International Journal for Housing Science and Its Applications
Publish August 5, 2025. Volume 46, Issue 3 Pages 4480-4490

https://doi.org/10.70517/ijhsa463384

Study on the Enhancement of Management Efficiency of Resource-Consuming Enterprises by Information Technology-Based Financial Sharing Model in Low-Carbon Economy

Ying Zhang[1,*]
[1] Accounting Financial Institute, Zhejiang Technical Institute of Economics, Hangzhou, Zhejiang, 310018, China
Corresponding authors: (e-mail: zhang86950454@163.com).

Abstract Enhancing the ability to analyze and process enterprise financial data is a key task in reducing enterprise resource consumption. This paper applies information technology in the collection and processing of financial data of resource-consuming enterprises. Combined with cluster analysis, the financial data are pre-processed by dimensionality reduction to obtain financial diagnostic indicators. Factor analysis is utilized to extract the common factors from the financial indicators, mine the financial risk influencing factors, and establish the factor analysis model. Apply the improved efficacy coefficient method to calculate the alarm value of enterprise financial risk and pay attention to the probability of occurrence of enterprise financial crisis. Combined with the results of financial risk analysis, we compare the effect of improving enterprise management ability and economic efficiency after taking targeted measures. The results show that: based on the financial sharing method of information technology, the resource-consuming enterprises have optimization effects of 51.61%, 43.90%, 56.63% and 69.01% in the four aspects of financial risk prediction accuracy, capital turnover rate, cost control deviation rate, and decision-making response time, respectively, and reach the goals of consumption decline and economic efficiency improvement.

Index Terms financial diagnosis, cluster analysis, factor analysis, improved efficacy coefficient method, financial risk, resource-consuming enterprises

I. Introduction

With the increasingly competitive business environment, improving the management efficiency of enterprises has become the goal pursued by every resource-consuming enterprise, and efficient management can help enterprises operate better, improve work efficiency and increase profits [1]-[4]. As a product under the background of global economic integration and enterprise management mode innovation, financial sharing mode has gradually become a popular choice for resource-consuming enterprises in management [5]-[7].

Financial sharing mode is a kind of financial data sharing platform based on information technology, centralized management of financial data from various departments of the enterprise, which can enable different departments in the enterprise to realize information sharing, and then help the enterprise accounting workers to further improve the quality and efficiency of enterprise management work [8]-[11]. Through the financial sharing model, enterprises can realize comprehensive horizontal and vertical sharing of financial data, improve the transparency and accuracy of data, and realize the optimal allocation and management of financial resources [12]-[14]. At present, most manufacturing enterprises have established their own financial sharing platform and carried out certain applications and practices [15], [16]. With the deepening of manufacturing enterprises' knowledge of financial sharing mode and the continuous improvement of technical support, financial sharing mode will become the mainstream mode of enterprise management in the future, so as to further reduce the cost of enterprise management and operation, improve the quality of service and work efficiency, and provide assistance for enterprise value creation [17]-[20].

This paper uses information technology to automate the collection and processing of financial data from resource-consuming enterprises. For the obtained financial data, cluster analysis is used to pre-process them and improve the accuracy of data mining. Factor loading calculation and common factor variance calculation are carried out on the financial index data obtained from mining, so as to extract the relevant common factors of the financial index data and establish the common factor model for enterprise financial risk early warning. Improve the efficacy coefficient method, optimize the proportion of basic score and adjustment score, and determine the evaluation standard of financial risk early warning. The financial risk analysis of resource-consuming enterprises is practiced to verify the application value of this paper's method.

II. Analysis of enterprise financial management based on information technology

This chapter analyzes the advantages of big data information technology for enterprise financial management. Based on cluster analysis and factor analysis and improved efficacy coefficient method, it preprocesses and calculates enterprise financial data and establishes financial risk early warning evaluation criteria.

II. A.Application of big data information technology in financial management

II. A. 1) Automated capture and processing of financial data

Traditional financial data collection usually relies on manual operation, which is not only time-consuming and labor-intensive, but also prone to errors. The application of big data information technology can completely change this status quo and realize efficient data collection and processing through automated means. For example, enterprises can utilize web crawler technology to automatically collect financial data from various financial systems, e-commerce platforms, bank interfaces and other sources, avoiding the tediousness and errors of manual input. At the same time, big data information technology can also improve the accuracy and consistency of data by automatically removing noise and repetitive items in data through data cleaning and preprocessing algorithms. In this way, finance staff can devote more energy to data analysis and decision support, rather than being consumed with repetitive manual operations. In addition, companies can use flash conversion layer (ETL) tools to store data from different sources in a unified format in a data warehouse for subsequent analysis and application.

II. A. 2) Risk prediction and management

Enterprises analyzing large amounts of historical financial data can build accurate risk prediction models to anticipate potential financial risks in advance. For example, enterprises can use machine learning algorithms to model past financial data and predict future credit risks, market risks and operational risks. In this way, enterprises can take preventive measures in advance to reduce the probability of risk occurrence and the degree of impact. In addition, big data technology can help enterprises conduct comprehensive risk assessment and management, identify key factors affecting financial health through multi-dimensional data analysis, and propose corresponding management countermeasures. For example, by analyzing a customer's transaction behavior and credit history, an enterprise can assess the customer's credit risk and decide whether to grant a credit line or take other credit management measures.

