Construction of Financial Performance Evaluation System based on Principal Component Analysis Algorithm and Its Application in Digital Transformation Enterprises

SUJING GUO
Lyceum of the Philippines University Manila Campus,
Manila 1002,
PHILIPPINES

Abstract: - In the context of a strong national push toward the growth of the "digital economy", traditional manufacturing companies are increasingly turning to new digital technologies for their digital transformation. This paper aims to investigate the suitability of using a financial performance evaluation system for assessing the success of digital transformation strategies employed by these enterprises. The application of principal component analysis in digital transformation enterprises involves repeatedly selecting the main indicators in the financial performance evaluation index system of manufacturing enterprises. Finally, a financial performance evaluation index system suitable for analyzing digital transformation enterprises is constructed. The differences in financial performance before and after transformation are analyzed, and a comprehensive evaluation and comparative analysis are conducted on the financial performance of digital transformation enterprises and non-digital transformation enterprises. The experimental results show that the average growth rate of total assets of enterprises is 7.07%. The average growth rate of operating revenue is 20.99%. The standard deviations are 17.42% and 235.9%. There is a significant difference between the maximum and minimum values of these two indicators, indicating that the average dispersion of these two indicators is relatively high. In the initial phases of digital transformation implementation, enterprises that adopt digital technology experience a certain level of profitability improvement, as shown by the results. Compared to businesses that have not undergone a digital transformation, digitally transformed enterprises possess greater advantages and flexibility in digital operations. Digital transformation has important theoretical and practical value in improving the financial management level of digital transformation enterprises.

Key-Words: - Principal Component Analysis; Digital Economy; Enterprise Transformation; Enterprise Competitiveness; Evaluation System.

Received: March 15, 2023. Revised: August 29, 2023. Accepted: September 28, 2023. Available online: November 11, 2023.

1 Introduction

Currently, the Chinese economy has shifted from rapid growth to high-quality development, in which the manufacturing industry, serving as the main body, has become the primary propeller of long-term stable growth and sustained, rapid economic progress, [1]. Traditional manufacturing enterprises are proactively responding to the digital strategy by utilizing new digital technologies to achieve digital transformation (DT). Manufacturing is crucial for China's economic development, and a new generation of digital technology serves as the core driving force for its transformation and upgrading efforts, [2], [3]. In the digital economy era, achieving successful transformation and development of manufacturing enterprises greatly relies on the effective integration of emerging digital technologies and traditional manufacturing practices, [4]. Promoting the integration of "digital + intelligent manufacturing" is of great significance to the country's high-quality development. At present, countries around the world have realized that the DT of enterprises is an inevitable choice of the times. The integration of cutting-edge digital technology into traditional enterprises is essential for their future growth. To achieve this objective, a set of national strategies has been developed under the umbrella of "moving from manufacturing to smart manufacturing", [5]. This shows that digitalization is also a national strategy, and the DT of the manufacturing industry through the use of new-generation digital technologies is also the focus of the state and society, [6]. The research objective is to investigate whether "Internet plus manufacturing" has a favorable impact on the high-quality growth of manufacturing firms, the operational performance of firms pre- and post-digital transformation, and the financial contrasts between digital transformation and non-digital transformation firms. After conducting a quantitative analysis of the text, the vocabulary of enterprise digital transformation obtained can be used to describe the degree of manufacturing enterprise digital transformation. Using factor analysis and entropy weight methods, this study investigates financial performance to analyze the scientific nature of evaluation methods for digital transformation. The aim is to provide more scientific and objective reference opinions for each evaluation subject.

2 Literature Survey

In the field of digitally transformed businesses, many scholars have studied various aspects of it over the years. [7], utilized the socio-technical perspective of ETICS theory to construct and define the proactive capacities of information technology and socially encoded knowledge processes. These capabilities yield business transformation processes in the digital age. The authors discovered varying results regarding the effects of mediation and direct relationships. Socialized knowledge processes directly influence the proactive capabilities of information technology and the digital business transformation of the company. Coded knowledge processes successfully support the proactive capabilities of information technology and provide stronger support for the company's corporate IT/IS strategy, providing excellent opportunities for coded knowledge practices to improve the digital approach to corporate business process transformation, [7].

