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Leveraging data visualization technologies to enhance corporate financial transparency and strengthen performance assessment functions

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Abstract Enterprise financial management in the digital era faces the problems of insufficient data transparency and single performance evaluation method. Effective use of data visualization technology can enhance financial transparency, while the performance evaluation model based on factor analysis can comprehensively consider multi-dimensional financial indicators, provide more comprehensive and objective financial performance evaluation for enterprise decision makers, and help enterprises optimize resource allocation and improve management efficiency. This study strictly follows the three principles of comprehensiveness, importance and operability, and selects 12 key financial indicators to construct the evaluation system, covering four dimensions of corporate solvency, profitability, operational capability and development capability. By applying KMO test (0.8321) and Bartlett's sphericity test (significance of 0.000) to the data of 66 beverage manufacturing companies in A-share, the data were verified to be suitable for factor analysis. The study extracted five public factors, which cumulatively explained 85.22% of the information of the original variables, and conducted a longitudinal comparative analysis of GLG's financial performance from 2020 to 2024. The results show that the composite score of Gree Electric's financial performance shows a decreasing trend since 2021 (0.43863), and falls to a five-year low in 2024 (0.36673); among them, profitability is the main constraint on corporate performance improvement, and the scores are all negative during the five-year period, suggesting that there is significant room for improvement in this area. The data visualization system constructed in the study can monitor the financial status of enterprises in real time and improve the compliance and safety of decision-making, while the evaluation model based on factor analysis provides a specific direction for the improvement of enterprise financial performance, which can effectively guide the optimization of enterprise financial management and strengthen the effectiveness of performance evaluation.

Index Terms data visualization, factor analysis, financial transparency, performance evaluation, financial indicators, enterprise financial management

I. Introduction

In today's digital era, organizations are facing unprecedented opportunities and challenges. In order to adapt to the competitive market, organizations must continuously improve their business models to increase efficiency, reduce costs, provide better customer experience and achieve sustainable growth [1], [2]. Traditional financial management models rely on manual operations and decentralized information systems, resulting in limited real-time and transparency of financial data, which in turn affects the efficiency and accuracy of business decisions [3], [4]. And by centralizing financial functions in a single data center, enterprises can better manage financial processes, standardize operations, reduce complexity and provide faster decision support [5].

With the rapid development of big data and other technologies, the digital financial management model has gradually become a core means for enterprises to improve management efficiency and competitiveness. Big data refers to large, diverse and high-speed generated data sets covering a wide range of information from internal and external sources [6]. These data include transactional data, social media activity, sensor data, and so on. Enterprises use big data technology to integrate financial information systems, enterprise resource planning systems, workflow management and other tools, which can realize the automated collection, processing and visual presentation of financial data, and the transparency and traceability of financial processes are significantly improved [7]-[10]. At the same time, digital financial management can enhance the real-time financial information, through real-time performance evaluation to provide more reliable data support for enterprise strategic decision-making [11], [12]. The introduction of data visualization technology also allows companies to better store, manage, and analyze these financial data to gain insights that help companies make more informed strategic and operational decisions [13], [14].

Financial transparency and performance evaluation are two core topics in enterprise financial management, which are directly related to the sustainable development of enterprises and the maintenance of competitive advantages. In recent years, along with the deep integration of information technology and digital economy, traditional financial management is facing great challenges. On the one hand, the financial data of enterprises is growing explosively, and information overload makes it difficult for managers to extract valuable information from massive data; on the other hand, traditional financial evaluation methods often focus on a single indicator or simple weighting, lack of systematicity and comprehensiveness, and are difficult to truly reflect the complexity of the financial situation of enterprises. As an emerging data processing tool, data visualization technology can help managers quickly grasp the key information and trend changes in financial data by transforming abstract figures into intuitive images. Compared with traditional text and table forms, visualization is more clear and concise, which is easy for stakeholders at different levels to understand and analyze, thus improving financial transparency. In addition, enterprise financial performance evaluation has always been the focus of financial management research, how to build a scientific and reasonable evaluation index system, objectively reflect the financial situation of the enterprise, and provide effective support for management decision-making is a persistent topic in the field of financial management. Financial performance evaluation is not only related to the summary of past business results, but also an important basis for future strategic planning. Existing research mostly examines financial performance from a single perspective, lacking multi-dimensional and dynamic comprehensive evaluation. Factor analysis, as a dimensionality reduction technique, is able to extract key factors from many related variables, simplify complex issues, retain the main information of the data, and is suitable for the comprehensive evaluation of multiple indicators of corporate financial performance. Therefore, combining data visualization technology with factor analysis to construct a scientific enterprise financial performance evaluation model is of great theoretical and practical significance to enhance the transparency of enterprise finance and strengthen the performance evaluation function. The study firstly, through literature review and theoretical analysis, explores the impact of digital financial management on corporate financial transparency, and clarifies the mechanism of data visualization technology in enhancing financial transparency; secondly, constructs an evaluation model of corporate financial performance based on the factor analysis method, selects representative financial indicators, and evaluates the corporate financial performance from the four dimensions of solvency, profitability, operation ability and development ability; finally, evaluates the financial performance of 66 A-share companies based on the combination of data visualization technology and factor analysis method. ; Finally, 66 beverage manufacturing companies in A-share are taken as samples for horizontal comparative analysis, and the financial data of Gree Electric Appliances for 2020-2024 are selected for longitudinal comparative analysis to verify the practicality and effectiveness of the model. The empirical study not only verifies the applicability of factor analysis in the evaluation of corporate financial performance, but also provides a specific direction for enterprises to improve their financial performance, so as to achieve the purpose of enhancing financial transparency and strengthening performance evaluation.

