0.0846	0.0532	0.0268	0.4652
	X1	0.8152	0.1426	0.0485	0.1345	0.1863
	X20	1.5532	0.1284	0.0535	0.0515	1.0465
	X14	1.3885	0.2642	0.0438	0.0845	0.8652
	X4	0.9852	0.4322	0.1846	1.3485	0.9487
	X17	0.8135	0.3485	0.0348	0.5955	0.0575
	X7	0.9152	0.0846	0.1685	0.0485	1.0485
	X15	0.1654	0.0546	0.0598	0.1325	0.5798
	X16	0.2485	0.0485	0.0658	0.0865	0.6152
	X21	0.3485	0.1524	0.2485	0.5132	0.0845
	X23	0.4625	0.0348	0.1886	0.1522	1.0455
	X13	0.3485	0.0285	0.0594	0.0865	1.2485
Non-financial indicators	X25	0.8655	0.8562	0.8653	0.9845	0.8562
	X24	82.6855	64.5485	71.7986	85.8653	87.2895

3.1.2. Analysis of calculation results

According to the risk level classification standard, it is determined that the risk level is divided into 10 levels, respectively, named according to the scoring interval of the financial risk warning value from low to high, the financial risk scoring interval between 0 and 10, the financial risk level 1, the financial risk scoring interval between 10 and 20, the financial risk level 2, and so on.

Table 5 is the statistics of the financial risk early warning value of Company A from 2020 to 2024, and according to the original data in Table 4, the financial risk early warning values of Company A from 2020 to 2024 are 73.6563, 55.877, 63.3313, 74.9454 and 84.545, respectively, and the risk levels are 8 risk, 6 risk, 7 risk, 8 risk and 9 risk. In the five years from 2020-2024, except for the financial risk early warning value decreasing in 2020-2021, the financial risk early warning value increasing year by year from 2021-2024.

After reviewing the relevant information, it is understood that due to the support of external factors such as government subsidies over the years, Company A has not experienced obvious financial difficulties, but the degree of financial risk is still large, making the financial risk of Company A is still a problem that should not be underestimated.

Table 5. The financial risk warning value of Company A from 2020 to 2024

Secondary indicator	2020	2021	2022	2023	2024
Solvency	8.7452	3.1535	4.9856	2.7152	7.5935
Operational capacity	7.2615	7.6258	7.7523	7.1685	6.3185
Profitability	10.6485	7.6158	7.6285	8.3485	11.7533
Cost control capability	5.1325	6.4525	7.7856	8.5123	7.9182
Growth ability	8.1865	6.0452	6.0563	5.5258	6.8156
Cash flow management capability	6.9785	4.6856	4.3152	5.5935	5.7686
R&D ability	12.5332	8.0645	9.7856	13.8564	13.5352
Government subsidy	6.3848	5.8485	7.5636	12.6266	12.8563
Equity property	7.7856	6.3856	7.4586	10.5986	11.9858
Financial risk warning value	73.6563	55.877	63.3313	74.9454	84.545
Level of risk	Level eight risk	Level six risk	Level seven risk	Level eight risk	Level nine risk

3.2. Analysis of the level of financial risk of enterprise A

3.2.1. Profitability

On behalf of the profitability of F_3 to analyze, so as to learn the operating profitability of company A, specific indicators for the return on net assets X8, earnings per share X9, return on total assets X10, net sales margin X11.

Figure 3 for company A 2020-2024 profitability indicators, company A from 2020 to 2024 to respond to changes in the four indicators of profitability trend is the same, are shown as a small decline in 2024, “cliff” type fall into negative values. Specifically, Company A's return on net assets declined year by year, on the one hand, indicating that the company's assets are not efficiently utilized, on the other hand, indicating that the increase in revenue, savings in the use of funds and other aspects did not achieve good results. The return on total assets indicates the profitability of utilizing assets, and this indicator of Company A starts to decline significantly from 16.28% in 2020 to 5.15% in 2023, and even bottoms out at -13.68% in 2024, a drop of 184.03%.The net sales margin of Company A also continues to fall, and a review of the annual reports of Company A in the past five years reveals that the enterprise's growth rate of profit in that period was much lower than that of assets. The growth rate of profit is much lower than the growth rate of asset value, the reason for this is found to be mainly due to the macro-environment of the company's new energy, new materials segment and chemical industry segment has too much influence, the overall market is in a downturn, and the company fails to do a good job of preventive measures in advance, but instead of blindly utilizing the existing resources to form a new production equipment, expanding the original production activities.