[8], examined the impact of corporate DT on the information environment. According to the findings, implementing DT in enterprises led to a noteworthy rise in analyst coverage and improved accuracy of public information. However, there has been no significant change in accuracy concerning private information. The quality of information disclosure and the content of stock price information are the primary factors influencing the relationship between them. Cyber-attacks, market competition, and social media all impact this relationship, making DT a promising avenue for investigation in emerging capital markets.

[9], applied enterprise architecture to urban digital transformation by developing an architecture that addresses system alignment and data integration issues in urban digital transformation. A qualitative method was employed to assess the suggested architecture. Data from a Norwegian municipality served as a case study and was gathered through interviews to authenticate the application of Enterprise Architecture to urban service digitization to emulate the digitization of e-mobility in a smart city.

Many organizations are embarking on digital transformation to prepare for the future. Digitally transformed organizations must be prepared to deal with unpredictable dynamics and ubiquitous digitization. Such an organization must incorporate the duality of exploitation and exploration and the convergence of business and technology into its organizational design. [10], presented a framework based on DBS Bank's digital transformation journey and provided new managerial insights for strategically driving digital transformation.

Much of the academic and professional interest in exploring DT and enterprise systems has focused on the external forces of technologies or organizations at the expense of internal factors. Dilek and Babak explored employee digital literacy as an organizational availability to capture the contextual factors that underlie the location and use of digital technologies. An evidence-based approach to information systems practice was used by examining the interaction between employee digital literacy and employee technology in the use of digital technologies. The interactive effect between literacy and employee skills contributes to the new concept of digital literacy available to organizations, [11].

The Financial Performance Evaluation (FPE) System aims to validate a direct approach to measuring relational capital via corporate brand estimation. Relationship capital management impacts both financial performance and brand development. Brand value serves as a reflection of relationship capital. Based on empirical data, a specific group of market and accounting metrics in the IFRS framework presents crucial information for assessing brand value. Altering the reference dataset and model assumptions does not yield significant alterations in the research findings, [12].

[13], introduced a new holdings-based procedure to assess fund performance. Determining whether a mutual fund's benchmark variance aligns with its investment strategy is crucial. Funds that exhibit benchmark discrepancies entail greater risks than what is disclosed in their prospectus. Before further risk adjustment, the funds on average outperformed the prospectus benchmarks.

To assess the use of hybrid renewable energy configurations in data center cooling units, [14], examined the importance of free cooling technology and compared it to the potential of renewable energy systems. The data center consumed a large amount of energy and the effectiveness of both methods in various configurations was evaluated through comparative analysis in terms of energy and water savings, net present value, and emission rates. To discover the maximum cooling energy-saving potential of this data center, the combination of these two methods was studied in the case of Tehran.

[15], examined an organizational theory approach to strategy, implementing performance indicators to assess economic relations. They developed a technique for comparative performance evaluation that considered cooperation strategy and identified economic performance as a crucial input-output indicator for firms. Seven financial indicators were selected, and timeliness was deemed essential for a thorough economic assessment of a company. After assessing the economic impact of 5G industry growth, they concluded that the information and telecommunication technologies were increasingly becoming a new driver of economic growth, [15]. [16], analyzed the prediction model for competitive dilemmas and discovered that there are inconsistent rankings that correlate with different standards and metrics of performance. To overcome this problem, a multi-criteria decision support tool for predicting corporate credit risk and distress has been proposed. It provided multi-criteria evaluation for competitive distress prediction models.

In summary, many scholars have launched research on enterprise DT, and the application of the FPE system in enterprise development is also very extensive. However, most studies concentrate on risk prediction models, and there is relatively little research regarding the evaluation of the financial and operational performance of digital enterprises using principal component analysis. The study chooses text mining and principal component analysis (PCA) to construct an FPE system and explore its application in DT enterprises.

3 Construction of FPE Index System for Digital Transformation Enterprises based on the PCA Method

Various stakeholders in a company have their concerns about the company's financial situation, but a single financial indicator can only reflect one aspect of the company. Thus, to ensure satisfactory outcomes for various stakeholders within the company, it is imperative to implement a comprehensive and reasonable FPE index system across different levels. This will enable a comprehensive and integrated evaluation of the organization's entire production and operational processes.