II. The construction of enterprise financial evaluation model based on factor analysis method

II. A. Impact of digital financial management on corporate financial transparency

II. A. 1) Real-time financial data generation

The generation of real-time financial data relies on enterprise resource planning systems (ERP), financial management information systems, data warehouses and other digital tools, the high degree of integration of these tools makes the collection, processing, analysis and presentation of financial data can be completed in the shortest possible time, to achieve seamless data flow and automated processing. The generation of real-time financial data also ensures the completeness and consistency of financial data, and enterprises can track the progress and abnormalities of various financial activities based on the real-time generated data to reduce the management risks caused by lagging financial data.

II. A. 2) Visualization of financial processes

The enterprise financial visualization process is shown in Figure 1. With ERP as the core application system architecture, the visualization of financial processes enables the enterprise resource planning (ERP) system to be tightly integrated with various types of subsystems to achieve financial management in a transparent and automated manner. The ERP system covers financial accounting, management accounting, cost control, project management, and other modules are integrated into a single platform, which enables the generation, processing and reporting of financial data to be highly automated and visualization.

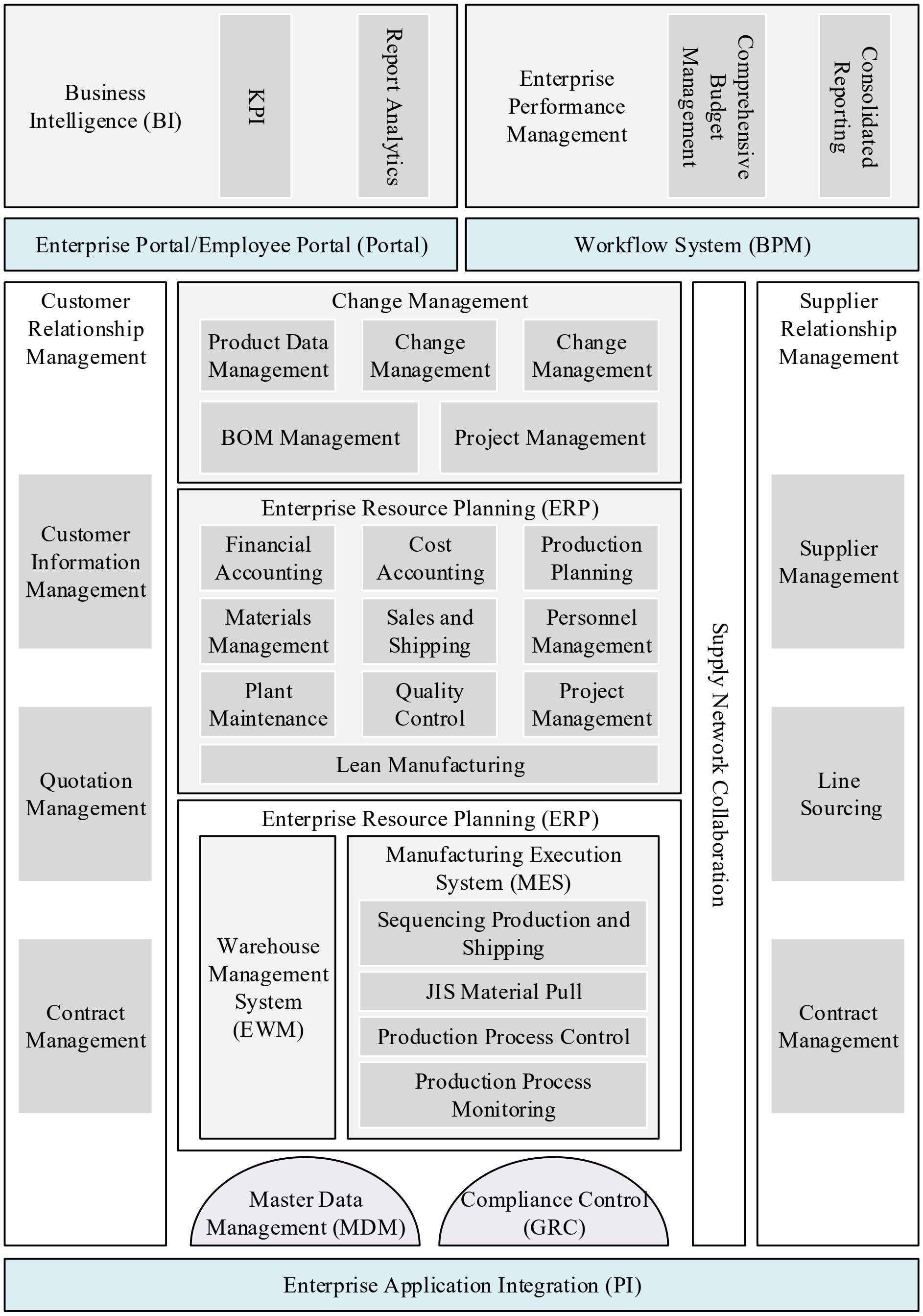

Figure 1: Enterprise financial visualization flow chart

II. A. 3) Precision in internal and external audits

In the process of internal audit, the auditors can obtain real-time financial data of the enterprise, covering accounting, revenue recognition, cost control, asset management and other financial aspects, to ensure the authenticity, accuracy and traceability of the audit data. External audit is based on the transparent presentation of enterprise financial data, external auditors can quickly access the real-time financial reports and transaction details of the enterprise, and fully grasp the financial status of the enterprise and business processes, thus reducing data delays and information asymmetry in the audit process.