II. B.Data preprocessing based on cluster analysis

Data preprocessing is the preprocessing of noisy, useless and random data that exist in the data, which is an important step in the data mining process and can improve the quality of the required mining data.

There are many financial indicators, and there is a close correlation between financial indicators, some indicators reflect a problem, if these financial indicators do not carry out in-depth dimensionality reduction processing, not only to increase the difficulty of data mining to delay the time of data mining, but also to affect the accuracy of the results of data mining, it can be seen that it is necessary to pre-process these indicators data.

(1) Data Standardization

In order to eliminate the impact of different dimensions of the original data, this paper uses cluster analysis to carry out data pre-processing, which requires standardization of the original data collected. The standardization formula is:

$$x_{ij} = \frac{y_{ij} - \bar{y}_j}{\sqrt{\operatorname{var}(y_j)}} \left(i = 1, 2, \cdots, n\right) \tag{1}$$

and: $\bar{y}_j = \frac{1}{n}\sum_{i=1}^{n} y_{ij}$.

$$\sqrt{\operatorname{var}\left(y_j\right)} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(y_{ij} - \bar{y}_j\right)^2} \tag{2}$$

where $\bar{y}$ and $\sqrt{var(y_j)}$ are the mean and variance of the j th variable, respectively. y_{ij} is the value of the indicator before normalization and x_{ij} is the value of the indicator after normalization out.

(2) Define the distance

There are n indicators, P observations, each indicator has P observations, let the i indicator of the j indicator observations for x , j , n indicators as n points in the P -dimensional space, then the degree of affinity between the two indicators can be used to measure the distance between the two points in the P-dimensional space. Let denote the distance between indicator X_i and X_j. Define the distance formula:

$$d_{ij} = \sqrt{\sum_{1}^{n} \left| x_{ik} - x_{jk} \right|^2} \tag{3}$$

Based on the requirements of the analysis, select the appropriate clustering method and standardization method, as well as choose to draw a dendrogram. Then, the software will automatically carry out cluster analysis and get the corresponding results, and the diagnostician can classify the results according to the output. After the clustering analysis, it will be able to obtain more representative financial diagnostic indicators, and these indicators will be able to provide a very clear analytical basis for financial diagnosis. In this paper, the R-type cluster analysis method is used to analyze the clustering of variables to achieve the purpose of dimensionality reduction processing.

II. C.Explanation of Factor Analysis

II. C. 1) Fundamentals of the Factor Analysis Approach

Factor analysis is a statistical method used when a large number of variables are involved in a statistical object, which carries out a scientific study of the dependencies that exist within the variables, and scientifically summarizes the related variables that have a complex relationship to form a small number of composite factors. That is, from a large number of variables, extract potentially representative factors, using the observation of the relationship between the variables, the variables are divided into several types of factors, these types of factors are known as public factors, which can be used to describe and analyze the relationship between the indicators or factors, and can reflect most of the information contained in the original data, to extract the key factors, that is, to be able to accurately find the factors that have the greatest impact on it.

II. C. 2) Mathematical modeling of the factor analysis approach

In the factor analysis model, there are n sample companies and p indicators (variables) $x_1, x_2, x_3, \cdots, x_p$. And, after standardization, each variable has a mean of 0 and a variance of 1. Factor analysis allows the expression of each of the original variables in terms of a linear combination of $k < p$ factors $F_1, F_2, F_3, \cdots, F_k$.

$$\begin{cases} x_1 = a_{11}F_1 + a_{12}F_2 + a_{13}F_3 + \cdots + a_{1k}F_k + \varepsilon_1 \\ x_2 = a_{21}F_1 + a_{22}F_2 + a_{23}F_3 + \cdots + a_{2k}F_k + \varepsilon_2 \\ x_3 = a_{31}F_1 + a_{32}F_2 + a_{33}F_3 + \cdots + a_{3k}F_k + \varepsilon_3 \\ \vdots \\ x_p = a_{p1}F_1 + a_{p2}F_2 + a_{p3}F_3 + \cdots + a_{pk}F_k + \varepsilon_p \end{cases} \tag{4}$$

Equation (4) is the mathematical model for factor analysis and is expressed in the form of a matrix as:

$$X = AF + \varepsilon \tag{5}$$

where F are called factors, also known as common factors because they appear in the linear expressions of each of the original variables, and each factor has a mean of 0 and a variance of 1.

II. C. 3) Several relevant concepts in factor analysis

In order to better understand the factor analysis method, several important related concepts in factor analysis need to be explained:

(1) Factor loadings

Factor loadings are the correlation coefficients between each original variable and the common factor, which reflects the importance of each variable to the common factor. Using the value of factor loading, we can get the importance of each variable associated with the public factor, which helps us better understand the connotation of the public factor and provides the basis for its naming. The larger the absolute value of the factor loading value, the stronger the relationship between the public factor and the original variables.