3.1 Construction of Financial Performance Evaluation Index System for DT Enterprises

The inadequate comprehensiveness and timeliness of the indicator system construction leads to suboptimal performance evaluation, making it essential to establish a scientifically and comprehensively designed FPE indicator system for digital transformation enterprises. This step is the foundation and most crucial aspect of achieving FPE within digital transformation enterprises, [17]. The method of combining qualitative analysis and PCA is utilized to construct a preliminary indicator system of 27 indicators for the FPE of manufacturing enterprises. The system is based on the dimensions of profitability, solvency, development, and operational capacity, adhering to the principles of relevance, systematicity, importance, and feasibility. The FPE index system of manufacturing enterprises is illustrated in Figure 1.

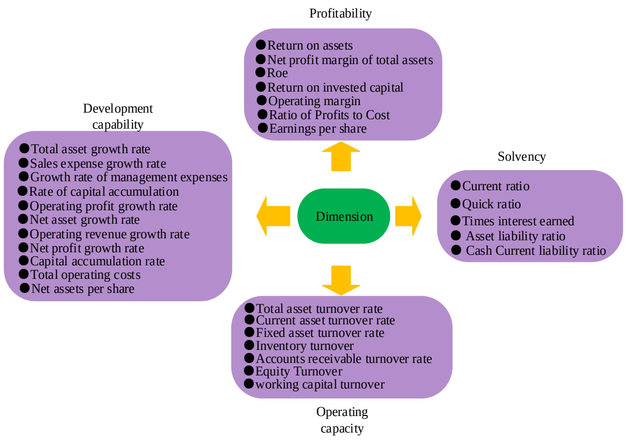

Fig. 1: FPE index system for manufacturing enterprises

In the optimization of the indicator system, the indicators are first screened, and the commonly used methods are: PCA, conditional generalized variance minimization method, great irrelevance method, expert consultation method, [18], [19]. The study carried out PCA on the initially selected financial indicators according to different dimensions, to establish a set of comprehensive and objective FPE index systems. The financial indicators related to the four dimensions of profitability, solvency, development ability, and operating ability were selected. Using PCA, the preliminary indicators under each dimension are screened, to obtain the representative indicators of each dimension. The screening steps of the indicators are shown in Figure 2.

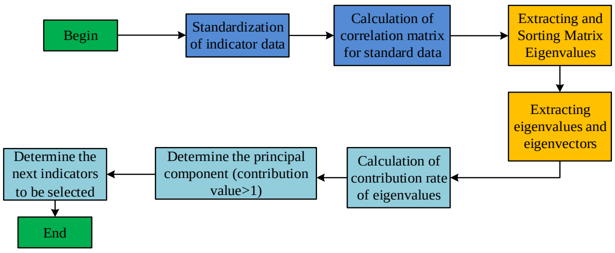

Fig. 2: Screening steps for indicators using principal component analysis

The representative indicators in each of the four selected dimensions were synthesized and subjected to PCA. All the selected indicators underwent multiple and repeated trial calculations and screening, augmented by subjective judgment and selection, to achieve the optimal FPE index system. The representative indicator system selected in the four dimensions is shown in Figure 3.

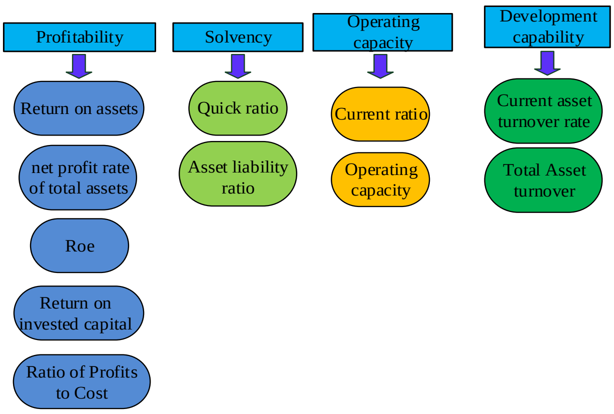

Fig. 3: A representative financial evaluation indicator system in four dimensions