II. A. 4) Improved compliance in financial decision-making

The financial decision-making process of fund allocation, cost control, tax planning and budget execution is supported by a digital system that automatically reviews and compares the requirements of laws and regulations and internal corporate policies to reduce the risk of non-compliance. Data visualization technology further strengthens the transparency of financial data, enabling decision makers to intuitively grasp the fluctuating trends of financial indicators and respond to possible compliance risks in a timely manner. The application of blockchain technology in financial transactions ensures the integrity and non-tamperability of data, and every transaction record can be traced back to ensure that the enterprise's financial activities comply with the relevant legal requirements, and enhances the compliance of financial decision-making.

II. A. 5) Enhanced security of financial data

The financial management information system and enterprise resource planning (ERP) system will provide strict hierarchical control of data access rights, ensuring that different departments and users can only access specific financial data according to their authorization and preventing unauthorized personnel from accessing sensitive financial information. The digital financial management system is also capable of real-time monitoring and automated risk warning systems to detect abnormal activities or potential security threats in financial data in a timely manner, ensuring that enterprises can take rapid risk response measures to avoid data leakage and financial losses.

II. B.Enterprise financial performance evaluation system construction

II. B. 1) Necessity and Feasibility of Using Factor Analysis

(1) Necessity

Factor analysis method [15], [16] can help researchers distill several important public factors from a large number of seemingly dispersed related indicators, which can represent the main source of information behind the original data, simplify the evaluation system, and quantitatively assess the extent of the contribution of these factors to the overall performance through factor analysis, so as to make the evaluation process clearer, more scientific, and fairer, and to avoid bias brought about by subjective judgment.

(2) Feasibility

First of all, when evaluating the financial performance of an enterprise, it is crucial to ensure the authenticity, accuracy and objectivity of the evaluation results. Factor analysis uses statistical software to automatically process data, transforming a large number of initial variables into several independent and highly integrated variables, making the evaluation results more objective and fair. At the same time, current statistical analysis software such as SPSS, R, Minitab, etc. all support the factor analysis function, which makes the theoretical method quickly and accurately implemented in practice.

II. B. 2) Principles for selecting financial performance evaluation indicators

In order to ensure the fairness, rigor and reasonableness of the financial performance evaluation conclusions, while fully considering the characteristics of the industry in which the enterprise is located and the specific financial situation of the enterprise, selecting the appropriate financial indicators for performance evaluation can truly respond to the operational status of the enterprise and its problems encountered in the process of operation and management, so as to provide the enterprise with a set of comprehensive and scientific improvement and optimization of the program. Therefore, in the construction of the financial indicator system, the selection of appropriate indicators need to follow certain basic principles.

(1) Comprehensiveness

When selecting evaluation indicators, should ensure that the financial situation and business activities of enterprises can be comprehensively covered, and throughout the whole process of the operation of the enterprise funds. Multi-faceted indicators reflecting the profitability, solvency, operating and development ability of the enterprise should be scientifically selected, and special financial indicators that have a significant impact on the financial performance of the enterprise should be given special attention.

(2) Principle of importance

On the basis of ensuring that the financial indicators of the four core competencies of the enterprise are covered, the selection of financial performance evaluation indicators should also follow the principle of importance. If all financial indicators are included in the evaluation system, it may lead to information overload and hinder the in-depth interpretation of the evaluation results. Therefore, when selecting indicators, make sure to eliminate those non-key indicators that have less impact on the evaluation results.

(3) Principle of operability

The selection of indicators should be closely integrated with the actual situation of the enterprise to ensure that the indicators are specific, not abstract, and the data are easy to obtain. The financial data disclosed in the financial report should accurately and comprehensively reflect the enterprise's financial situation and business performance.

II. B. 3) Construction of enterprise financial performance evaluation index system

Drawing on the standards of previous generations regarding the selection of financial evaluation indicators, the three basic principles of comprehensiveness, importance and operability are strictly observed in the establishment of the financial evaluation system. Specifically, the financial performance evaluation system is comprehensively constructed through the 12 representative financial indicators selected, and is divided into three layers in accordance with the principle of hierarchy.

(1) Selection of Indicators on Solvency

According to stakeholder theory, many stakeholders of the enterprise are highly concerned about the solvency of the enterprise, and the solvency can directly reflect the ability of the enterprise to repay all kinds of debts on time. By evaluating the solvency of an enterprise, it can determine whether the enterprise has long-term stable operation conditions and reveal its potential financial risks. The current ratio, quick ratio and cash ratio are selected to evaluate the solvency of the enterprise.

(2) Selection of Profitability Indicators

Profitability, i.e. capital appreciation ability, is used to measure the ability of an enterprise to create profits. It is the cornerstone and guarantee for the survival and long-term development of the enterprise. According to the stakeholder theory, the goal of enterprise financial management determines that the enterprise should not only consider the maximization of shareholders' wealth, but also try to satisfy the maximization of other stakeholders' wealth. The cost and expense ratio, return on net assets, and return on total assets are selected to evaluate the profitability.