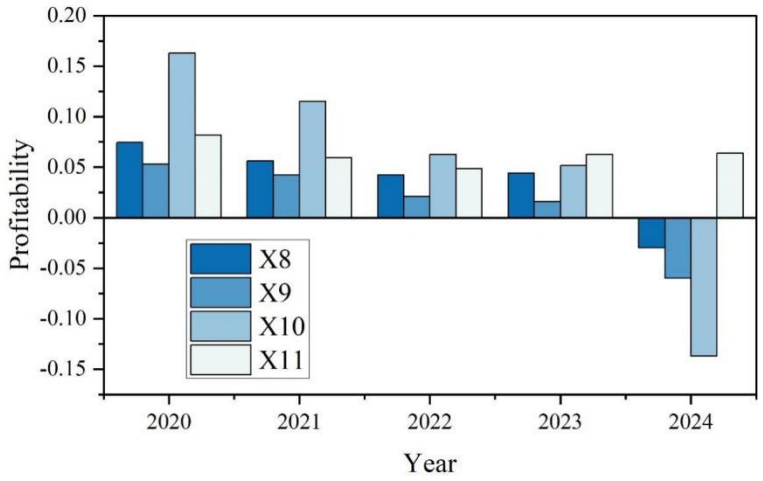

Figure 3. A company's 2020-2024 profitability indicator

3.2.2. Debt service capacity

F_1 representing solvency are analyzed by current ratio X1, quick ratio X2 representing solvency and gearing ratio X3 representing long-term solvency.

Figure 4 shows the analysis of solvency, Company A's current ratio and quick ratio from 2020 to 2024 are synchronized, both showing a wave pattern of decline, then rise and then decline, and the value of the two indicators is relatively close to each other, in the past five years, except for the difference in 2020 is slightly higher, and the difference in the rest of the years is not higher than 20%, which indicates that inventory accounts for a relatively small proportion of the current assets, and checking the annual report of Company A from 2020 to 2024 further confirms that the book value of inventory accounts for a relatively stable ratio of current assets in the past five years. The annual report of Company A from 2020 to 2024 further confirms that the ratio of the book value of the company's inventory to the current assets is relatively stable in the past five years, and after excluding the influence of assets with weak liquidity and poor stability, it can be found that the short-term solvency of Company A is still further weakened. The reason for this is found that Company A borrowed some more short-term borrowings in 2021 in order to repay the maturing corporate bonds issued in 2019, forcing huge repayment pressure, causing the company's cash borrowings and certificated borrowings that need to be repaid within the one-year period to surge, and although the company's quick ratio shows a small upward trend after 2022, it is found that by comparing with the industry, Company A is compared with the industry average its quick ratio is much lower than the industry average, which are 0.9232 and 1.5666 respectively. It is not difficult to find that the changes in the asset and liability structure of Company A caused by the large number of bonds issued in the previous period, which in turn caused unsuitable quick assets and unreasonable quick ratios, are the important reasons why Company A's short-term solvency is in a weak state in 2021-2024, especially the weak liquidity of assets.

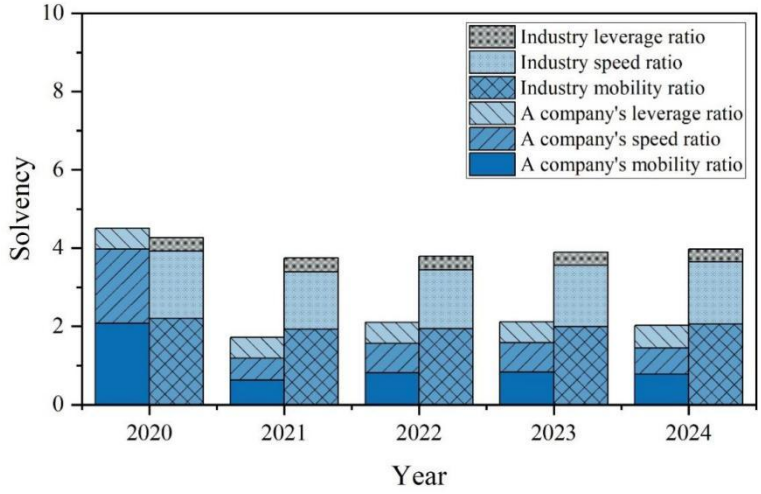

Figure 4. Solvency analysis

3.2.3. Cash flow management capacity

To analyze the F_6 representing cash flow according to the risk early warning model constructed in the previous section, so as to learn the cash flow situation of Company A. The specific indicators are cash ratio X19, net cash flow from operations/debt X20, net cash flow from operations/sales revenue X21.