(2) Common factor variance

The sum of squares of the elements in the i th row of the factor loading matrix. The formula is calculated as:

$$h_i^2 = \sum_{j=1}^{m} a_{ij}^2 \tag{6}$$

This value gives an idea of the degree of omission of information from the variables. If the common degree of most of the variables is greater than 0.85, then it shows that the extracted common factors basically reflect more than 85% of the information of each original variable, and only a smaller amount of information is lost, indicating that the factor analysis is more effective.

(3) Variance contribution ratio of the public factor F_j

The variance contribution of the public factor F_j refers to the sum of squares of the elements in the j th column of the factor loading matrix, which is calculated by the formula:

$$F_j = \sum_{i=1}^{p} a_{ij}^2 \tag{7}$$

The variance contribution rate is used to illustrate the magnitude of the influence of the common factor on the original variable; the greater the variance contribution rate, the greater the influence of the common factor on the original variable.

II. D.Calculation of the enterprise financial risk warning value

II. D. 1) Application of the improved efficacy coefficient method

The traditional efficacy coefficient method is to determine the optimal value and the worst value of each financial indicator, and calculate the financial risk early warning value according to the weight of the indicator, but there are certain defects. First of all, the traditional efficacy coefficient method accounts for 65% of the weight of the basic score and 35% of the adjusted score, and the fixed allocation of the weight directly determines the results of the final composite score, making it lack of relevance and effectiveness. Different industries and companies use the same calculation criteria, making it difficult to highlight their respective characteristics and differences. Secondly, the evaluation criteria only have two grades, the optimal and the worst, which leads to excessive differences between the grades and reduces the sensitivity of the indicators, thus affecting the accuracy of the evaluation results. In order to improve the shortcomings of the traditional efficacy coefficient method, this paper will use the improved efficacy coefficient method, and the specific content of the improvement is mainly divided into the following two aspects:

First, the standard value interval is refined to improve the sensitivity of the indicators. The traditional efficacy coefficient method has only two gear standards, and the gap between the optimal value and the worst value is too large, which affects the accuracy of early warning. The optimized efficacy coefficient method adds multi-level evaluation criteria on the basis of the traditional method, and newly sets good value, average value and lower value, the upper standard value is higher than the actual value of the indicator, and the current standard value is lower than the actual value of the indicator but closest to the actual value of the indicator, so as to better refine the evaluation results and improve the accuracy of the early warning results.

Second, optimize the proportion of the basic score and adjustment score. In the traditional efficacy coefficient method, the allocation of weights is often unchanged and lacks the necessary flexibility. Therefore, the improved efficacy coefficient method re-adjusts the weights, so that the calculation of the base score is linked to the weights of the indicators, and the calculation of the adjustment score is closely linked to the efficacy coefficient.

The improved efficacy coefficient method consists of six steps: 1) calculating the base score, the base score of this grade = the weight of a single indicator x the standard coefficient of this grade, and the base score of the upper grade = the weight of a single indicator x the standard coefficient of the upper grade; 2) calculating the efficacy coefficient value, the value of the efficacy coefficient = (the actual value of a single indicator - the standard value of this grade) / the standard value of the upper grade - the standard value of the grade; 3) calculating the adjusted score, the adjusted score = efficacy coefficient (3) Calculate the adjustment score, adjustment score = efficacy coefficient x (the base score of the upper gear - the base score of the gear); (4) Calculate the score of a single indicator, a single indicator score = the base score of the gear + adjustment score; (5) Calculate the total score, the total score = the sum of individual indicator scores; (6) Calculate the index evaluation coefficients, single indicator evaluation coefficients = a single indicator scores / single indicator weights, the index evaluation coefficients = the index score / index weights, the comprehensive evaluation coefficients = the sum of individual indicator scores / single indicator weights. Indicator class evaluation coefficient = indicator class score/indicator class weight, and comprehensive evaluation coefficient = single indicator score/indicator weight summation.

Among them, when the real value of an indicator exceeds the threshold of excellence of the industry standard, its efficacy coefficient is set to 1; on the contrary, if the real value of the indicator is lower than the threshold of inferiority of the industry standard, its efficacy coefficient is set to 0.

II. D. 2) Determination of criteria for early warning evaluation of financial risks

According to the analysis of the efficacy coefficient method, appropriate evaluation criteria must be selected when using the method to calculate the warning value of corporate financial risk. The improved method of the efficacy coefficient method refines the evaluation grade, while referring to the Standard Values for Enterprise Performance Evaluation, which divides the ratings into five grades: excellent, good, average, low and poor. The division of this grade combines the authoritative reference standards and improves the scientific and authoritative nature of the model. Table 1 shows the values of the improved evaluation criteria coefficients.