(3) Selection of Indicators for Operating Capacity

Operating capacity, i.e., the measure of the efficiency of enterprise capital recycling. The stronger the operating ability of an enterprise means the higher the efficiency of its capital utilization, and also highlights the excellent management ability of the enterprise management at the operation level. The three financial indicators of accounts turnover ratio, current assets turnover ratio and total assets operation ratio are selected.

(4) Selection of development capability indicators

The development ability of an enterprise is closely related to its profitability, solvency and operating ability. If the enterprise's business scale continues to expand, its competitive position in the market is gradually stabilized, and its profit maintains steady growth. In order to more accurately evaluate the development status of the enterprise, the growth rate of operating income, the growth rate of net assets and the growth rate of total assets are selected, which reveal the dynamic changes of the enterprise's development and the possibility of future growth from different sides.

To summarize, this paper selects the financial performance evaluation indicators suitable for the enterprise, totaling 12 financial indicators, and the specific financial indicators are described as shown in Table 1.

Table 1: Specific financial indicators

First level	Second level	Third level	Label quality
Comprehensive evaluation system of financial performance	A:Solvency	A1:Mobility ratio	Moderation
		A2:Speed ratio	Moderation
		A3:Cash ratio	Moderation
	B:Profitability	B1:Cost adoption rate	Forward
		B2:Return on equity	Forward
		B3:Total asset returns	Forward
	C:Operational capacity	C1:Payable turnover rate	Forward
		C2:Turnover of current assets	Forward
		C3:Total asset turnover	Forward
	D:Development ability	D1:Revenue growth	Forward
		D2:Total asset growth rate	Forward
		D3:Net equity growth rate	Forward

II. C.Factor analysis methods

II. C. 1) Factor analysis model

Factor analysis modeling is a type of multivariate statistical analysis by dimensionality reduction and simplification of the data for comprehensive evaluation of the analysis according to the magnitude of the correlation of the original variables are grouped together, so that the correlation of variables within the same group is high, while the correlation of variables between different groups is low. Each group of variables represents a basic structure and is described by an unobservable composite variable, which is called a common factor. For a specific problem under study, the original variables can be decomposed into the form of the sum of two parts, one being a linear combination of a few unobservable so-called common factors, and the other being a special factor unrelated to the common factors.

General factor analysis model:

Given n samples, each containing p observations, $X=\left(X_1,X_2,X_3,\cdots,X_4\right)^T$ denoting the random vector, and denoting the common factor by $F_1,F_2,\cdots,F_m\left(m<p\right)$ to denote the common factors, then there is a factor model as follows:

$$\begin{cases} X_1 = a_{11}F_1 + a_{12}F_2 + \cdots + a_{1m}F_m + \varepsilon_1 \\ X_2 = a_{21}F_1 + a_{22}F_2 + \cdots + a_{2m}F_m + \varepsilon_2 \\ \cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots \\ X_p = a_{p1}F_1 + a_{p2}F_2 + \cdots + a_{pm}F_m + \varepsilon_p \end{cases} \tag{1}$$

where $X_1,X_2,\cdots,X_p$ are the actual variables, the matrix $A=(a_{ij})$ denotes the factor loading matrix, a_{ij} are the factor loadings, $F_1,F_2,\cdots,F_m$ are the common factors, and ε_i are the special factors, which denote the special variables that cannot be explained by the common factors, and which were ignored in the actual analysis.

Factor loadings a_{ij} represent the loadings of the i th indicator data on the j th principal factor, indicating the degree of dependence between the variable X_i and the public factor F_j, when the loadings on a particular public factor are both larger, it means that the correlation between X_i and F_j is stronger, and when the loadings on a particular public factor are both smaller, it means that the correlation between X_i and F_j is stronger, and that the correlation between X_i and F_j is stronger. X_i is weakly correlated with F_j. The a_i whose square indicates the proportion of X_i variance explained by the common factor F.

The variable commonality is the sum of the squares of the elements of the i th row of the factor loading matrix A, also known as the ratio of the variance of the common factors is recorded as h_i^2, which indicates the contribution made by all the common factors to the variable X_i. To wit:

$$h_i^2 = \sum_{i=1}^{p} a_{ij}^2, i = 1,2,3\cdots p \tag{2}$$

II. C. 2) Factor loading matrices

The actual establishment of the factor model process, the need to use sample data to estimate the factor loading matrix, to further analyze the original variables, commonly used methods for estimating the factor loading matrix are: great likelihood estimation method [17], principal component method, principal axis factor method, etc., this paper takes the principle of calculation of great likelihood estimation as an example to illustrate that solving the factor loading matrix.

Assuming that the public factor F and the special factor ε obey normal distribution in the factor model, the principle of great likelihood estimation of mathematical statistics, the great likelihood estimates of the public factor F and the special factor ε are obtained. Let $X_1,X_2,\cdots X_n$ be random samples of the normal population $N_p(u,\Sigma)$ and $\Sigma = AA' + \Sigma_\varepsilon$, $A' + \sum_\varepsilon^{-1} A = \Lambda$, Λ is a diagonal matrix, then the likelihood function can be constructed:

$$\begin{aligned} L\left(\hat{u},\hat{A},\hat{D}\right) &= f(x) = f(X_1) * f(X_2) * f(X_3) \cdots f(X_n) \\ &= \prod_{i=1}^{n} (2\pi)^{-\frac{p}{2}} |\Sigma|^{\frac{1}{2}} \exp\left[-\frac{1}{2}(X_i - u) \Big/ \sum{}^{-1} \left(X_i - u\right)\right] \end{aligned} \tag{3}$$

The likelihood function is co-determined by $\Sigma = AA/+\Sigma\grave{o}$ through the uniqueness condition, and the computational principle of maximization is applied to obtain the great likelihood estimates $\hat{A}$ and $\hat{\Sigma}\grave{o}$ to compute the corresponding factor loading matrices.