Figure 3 presents the results of the study's analysis of seven profitability indicators to illustrate PCA. The selected indicators accurately represent the profitability dimension. Profitability is a company's ability to generate earnings over a period of time. Using PCA, after screening the initial selection of indicators for the profitability dimension, five representative indicators were selected: return on assets, net profit margin on total assets, return on net assets, return on invested capital, and cost and expense margin. Asset return rate refers to the ratio of the sum of net profit, interest expense, and income tax of a company over a certain period of time to the average total amount of assets. The net profit margin of total assets refers to the percentage of a company's net profit to the average balance of total assets. Return on equity (ROE) is a measure of a company's profitability through investment over a certain operating period. The return on investment capital is an indicator used to evaluate the historical performance of a company, mainly measuring the effectiveness of the invested funds. Cost expense profit margin refers to the ratio between a company's net profit and the total cost expense. Solvency refers to the company's ability to use its assets to repay short-term and long-term debts. The quick ratio and gearing ratio were chosen as the two indicators for the study. The quick ratio is a representative indicator of a company's short-term solvency, mainly representing the proportion of quick assets in the company's current liabilities. The debt-to-asset ratio to a certain extent represents the size of a company's long-term debt repayment risk, mainly reflecting the proportion of the company's total liabilities to total assets. The company's development ability pertains to its potential for future expansion and the consequential changes in business operations that will reflect the speed and prospects for future growth. The study chooses two representative indicators, namely the growth rate of total assets and the operating income. The total asset growth rate is a positive indicator that mainly reflects the changes in the total assets of the enterprise. It can provide more timely feedback on changes in the enterprise's business strategy. The growth rate of operating revenue is a direct manifestation of a company's operating situation. Compared to profits, operating revenue is less affected by accounting and can reflect changes in the company's operating situation more quickly. The operational capability of an enterprise is the operational management capability of an enterprise in a particular operational cycle. On this basis, the current asset turnover ratio and total asset turnover ratio are proposed to represent the operational capability of an enterprise in a particular period. The turnover rate of current assets primarily indicates an enterprise's capacity to utilize current assets for generating operating income, thus serving as a favorable indicator. The total asset turnover rate refers to the ratio of a company's net operating income to its total assets over a certain period of time.

3.2 Comprehensive FPE of Digital Transformation Enterprises based on FA and Entropy Weight Method

When evaluating a company's financial performance using the performance appraisal method, each financial indicator's significance is determined. This is achieved by assigning a power to each financial indicator. The methods of assigning power to financial indicators are categorized as shown in Figure 4.

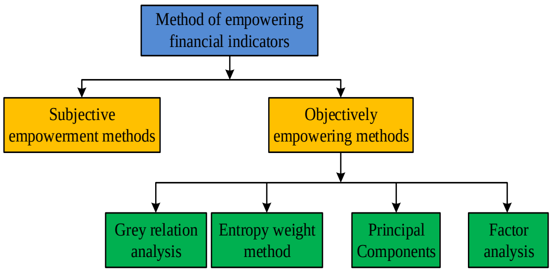

Fig. 4: Classification of methods for empowering financial indicators

In Figure 4, it consists of subjective empowerment and objective empowerment. Grey correlation analysis, entropy weight method, PCA, and FA are currently commonly used objective empowerment methods. The study uses objective empowerment methods such as PCA, FA, and entropy weight methods to study the empowerment of financial indicators and the evaluation method of financial performance. The steps of the PCA method are shown in Figure 5.

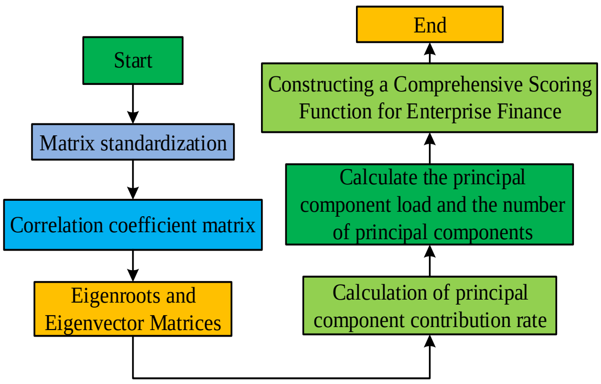

Fig. 5: Steps of PCA

In the step of the PCA method in Figure 5, the raw data matrix of the sample is shown in Equation (1).

$$X = \begin{Bmatrix} X_{11}, X_{12} \dots X_{1p} \\ X_{21}, X_{22} \dots X_{2p} \\ \dots \\ X_{n1}, X_{n1} \dots X_{np} \end{Bmatrix} \quad (1)$$

Equation (1), Xij is the j-th financial indicator data of the i-th company to standardize the indicator matrix as shown in Equation (2).