Table 1: Company's evaluation standard coefficient value

Gear level	Classification criteria	Standard coefficient
Excellent grade	True value≥Excellent value	1
Good gear	Good value < True value < Excellent value	0.85
Average range	Average value < True value < Good value	0.65
Lower grade	Difference value < True value < Lower value	0.45
Poor grade	True value < Differential value	0.25

III. Analysis of information technology-based financial sharing model

This chapter applies the information technology-based financial sharing model to the financial data processing of resource-consuming enterprises. By mining and calculating the financial data of the enterprise, the financial risk situation of the enterprise is found and corresponding measures are taken to improve it.

Table 2: Financial indicator data of Enterprise A

Index	2023	2022	2021	2020	2019	2018
Current ratio	5.26	2.16	2.21	2.06	2.11	4.27
Quick ratio	4.26	2.28	1.84	1.65	1.55	4.25
Cash flow liability ratio	0.23	0.63	0.73	0.77	0.98	0.96
Asset-liability ratio	0.15	0.32	0.35	0.34	0.33	0.14
Equity multiplier	1.17	1.41	1.56	1.57	1.42	1.16
Interest multiple obtained	-12.5	-16.3	-16.81	-30.52	-40.96	-13.54
Inventory turnover rate	0.94	1.30	1.30	1.24	1.38	1.85
Accounts receivable turnover rate	315.90	347.35	246.75	161.81	206.25	1326.22
Total asset turnover rate	0.57	0.64	0.63	0.67	0.62	0.65
Fixed asset turnover rate	4.32	4.25	3.30	2.35	1.96	1.75
Current asset turnover ratio	0.64	0.82	0.84	0.93	1.00	1.01
Return on assets	0.19	0.24	0.17	0.17	0.23	0.14
Return on net assets	0.21	0.30	0.29	0.26	0.26	0.17
Net profit margin on sales	0.33	0.35	0.26	0.24	0.24	0.23
Profit margin of main business	0.45	0.52	0.41	0.38	0.42	0.36
Cost and expense profit margin	0.97	1.24	0.84	0.71	0.86	0.43
Net profit margin on total assets	0.18	0.22	0.18	0.13	0.17	0.15
Basic earnings per share	2.11	2.61	1.63	1.10	0.87	0.42
Total operating income per share	6.52	7.16	5.37	4.07	2.92	2.06
Capital accumulation rate	0.15	0.32	0.24	0.25	0.25	0.13
Growth rate of total assets	-0.03	0.24	0.27	0.37	0.53	0.16
Net profit growth rate	-0.30	-0.21	-0.09	-0.11	0.40	-0.23
Growth rate of operating profit	-0.26	-0.22	-0.07	-0.08	0.42	-0.25
Growth rate of total operating revenue	-0.08	0.36	0.33	0.41	0.45	0.07
Cash liability ratio	0.15	0.61	0.84	0.92	1.47	0.96
Cash meets the investment ratio	2.22	2.98	3.16	2.96	2.84	2.52

III. A. Application of IT-based financial diagnostic models

III. A. 1) Enterprise data collection and preliminary analysis

In this paper, we study the data from 2018 to 2023 and collect the raw data before pre-processing the data clustering analysis. The collection process is mainly embodied in the acquisition and screening of data, with the aim of obtaining a data system that can provide our study with the data needed in the financial diagnosis process. In this paper, the balance sheet, income statement, cash flow statement, etc. of enterprise A from 2018 to 2023 are collected in a large database, and combined with enterprise A's own situation, the financial indicator system is calculated to get a total of 26 indicators. This is the most original data, and make some adjustments to these data. Table 2 shows the specifics of the enterprise's financial indicator data.The 26 indicator data show a year-by-year change in the law, and overall, the financial data of enterprise A in 2018 is more similar to the financial data in 2023, and the enterprise is likely to have the problem of stagnation or even retrogression in development, and it is urgent to carry out in-depth excavation and analysis of the financial data.

III. A. 2) Pre-processing of financial data based on cluster analysis

Cluster analysis will be categorized without guidance, so this paper first preprocesses the financial indicators using cluster analysis R-type clustering. Open the SPSS interface, in the “analysis” under the “classification” - “systematic clustering”, to get the results of financial data clustering analysis. Table 3 shows the results of the cluster analysis. As can be seen from Table 3, the data of financial indicators can be divided into four categories from right to left: the first category is current ratio, quick ratio, and interest earned multiple; the second category is accounts receivable turnover; the third category is inventory turnover, basic earnings per share, return on net assets, net profit margin on total assets, net assets per share, inventory turnover, cost-expense margin, turnover of current assets, cash debt ratio, operating Profit Margin, Main Operating Profit Growth Rate, Capital Accumulation Ratio, Total Asset Turnover, Total Asset Growth Rate, Net Income from Sales, Return on Assets, Total Operating Income per Share; Net Income Growth Rate, and Cash Current Liability Ratio. Category 4 is the cash meets investment ratio, gearing ratio, equity multiplier, and growth rate of total operating income.