There are two major categories of factor rotation methods, orthogonal rotation and oblique rotation, which can be subdivided into variance maximum rotation method, quadratic maximum rotation method, equal maximum rotation method, direct oblique rotation and oblique rotation method, etc. The principle of quadratic maximum rotation method is described below.

The quadratic maximum rotation method starts from the rows of the loading matrix and rotates the initial factors so that each variable exhibits high loadings on one factor and low loadings on other factors as much as possible, so that the variance of the square of the factor loadings in each row of the factor loading matrix is maximized, and the rotation is calculated as follows:

$$Q=\sum_{i=1}^{p}\sum_{j=1}^{m}\left(b_{ij}^{2}-1/m\right)^{2}=\max \tag{4}$$

$$\begin{aligned}Q&=\sum_{i=1}^{p}\sum_{j=1}^{m}\left(b_{ij}^{2}-1/m\right)^{2}=\sum_{i=1}^{p}\sum_{j=1}^{m}\left(b_{ij}^{2}\right)^{2}\\&-2\sum_{i=1}^{p}\sum_{j=1}^{m}\frac{1}{m}b_{ij}^{2}+\sum_{i=1}^{p}\sum_{j=1}^{m}\frac{1}{m^{2}}\\&=\sum_{i=1}^{p}\sum_{j=1}^{m}b_{ij}^{4}-2\sum_{i=1}^{p}b_{ij}^{2}+\frac{m}{p}\end{aligned} \tag{5}$$

Simplified guidelines are obtained:

$$Q=\sum_{i=1}^{p}\sum_{j=1}^{m}b_{ij}^{4}=\max \tag{6}$$

II. C. 3) Factor scores

Once the factor model has been established, it is often necessary to examine the nature of each sample and the correlations between the samples to calculate the factor scores. The scores of the common factors $F_1,F_2,\cdots,F_m$ are calculated for each sample point, giving a linear expression of the common factors in terms of the original variables. After calculating the common factor scores, further analysis can be done in order to take the research question to a deeper level. Commonly used methods for calculating factor scores are Thomson regression analysis and Bartlett factor score analysis.

In the factor model $X=AF+\varepsilon$, the Thomson regression method assumes that the common factor F_j can do regression calculations on p variables:

$$\hat{F}_j=b_{j0}+b_{j1}X_1+b_{j2}X_2+\cdots+b_{jp}X_p,\ j=1,2,3\cdots m \tag{7}$$

For F_j and X_i after normalization has been done, the constant term $b_{j0}=0$. From the factor loading point of view, for any $i=1,\cdots p$, $j=1,2,3\cdots m$, it is obtained:

$$\begin{aligned}a_{ij}&=r_{x_iF_j}=E(r_{x_iF_j})=E\left[X_i\left(b_{j1}X_1+b_{j2}X_2+\cdots+b_{jp}X_p\right)\right]\\&=b_{j1}r_{i1}+b_{j2}r_{i2}+\cdots+b_{jp}r_{ip}\end{aligned} \tag{8}$$

Put $B=\begin{bmatrix}b_{11}&\cdots&b_{1p}\\\vdots&\ddots&\vdots\\b_{m1}&\cdots&b_{m1}\end{bmatrix}$ are noted as the corresponding coefficient matrices to obtain $A=RB'$, and the factor scores are estimated in the form of $\hat{F}=A'R^{-1}X$.

The factor scores are calculated, and the composite score of the factor analysis model is calculated based on the scores of each variable on the common factor, and the contribution of each new variable, and the final computed composite score is analyzed as a whole to determine the practical significance.

III. Enterprise financial performance evaluation results and analysis

III. A. Cross-sectional comparative analysis of corporate financial performance

III. A. 1) Factor analysis applicability test

Selection of sample data: this paper takes 66 sizes of sample enterprises listed in A-share market in the beverage manufacturing industry as the test. The 2024 relevant data of the 66 sample companies are imported into SPSS. KMO and Bartlett's test of sphericity were first performed, which was used to assess whether the data were suitable for factor analysis. When the value of the KMO test statistic is greater than 0.6, it indicates that there is not much difference in the degree of correlation between the variables and the data are suitable for factor analysis. When the value of Bartlett's test of sphericity is less than 0.01, it indicates that there is correlation between the original variables and the data is suitable for factor analysis. Based on the results of the test, it can be seen that the KMO sampling suitability measure is 0.8321, which is greater than 0.6, and the significance of the Bartlett's test of sphericity is 0.000, which is less than 0.01, which suggests that there is a correlation between the original variables and that the data are suitable for factor analysis.

III. A. 2) Extraction of the common factor

Table 2 shows the variance of the common factors obtained through SPSS software collation. The common factor variance is an important indicator of how well the extracted factors in factor analysis explain 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. The common factor variance is shown in Table 2. It can be seen that the total return on assets has the highest resolution of 0.9891, followed by the return on net assets with a resolution of 0.9813, and then the cost-expense ratio with a resolution of 0.9427, which shows that the extracted factors have a relatively high resolution for the original variables.