Figure 5 shows the cash flow analysis, the company's cash ratio since 2020 0.9264 small decline to 0.8496 in 2021, in 2021-2024 the indicator has been fluctuating, but are lower than the value of 2020, and are lower than 1. At the same time, since 2021, the company A this indicator has been in the industry average value below the industry average since 2021, which side by side indicates that the actual quality of the company's earnings is not good and needs to draw management's attention.

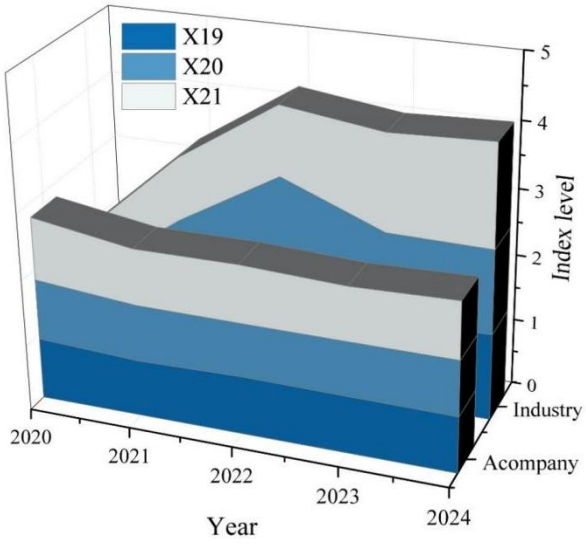

Figure 5. Cash flow analysis

3.3. Financial management responses

Company A's main financial strengths in 2020 are its debt servicing ability, profitability and cash flow management ability. However, at the same time, there will inevitably be relative shortcomings appear, such as asset management ability and the company's growth ability is relatively weak, in order to avoid financial risks as much as possible, we should start from the improvement of both asset management ability and growth ability.

3.3.1. Rationalization of capital structure

At present, there are various ways to raise debts in China, which provide more borrowing channels for enterprises, and at the same time greatly increase the financial risk of enterprises. In the face of the relatively weak long-term solvency, Company A should analyze the company's internal operation and asset holdings in depth, grasp the ratio of assets and liabilities, select the appropriate debt raising methods according to the company's characteristics, plan the capital structure reasonably and reduce the enterprise risk. At the same time, it can arrange a reasonable debt repayment plan according to the signals of risk warning, maintain the credibility and good image of the enterprise, avoid the risk of capital chain breakage, and ensure that the daily business activities of Company A can be carried out smoothly.

3.3.2. Strengthening cash flow management

Company A's cash ratio X19, net cash flow from operations/debt X20, and net cash flow from operations/sales revenue X21 are all low compared to the industry as a whole. Therefore, Company A should strengthen the management of cash flow, and reasonably formulate the production and sales plan, so as not to affect the company's liquidity as well as its liquidity ability, and to increase the probability of a certain amount of financial risk.

3.3.3. Establishment of a sound early warning system for financial risks

A sound financial risk early warning system can largely help companies to predict the upcoming financial risks that may occur, and can provide some assistance to the enterprise to make decisions to help companies get rid of financial difficulties, to avoid the occurrence of financial crises. It can be seen that a company has a sound, suitable for their own financial risk early warning system is important. For Company A, which has relatively low cash ratios, net cash flow from operations/liabilities, and net cash flow from operations/sales revenue, it is even more important to establish a sound financial risk early warning system to avoid irreparable losses.

4. Conclusion

Based on Logistic regression model, this paper constructs enterprise operation risk early warning system. By analyzing the financial data of enterprises in previous years, the usability of the financial

risk early warning model is examined, and the importance indicators affecting the financial operation risk are obtained. The model is applied to the actual enterprise operation to analyze its financial risk level and put forward relevant financial management countermeasures.

The P-value of the financial risk early warning model constructed in this paper is 0.8752, indicating that the early warning model constructed based on Logistic has a better fitting effect. Meanwhile, the specificity, recall and accuracy of the model are 0.7, 0.913 and 0.8, respectively, and the model has a good prediction accuracy.

Statistics of financial risk early warning value of Company A in 2020-2024, the financial risk early warning value of Company A in these five years are 73.6563, 55.877, 63.3313, 74.9454, 84.545, and the risk level is 8 risk, 6 risk, 7 risk, 8 risk, 9 risk, and the risk value shows that 2021-2024 financial risk Early warning value increases year by year.

Specifically analyzing the level of financial risk of Enterprise A, in terms of profitability, the return on total assets of Company A has dropped significantly from 16.28% in 2020 to -13.68% in 2024, a drop of 184.03%, indicating that the overall market is in the doldrums, and Company A fails to take precautions ahead of time, resulting in the decline of profitability and a high level of financial risk.

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