Table 3: Cluster analysis results

Stage	Cluster combination		Coefficient	Order cluster emerged for the first time		Next stage
	Cluster 1	Cluster 2		Cluster 1	Cluster 2	
1	5	6	0.281	0	0	13
2	21	22	0.384	0	0	20
3	17	15	0.466	0	0	1
4	12	18	0.550	0	0	5
5	2	1	0.585	0	0	23
6	13	19	0.613	5	0	12
7	15	16	0.906	0	2	21
8	11	18	1.037	0	0	0
9	11	12	1.058	7	0	10
10	6	11	1.101	0	0	15
11	11	21	1.202	8	0	12
12	4	24	1.284	0	0	14
13	13	13	1.475	5	10	17
14	5	27	1.706	0	0	18
15	4	20	1.743	11	0	14
16	6	8	1.772	19	0	16
17	4	7	2.056	14	15	12
18	2	11	2.134	16	12	21
19	5	23	2.232	13	0	25
20	3	12	2.341	17	6	22
21	2	20	2.476	21	1	20
22	2	27	2.567	20	0	24
23	2	9	2.890	23	0	26
24	2	7	2.973	4	0	24
25	1	5	3.117	23	22	23
26	5	6	3.236	24	16	26

From the clustering results, after eliminating the indicators with too much similarity, this paper takes quick ratio, gearing ratio, and earned interest multiple as solvency indicators, inventory turnover ratio, accounts receivable turnover ratio, and total asset turnover ratio as operating capacity, return on assets, return on net assets, net sales margin, profit margin of main business, and total operating income per share as profitability indicators, operating profit growth rate, total asset growth rate, net profit growth rate, and total operating income growth rate as development capacity indicators, and cash liability ratio and cash to meet investment ratio as cash flow analysis indicators, with a total of 17 indicators. Growth rate of operating profit, growth rate of total assets, growth rate of net profit, growth rate of total operating income as indicators of development ability, cash debt ratio, cash meets investment ratio as indicators of cash flow analysis, totaling 17 indicators.

III. B. Constructing a factor analysis model

III. B. 1) Extracting the common factor

Factor analysis was performed on the financial indicator data preprocessed by cluster analysis to construct the factor analysis model. Table 4 shows the common factor variance obtained through the SPSS25.0 software collation. The common factor variance is an important indicator to measure the degree of explanation of the factors extracted in the factor analysis on the variability of the original variables. In factor analysis, the higher the value of the common factor variance, the higher the representativeness or explanatory rate of the extracted factors for the original variables, and the better the overall effect. As can be seen from Table 4, the resolution of return on assets is the highest at 0.978, followed by total asset turnover with a resolution of 0.977, and then the growth rate of total operating income with a resolution of 0.970, which shows that the extracted factors have a relatively high resolution for the original variables.

Table 4: Common factor variance

Variable	Initial	Extract
Quick ratio	1.000	0.868
Asset-liability ratio	1.000	0.878
Interest multiple obtained	1.000	0.758
Inventory turnover rate	1.000	0.933
Accounts receivable turnover rate	1.000	0.965
Total asset turnover rate	1.000	0.977
Return on assets	1.000	0.978
Return on net assets	1.000	0.805
Net profit margin on sales	1.000	0.610
Profit margin of main business	1.000	0.773
Total operating income per share	1.000	0.886
Growth rate of operating profit	1.000	0.909
Growth rate of total assets	1.000	0.734
Net profit growth rate	1.000	0.966
Growth rate of total operating revenue	1.000	0.970
Cash liability ratio	1.000	0.862
Cash meets the investment ratio	1.000	0.821

III. B. 2) Total Variance Interpretation

Table 5 shows the total variance interpretation obtained by SPSS 25.0 software collation. Among the 17 components, the initial eigenvalue of the 1st component is 7.507, and the percentage of variance is 41.795%; the initial eigenvalue of the 2nd component is 3.239, and the cumulative total is 59.781%; the initial eigenvalue of the 3rd component is 1.697, and the cumulative total is 69.215%; the initial eigenvalue of the 4th component is 1.679, and the cumulative total is 78.583%; and the 5th component initial eigenvalue is 1.367 and cumulative is 87.050%, the first 5 components can reflect more than 85% of the information of the original variables, and the first 5 principal components are extracted as the public factors.

III. B. 3) Factor Rotation and Naming

Factor rotation aims to simplify the factor structure by changing the axes of the factor loading matrix, making the factors easier to interpret and understand. The purpose of factor rotation is not only to simplify the factor structure, but more importantly to better understand the meaning of each common factor and how to assign the original variables to these factors. Factor rotation can make the rotated factors easier to interpret and name, thus increasing the application value of factor analysis. The factors were rotated using the maximum variance method using SPSS 25.0 software.

Table 6 shows the total variance interpretation after rotation. Table 6 shows that the eigenvalues and the percentage of variance were changed after the rotation; the eigenvalue of the first common factor decreased from 7.507 to 5.435, and the percentage of variance decreased from 41.795% to 30.178%; the eigenvalue of the second common factor increased from 3.239 to 4.068, and the percentage of variance increased from 17.986% to 24.583%; the third common factor The eigenvalue of the third common factor increases from 1.697 to 2.014, and the percentage of variance increases from 9.434% to 13.177%. The cumulative percentage of variance of the first three common factors after rotation is 67.938%, which explains more than half of the information of the original variation. The eigenvalue of the fourth common factor increased from 1.679 to 1.939, and the percentage of variance increased from 9.368% to 12.766%; the eigenvalue of the fifth common factor decreased from 1.367 to 1.262, and the percentage of variance decreased from 8.467% to 8.467%. The cumulative eigenvalue of the first five common factors is 87.050% both before and after rotation, which indicates that the five extracted common factors are reasonable.