Table 2: Common factor variance

Variable	Initial	Extraction
A1:Mobility ratio	1	0.8789
A2:Speed ratio	1	0.8809
A3:Cash ratio	1	0.7671
B1:Cost adoption rate	1	0.9427
B2:Return on equity	1	0.9813
B3:Total asset returns	1	0.9891
C1:Payable turnover rate	1	0.8127
C2:Turnover of current assets	1	0.6281
C3:Total asset turnover	1	0.7811
D1:Revenue growth	1	0.8964
D2:Total asset growth rate	1	0.9102
D3:Net equity growth rate	1	0.7439

The results of total variance explained are shown in Table 3. Among the 12 components, the initial eigenvalues of the 1st~5th components are 3.5609, 2.2679, 1.7160, 1.6756 and 1.0059, respectively, and the cumulative percentage of variance is 29.67%, 48.57%, 62.87%, 76.84%, and 85.22%, respectively. The first 5 components can reflect more than 85.22% of the original variable information, and the first 5 principal components are extracted as public factors. It can be seen that the eigenvalues of the first 5 factors have a large difference, and from the 6th factor, the eigenvalues gradually decrease and the difference is not large, therefore, the first 5 principal components are selected as the common factor.

Table 3: The total variance explains the result

Constituent	Initial eigenvalue			Extracting the load of the load		
	Total	Percentage of variance	Cumulative (%)	Total	Percentage of variance	Cumulative (%)
1	3.5609	0.2967	29.67	3.5609	0.2967	29.67
2	2.2679	0.1890	48.57	2.2679	0.1890	48.57
3	1.716	0.1430	62.87	1.7160	0.1430	62.87
4	1.6756	0.1396	76.84	1.6756	0.1396	76.84
5	1.0059	0.0838	85.22	1.0059	0.0838	85.22
6	0.4899	0.0408	89.30			
7	0.3425	0.0285	92.16			
8	0.3401	0.0283	94.99			
9	0.2538	0.0212	97.11			
10	0.1503	0.0125	98.36			
11	0.1088	0.0091	99.26			
12	0.0883	0.0074	100.00			

III. A. 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.

The total variance explained after rotation is shown in Table 4. As can be seen from the table, the eigenvalues and variance percentages were changed after the rotation, the eigenvalue of the first common factor decreased from 3.5609 to 2.9609, and the percentage of variance decreased by 10%; the eigenvalue of the second common factor decreased by 0.01, and the percentage of variance increased from 18.9% to 21.4%; the eigenvalue of the third common factor increased from 1.7160 to 1.816, and the percentage of variance increased from 14.3% to 15.13%, and the cumulative percentage of variance of the first three public factors after rotation is 61.21%, which can explain more than half of the information of the original variation. The cumulative eigenvalue of the first five common factors is 85.22% both before and after rotation, which indicates that the five extracted common factors are reasonable.

Table 4: The total variance interpretation table after rotation

Constituent	Initial eigenvalue			Extracting the load of the load		
	Total	Percentage of variance	Cumulative (%)	Total	Percentage of variance	Cumulative (%)
1	3.5609	0.2967	29.67	2.9609	0.2467	24.67
2	2.2679	0.1890	48.57	2.5679	0.2140	46.07
3	1.7160	0.1430	62.87	1.816	0.1513	61.21
4	1.6756	0.1396	76.84	1.6756	0.1396	75.17
5	1.0059	0.0838	85.22	1.2059	0.1005	85.22
6	0.4899	0.0408	89.30			
7	0.3425	0.0285	92.16			
8	0.3401	0.0283	94.99			
9	0.2538	0.0212	97.11			
10	0.1503	0.0125	98.36			
11	0.1088	0.0091	99.26			
12	0.0883	0.0074	100.00			

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 facilitating the understanding of what each factor represents. Orthogonal rotation of the component matrices was performed using SPSS statistical software and the rotated component matrices are shown in Table 5.

According to the load size of the factors on each variable, the factors are named as follows: the public factor F1 has a larger load on the three variables of current ratio, quick ratio and cash ratio, and the factor loadings are all greater than 0.95, so F1 is named as solvency. Common factor F2 has the largest loadings on the three variables of cost-expense ratio, return on net assets and total return on assets, and its factor loadings are all greater than 0.98, so F2 is named as profitability. Public factor F3 has a loading value of more than 0.9609 on the three variables of operating income growth rate, total assets growth rate and net assets growth rate, so F3 is named as development ability. Public factor F4 has in and maximum on the variables of accounts payable turnover, current asset turnover and total asset turnover, which are 0.9844, 0.9542 and 0.9336 respectively, therefore, F4 is named as operating ability. The loading value of public factor F5 on the variables of return on net assets, current assets turnover and operating income growth rate is greater than 0.96, and this paper names F5 as capital turnover capacity.

III. A. 4) Factor model analysis

Table 6 shows the matrix of component score coefficients obtained through the SPSS software. The composite score function for each of the five male factors was calculated to be 85.74.In the horizontal comparison, factor analysis was conducted using SPSS software to name the five extracted male factors.In the vertical comparison, by calculating the composite scores and the scores of the factors, it was found that the lowest scores were for the operational and solvency capacity, followed by the profitability factor, and the highest scores were for the capital turnover capacity factor.