Table 5: Explanation of total variance

Component	Initial eigenvalue			Extract the sum of the load squares		
	Total	Percentage of variance	Cumulative %	Total	Percentage of variance	Cumulative %
1	7.507	41.795	41.795	7.507	41.795	41.795
2	3.239	17.986	59.781	3.239	17.986	59.781
3	1.697	9.434	69.215	1.697	9.434	69.215
4	1.679	9.368	78.583	1.679	9.368	78.583
5	1.367	8.467	87.050	1.367	8.467	87.050
6	0.888	3.276	90.326			
7	0.640	2.560	92.886			
8	0.541	2.002	94.888			
9	0.354	1.673	96.561			
10	0.202	1.111	97.672			
11	0.147	0.822	98.494		-	
12	0.095	0.451	98.945			
13	0.053	0.400	99.345			
14	0.041	0.332	99.677			
15	0.034	0.212	99.889			
16	0.020	0.098	99.987			
17	0.009	0.013	100.000			

Table 6: Explanation of the total variance after rotation

Component	Initial eigenvalue			Sum of squared rotating loads		
	Total	Percentage of variance	Cumulative %	Total	Percentage of variance	Cumulative %
1	7.507	41.795	41.795	5.435	30.178	30.178
2	3.239	17.986	59.781	4.068	24.583	54.761
3	1.697	9.434	69.215	2.014	13.177	67.938
4	1.679	9.368	78.583	1.939	12.766	80.704
5	1.367	8.467	87.050	1.262	8.467	87.050
6	0.888	3.276	90.326			
7	0.640	2.560	92.886			
8	0.541	2.002	94.888			
9	0.354	1.673	96.561			
10	0.202	1.111	97.672			
11	0.147	0.822	98.494		-	
12	0.095	0.451	98.945			
13	0.053	0.400	99.345			
14	0.041	0.332	99.677			
15	0.034	0.212	99.889			
16	0.020	0.098	99.987			
17	0.009	0.013	100.000			

III. B. 4) Factor model analysis

The rotated component matrix is obtained by performing a rotation operation on the original component matrix in the factor analysis principal component analysis method. This rotation operation is intended to improve the interpretability of the factor loading matrix, making the relationships between the factors clearer and making it easier to understand what each factor represents. Orthogonal rotation of the component matrices was performed using SPSS 25.0 statistical software. Table 7 shows the rotated component matrix.

The factor loading matrix is an important concept in factor analysis, which describes the relationship between each original variable and the extracted common factor. The larger the absolute value of the factor loadings, the higher the closeness of the correlation. By looking at Table 7, the factors are named according to the magnitude of their loadings on each variable as follows:

The public factor F1 has a large loading on three variables: quick ratio, gearing ratio, and earned interest multiple, and the factor loadings are all greater than 0.970; therefore, F1 is named as the solvency factor. The public factor F2 has the largest loadings on the three variables of return on net assets, net sales margin, and profitability of main business, all of which are more than 0.80, therefore, F2 is named as the profitability factor. Public factor F3 has the largest loadings on the 3 variables of operating profit growth rate (0.851), total assets growth rate (0.663), and net profit growth rate (0.582), and F3 is named as the development ability factor. The public factor F4 has the largest loadings on 2 variables: growth rate of total operating income (0.912) and cash debt ratio (0.823), naming F4 as the cash flow and development factor. The public factor F5 has a larger loading on the cash meets investment ratio, which is 0.718, naming F5 as the cash flow analysis factor. Thus the factor analysis model representing the financial data situation of the enterprise is constructed.

Table 7: The rotated component matrix

Variable component	F1	F2	F3	F4	F5
Quick ratio	0.984	0.081	-0.014	0.062	-0.024
Asset-liability ratio	0.976	0.076	-0.031	0.084	-0.077
The interest multiple obtained	0.971	0.078	-0.060	0.078	-0.081
Inventory turnover rate	0.853	0.341	0.175	0.044	0.303
Accounts receivable turnover rate	0.804	0.370	0.187	0.063	0.373
Total asset turnover rate	0.651	0.574	0.124	0.016	0.394
Return on assets	0.555	0.401	-0.140	0.494	-0.006
Return on net assets	0.278	0.865	-0.072	0.227	0.042
Net profit margin on sales	0.155	0.851	-0.054	-0.095	-0.223
Profit margin of main business	0.138	0.805	-0.205	0.174	-0.181
Total operating income per share	0.120	0.684	-0.500	0.155	-0.037
Growth rate of operating profit	0.187	-0.317	0.851	-0.090	-0.088
Growth rate of total assets	-0.362	-0.523	0.663	-0.087	0.071
Net profit growth rate	0.060	0.066	0.582	0.021	0.280
Growth rate of total operating revenue	-0.071	0.023	-0.141	0.912	-0.072
Cash liability ratio	0.352	0.178	0.101	0.823	0.245
Cash meets the investment ratio	0.092	0.176	0.233	-0.004	0.718

III. C. Trends in the early warning status of enterprise financial risks

Combining the factor analysis model and the improved efficacy coefficient method, etc., the financial early warning composite index F of enterprise A is calculated from 2018 to 2023, so as to find the trend of financial risk early warning status of enterprise A. Figure 1 shows the trend of financial risk early warning status of enterprise A. From the trend chart, it can be seen that the financial situation of the enterprise tends to be benign in 6 years, but it is not very stable, and it is still in the middle of bad financial risk: the financial risk in 2018 and 2023 belongs to the heavy warning area, 2019, 2020 and 2021 belong to the precautionary area, and 2022 belongs to the normal area, and the management of the enterprise should combine with the enterprise's business situation and the industry situation to make a The management of the enterprise should make qualitative analysis and take practical risk countermeasures to utilize or resolve the financial risks of the company in light of the operating conditions of the enterprise and the industry.

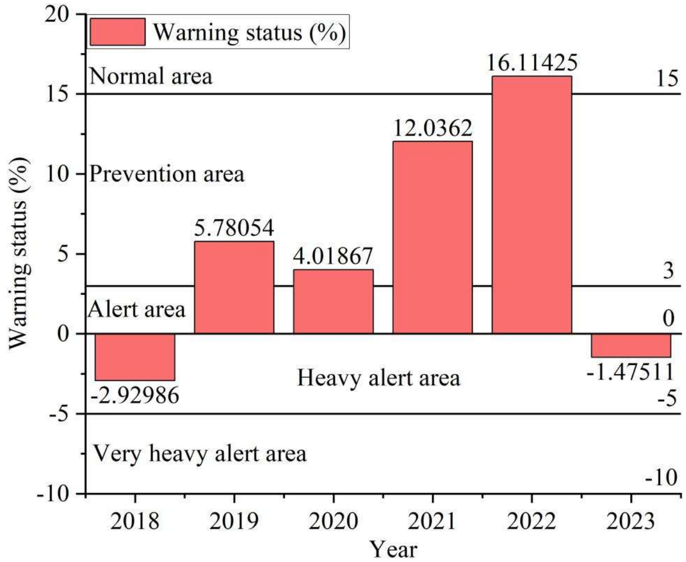

Figure 1: The trend of enterprise financial risk early warning status

III. D. Analysis of the effect of application in resource-consuming enterprises

After the previous study, the effectiveness of financial data and financial risk diagnosis based on information technology is verified.As a resource-consuming enterprise, enterprise A has a huge amount of financial data, and it is impossible to efficiently complete the data mining and analysis only by relying on human resources, so as to find out the financial risks and take corresponding management measures. The method of this paper can effectively improve the financial management level of resource-consuming enterprises. We further analyze the comparison of the effect of financial forecasting before and after the application of this paper's method and the level of economic benefit improvement of Enterprise A as a representative of resource-consuming enterprises.

Table 8 is the comparison of the effect of financial forecasting of enterprises. Table 9 is the quantitative assessment of the economic benefits of the enterprise after applying the method of this paper. Analyzing the data in the table, it is found that the resource-consuming enterprises, after using the financial analysis method based on information technology to deal with a large amount of complex internal financial data, have increased the accuracy of their own corporate financial risk prediction by 51.61%, while the capital turnover rate has been increased by 43.90%, the deviation rate of cost control has been reduced by 56.63%, and the decision-making response time has been increased by 69.01%. After making corresponding management improvements based on the results of the financial analysis, the enterprise's operation and management status was improved. Quantifying the economic benefits gained by the enterprise, it is found that the resource-consuming enterprise has achieved the goal of cost reduction and efficiency enhancement in four aspects, namely, cost saving, efficiency enhancement, risk reduction, and optimization of management. The application of financial analysis methods based on information technology can help resource-consuming enterprises clarify their internal financial risks, improve their management capabilities and promote their optimized development.

Table 8: Comparison of the effects of enterprise financial forecasting

Evaluation indicators	Before application	After application	Improvement range (%)
Prediction accuracy rate (%)	62	94	51.61
Capital turnover rate (times/year)	4.1	5.9	43.90
Cost control deviation rate (%	8.3	3.6	56.63
Decision response time (h)	71	22	69.01

Table 9: Quantitative assessment of economic benefits

Benefit type	Annualized income (Ten thousand yuan)	Investment cost (Ten thousand yuan)	Payback period (year)
Cost savings	2900	1300	1.4
Efficiency improvement	1550	850	1.7
Risk reduction	1300	600	1.5
Management optimization	800	500	1.4