Table 5: The component matrix after rotation

Variable	F1	F2	F3	F4	F5
A1:Mobility ratio	0.9641	0.5508	0.3871	0.5353	0.5784
A2:Speed ratio	0.9704	0.5948	0.2579	0.5586	0.2632
A3:Cash ratio	0.9989	0.7388	0.3078	0.4843	0.4936
B1:Cost adoption rate	0.2501	0.9893	0.2903	0.3455	0.2586
B2:Return on equity	0.1175	0.9896	0.48237	0.3845	0.9936
B3:Total asset returns	1.1562	0.9945	0.5367	0.4496	0.4331
C1:Payable turnover rate	0.1429	0.2485	0.5424	0.9844	0.5522
C2:Turnover of current assets	0.2632	0.1447	0.6731	0.9542	0.9627
C3:Total asset turnover	0.1329	0.1796	0.5306	0.9336	0.0333
D1:Revenue growth	0.2634	0.2762	0.9901	0.2671	0.9636
D2:Total asset growth rate	0.1277	0.2752	0.9609	0.3275	0.6487
D3:Net equity growth rate	0.1665	0.27092	0.9809	0.1109	0.5142

Table 6: Component score coefficient matrix

Variable	Constituent				
	1	2	3	4	5
A1:Mobility ratio	0.0985	0.1629	0.0514	0.0294	-0.1554
A2:Speed ratio	0.223	0.1411	0.4266	0.0277	0.2016
A3:Cash ratio	0.4101	0.3847	-0.0188	0.1184	-0.261
B1:Cost adoption rate	0.2259	0.1264	0.0713	0.5238	0.0806
B2:Return on equity	0.0944	0.256	-0.0743	0.2756	0.2545
B3:Total asset returns	0.1203	0.094	0.1845	0.1461	0.3026
C1:Payable turnover rate	-0.0064	-0.161	0.4572	-0.2381	-0.1028
C2:Turnover of current assets	0.0298	0.0268	0.2418	0.3281	0.3659
C3:Total asset turnover	0.2473	0.2432	-0.1836	0.002	0.5049
D1:Revenue growth	0.0505	0.3816	0.0183	0.1941	0.1221
D2:Total asset growth rate	0.1564	0.4316	0.4198	-0.1183	-0.0844
D3:Net equity growth rate	0.6251	0.15	0.1939	-0.0304	0.2081

III. B. Longitudinal comparative analysis of corporate financial performance

III. B. 1) Reference data

In order to ensure the precision and reliability of the results of the longitudinal comparison evaluation, this paper organizes 12 financial indicators of Gree Electric during the period of 2020-2024. The values of financial indicators of Gree Electric Appliances in the past five years are shown in Table 7. The results show that during the period of 2020-2024, there is a certain volatility in the solvency ability of the enterprise based on the three indicators of "current ratio, quick ratio and cash ratio", which is inseparable from the company's current operating situation; in addition, the enterprise's operating ability is closely related to its operational ability. It is worth noting that the enterprise's total asset operation rate decreases year by year, indicating that the enterprise's utilization may have a bottleneck, and it is necessary to innovate in related fields and strengthen the performance management of enterprise finance to reduce losses. This has also resulted in extreme variations in the revenue growth rate, net assets growth rate, and total assets growth rate of the enterprise, indicating that the ability of GL to grow has been extremely unstable or even regressive during these five years.

III. B. 2) Results of longitudinal comparative analysis

After pre-processing the financial data of Gree Electric Appliances for the years 2022-2024 and substituting them into the factor score function, the results of the composite score for longitudinal comparison are obtained as shown in Figure 2. The results demonstrate that the financial performance composite score in the first two years shows an upward trend, however, in 2021-2024, this score shows a downward trend year by year. Analyzing the data of these five years in detail, it is easy to find that Gree Electric's composite score F peaked in 2021 (0.43863); however, it ranked in the bottom of the list in 2024 (0.36673). It can be seen that although the financial performance level of Gree Electric showed a positive trend in 2022 and 2021, it began to show a downward trend since 2021, and the financial performance performance in 2024 needs to be improved.

Table 7: Gree electric appliance nearly five years financial index

Variable	Constituent				
	2020	2021	2022	2023	2024
A1:Mobility ratio	0.1695	0.1607	0.1207	0.0113	0.1297
A2:Speed ratio	1.1398	1.1199	1.1696	0.9313	1.0031
A3:Cash ratio	0.1704	0.1598	0.119	0.0092	0.1296
B1:Cost adoption rate(%)	19.4795	17.9894	18.9414	17.2208	17.6591
B2:Return on equity(%)	33.36	25.7205	18.8792	21.3407	24.1898
B3:Total asset returns(%)	12.8508	10.21	8.4309	8.1197	7.5293
C1:Payable turnover rate(%)	29.3194	24.5295	19.5791	16.6394	13.1884
C2:Turnover of current assets(%)	7.5601	6.5091	4.7798	4.0293	3.4499
C3:Total asset turnover(%)	0.8603	0.7499	0.6106	0.6295	0.5599
D1:Revenue growth(%)	33.6091	0.0204	-15.0297	11.6911	0.6002
D2:Total asset growth rate(%)	11.6895	0.5995	-1.3297	14.4503	11.0809
D3:Net equity growth rate(%)	18.6503	-4.4903	-12.0306	2.4301	2.2699

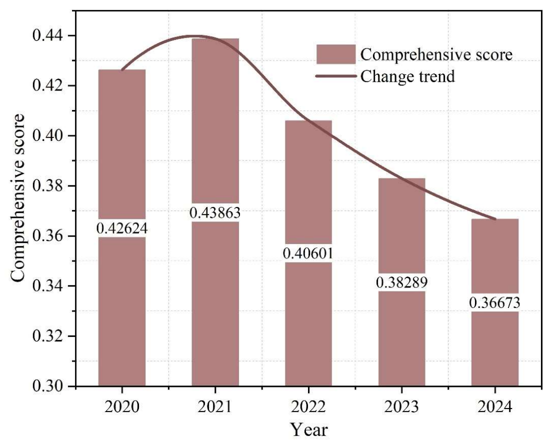

Figure 2: Vertical comparison results

The trend of changes in the composite scores of the five public factors of Greeley in 2020-2024 is shown in Figure 3. It can be seen that the change in the score of the solvency factor F1, from 2020 to 2022, it has increased, but the growth is tiny, showing a slow upward trend. However, since 2022, this score has begun to decline, from 0.804 to 0.618, this plummeting trend undoubtedly highlights the decline of Gree Electric in the last two years in profitability. The overall trend of the profitability factor F2 and the operating capacity factor F4 is S-shaped, and they are in good condition from 2020 to 2022, showing an upward trend, while showing a downward trend from 2022 to 2023, and then starting to rise from 2023 to 2024; and F2 and F4 are the best performers in 2022. At the same time, the score of the profitability factor is less than 0 from 2020 to 2024, and is at the bottom of the five public factors during the five-year period, which shows that there is a big hidden problem of profitability.

The development ability factor F3 shows a decreasing trend between 2020 and 2022, and steadily increases from 2022 to 2023, indicating that the situation of the development ability of the enterprise has improved. The development ability factor F3 reaches a trough (0.2527) in 2022 and a peak (0.5666) in 2023. The financial performance level of GLG can be further improved by exploring the root factors affecting the development capability in depth. The capital turnover factor F5 fluctuates more frequently during the five-year period, first decreasing between 2020 and 2022, then increasing from 2022 to 2023, and then beginning to decline after 2023.

III. B. 3) Comprehensive comparative analysis

In summary, the degree of influence of each public factor on the composite score from high to low is the solvency factor F1, the profitability factor F2, the development ability factor F3, the operating ability factor F4, and the capital turnover ability factor F5. As can be seen from the results of the first two parts of the comparison between the horizontal and vertical, the composite score of the year 2024 is ranked the last place in the last five years. The analysis reveals that Gree Electric's current financial performance deserves further improvement, and the reason for Gree Electric's low composite score is mainly due to the unsatisfactory score of F2 profitability factor. In the later stage, the profitability of Gree Electric Enterprises can be analyzed in depth, while focusing on the performance of the other four factors, in an effort to effectively improve the financial performance of Gree Electric Enterprises.

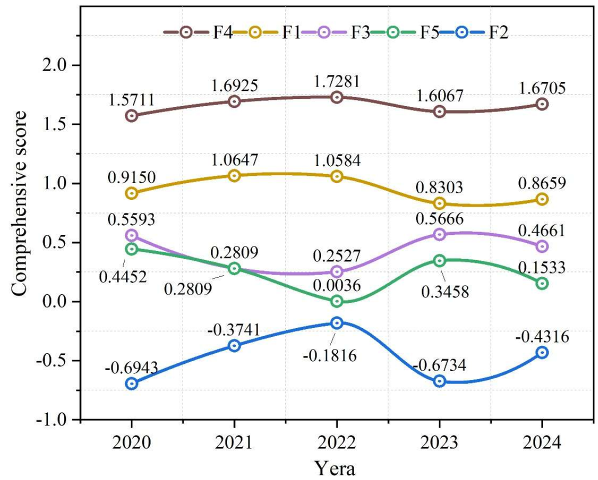

Figure 3: The five common factors changed the overall score in 2020-2024

IV. Conclusion

The enterprise financial performance evaluation model constructed by using data visualization technology combined with factor analysis provides an innovative methodological tool for enterprise financial management. The scientificity and validity of the model are verified through the horizontal comparison of 66 beverage manufacturing enterprises in A-share and the vertical comparison of Gree Electric from 2020 to 2024. The empirical results show that the five constructed public factors can explain 85.22% of the information of the original 12 financial indicators, which is highly representative. Gree Electric's financial performance composite score began to decline since reaching a peak of 0.43863 in 2021, and dropped to a five-year low of 0.36673 in 2024, indicating that its financial situation has faced challenges in recent years. In-depth analysis reveals that the solvency factor has the greatest impact on the composite score, while the profitability factor score is negative in 2020-2024, which is a key shortcoming that restricts the improvement of GLG's financial performance. Based on this, the enterprise should pay attention to the construction of data visualization system, integrate financial data through the ERP system, realize the visualization of financial processes, enhance the accuracy of internal and external auditing, and improve the compliance and security of financial decision-making. At the same time, targeted improvement strategies should be formulated for the performance of different capability factors, especially to enhance profitability. Future research can further explore the characteristics of financial indicators in different industries, refine the evaluation model, and combine it with artificial intelligence technology to achieve dynamic prediction and monitoring of corporate financial performance.

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