IV. Conclusion

This paper uses information technology to process and analyze the financial data of resource-consuming enterprises, to find out the financial risks of enterprises, and to assist enterprises to improve their financial management level and reduce the consumption of resources. The five extracted financial indicator public factors are solvency factor, profitability factor, development ability factor, cash flow and development factor, and cash flow analysis factor. Calculating the early warning value of the financial risk of the enterprise, it was found that 2 out of 6 years were in the region of heavy warning, 3 years were in the region of prevention, and only 1 year was in the region of normal, which required intervention in the current state of financial management of the enterprise. After the intervention, the enterprise achieves the optimization of financial risk prediction accuracy (51.61%), capital turnover rate (43.90%), cost control deviation rate (56.63%), and decision-making response time (69.01%), and reaches the goal of reducing losses and improving efficiency. In the future, we can deeply study how to improve the real-time performance of the method in this paper and enhance the effect of enterprise financial risk discovery.

Funding

A Project Supported by Scientific Research Fund of Zhejiang Provincial Education Department (Y202456251).

References

[1] Miahkykh, I. M., Shkoda, M. S., & Pasichuk, A. M. (2020). Process management to ensure enterprise efficiency. Bulletin of the Kyiv National University of Technologies and Design. Series: Economic sciences, 145(2), 56-64.

[2] Aliyev, A. G. (2020). Some methodological problems of improving the effectiveness of the management of innovative enterprises. Management dynamics in the knowledge economy, 8(2), 175-192.

[3] Vedernikov, M., Chernushkina, O., Volianska-Savchuk, L., & Zelena, M. (2019, September). Modern Aspects of Industrial Enterprises' Production Efficiency Management. In 6th International Conference on Strategies, Models and Technologies of Economic Systems Management (SMTESM 2019) (pp. 444-449). Atlantis Press.

[4] Akhmetshin, E. M., Vasilev, V. L., Vlasova, N. I., Kazakov, A. V., Kotova, X. Y., & Ilyasov, R. H. (2019). Improving management functions at an enterprise: levels of the internal control system. Calitatea, 20(171), 39-43.

[5] Fang, L. F. L. (2021). Application of financial sharing center in enterprise financial management. International Journal of Management and Education in Human Development, 1(04), 074-078

[6] Wang, W. (2024). Research on digital transformation of enterprise finance and accounting under financial sharing model. Advances in Economics and Management Research, 11(1), 506-506.

[7] Yu, K., & Ye, S. (2021). Analysis of the effects of financial sharing on enterprise working capital management: taking sinochem holdings' financial sharing model as an example. Financ. Eng. Risk Manag., 4(4), 1-18.

[8] Jiang, L. (2024). The use of blockchain technology in enterprise financial accounting information sharing. Plos one, 19(2), e0298210.

[9] Li, R. (2020, April). Research on financial shared service mode of enterprise group. In International conference on arts, humanity and economics, management (ICAHEM 2019) (pp. 149-153). Atlantis Press.

[10] Zhang, Y., Zhang, X., & Song, J. (2024). Enterprise intelligent financial sharing mechanism in the security environment of the internet of things. International Journal of Information and Computer Security, 24(1-2), 80-97.

[11] Chen, Y. (2022). Enterprise Financial Data Sharing Based on Information Fusion Cloud Computing Environment. Wireless Communications and Mobile Computing, 2022(1), 5994628.

[12] Zheng, K., Zheng, L. J., Gauthier, J., Zhou, L., Xu, Y., Behl, A., & Zhang, J. Z. (2022). Blockchain technology for enterprise credit information sharing in supply chain finance. Journal of Innovation & Knowledge, 7(4), 100256.

[13] Xue, X. (2022). Design of enterprise financial information fusion sharing system based on blockchain technology. Computational Intelligence and Neuroscience, 2022(1), 5402444.

[14] Qiu, Y. L., & Xiao, G. F. (2020). Research on cost management optimization of financial sharing center based on RPA. Procedia Computer Science, 166, 115-119.

[15] Han, Z. (2021, June). The Construction and Application of Financial Sharing Service Center of Enterprise Group. In International Conference on Applications and Techniques in Cyber Security and Intelligence (pp. 80-86). Cham: Springer International Publishing.

[16] Zhou, X., & Weng, H. (2022). Assessing information security performance of enterprise internal financial sharing in cloud computing environment using analytic hierarchy process. International Journal of Grid and Utility Computing, 13(2-3), 256-271.

[17] Xiwen, L., Xu, D., & Shiyu, S. (2021). Research on the Internal Control Problems Faced by the Financial Sharing Center in the Digital Economy Era1—An example of Financial Sharing Center of H Co. Ltd. Procedia Computer Science, 187, 158-163.

[18] Li, L., Feng, Y., & Li, L. (2020). Big data audit based on financial sharing service model. Journal of Intelligent & Fuzzy Systems, 39(6), 8997-9005.

[19] Deng, Y. (2022). Optimising enterprise financial sharing process using cloud computing and big data approaches. International Journal of Grid and Utility Computing, 13(2-3), 272-281.

[20] Jia, S. (2020). Problems and solutions of financial management transformation under the establishment of financial shared service center. Open Journal of social sciences, 8(03), 251.