$$X^* = \begin{Bmatrix} X*_{11}, X*_{12} \dots X*_{1p} \\ X*_{21}, X*_{22} \dots X*_{2p} \\ \dots \\ X*_{n1}, X*_{n1} \dots X*_{np} \end{Bmatrix} \quad (2)$$

The matrix of correlation coefficients is calculated as shown in Equation (3).

$$R = \begin{Bmatrix} r_{11}, r_{12} \dots r_{1p} \\ r_{21}, r_{22} \dots r_{2p} \\ \dots \\ r_{n1}, r_{n1} \dots r_{np} \end{Bmatrix} \quad (3)$$

The eigenroots and eigenvectors are calculated to get the matrix as shown in Equation (4).

$$r_{ij} = \frac{\sum_{k=1}^{n}(x_{ki} - x_i)(x_{kj} - x_j)}{\sqrt{\sum_{k=1}^{n}(x_{ki} - x_i) - \sum_{k=1}^{n}(x_{kj} - x_j)^2}} \quad (4)$$

The contribution of principal components is calculated to determine the principal components as shown in Equation (5).

$$\begin{Bmatrix} M_{Z_i} = \dfrac{\lambda_j}{\sum_{i=1}^{p} \lambda_j} \\ M = \dfrac{\sum_{j=1}^{m} \lambda_j}{\sum_{j=1}^{p} \lambda_j} \end{Bmatrix} \quad (5)$$

Equation (5), M represents the cumulative contribution rate and M_{Z_i} stands for the contribution rate of the principal component Z_i.

Principal component loadings can be calculated based on the results of principal component analysis and then combined with qualitative analysis to determine their significance. Principal components refer to a linear combination of the original financial indicators. In this linear combination, the coefficients of the individual variables are large or small. They are both positive and negative. The function for the composite score of a company's financial performance is shown in Equation (6), with the corresponding formula for FA also presented in Equation (6).

$$X_i = a_{i1}F_1 + a_{i2}F_2 + \ldots + a_{im}F_m + \varepsilon_i (i = 1, 2, \ldots, p) \quad (6)$$

In Equation (6), $F_1, F_2, \ldots, F_m$ is the public factor. ε_i is the special factor, and a_{im} is the factor loading coefficient. The core of FA is to analyze the correlation between numerous observed variables through dimensionality reduction. The fundamental structure of a significant volume of observational data has been examined. Variables with a common essence are grouped into a single factor to represent the basic data structure with a limited number of public factors. The method can extract the common factors from the cluster of variables to explain the structure among the variables at the cost of minimum information loss. The flow of the FA method used in the study is shown in Figure 6.

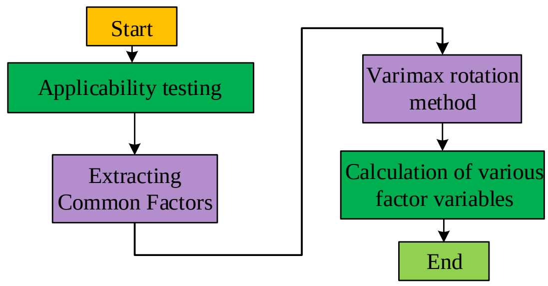

Fig. 6: Factor analysis process

In Figure 6, the first step of FA is to evaluate its applicability. If the factors are independent and the correlation is not strong, common factors cannot be obtained, rendering the FA unfeasible. So FA is done to determine the correlation between the original variables being analyzed and their applicability. Generally, Bartlett's Spherical test and KMO test are chosen for suitability analysis, [20]. The correlation matrix is tested by the Bartlett Spherical test. If it is an identity matrix, the observed data is not suitable for FA and vice versa. Overall, at a significant level of < 0.05, it indicates that there is a significant correlation in the original variables and can be used for FA. KMO values above 0.9 are most suitable for FA. KMO values located in the middle of 0.7-0.8 are well-suited. 0.5-0.7 are suitable. Values below 0.5 should be chosen to be discarded. The study utilizes PCA for extracting public factors. In determining the initial factors, the eigenvalues, cumulative variance contribution ratio of the factors, and fragmentation diagram are examined. Furthermore, it is verified if the selected principal components, which meet the requirement of eigenvalues ≥ 1, encompass 85% of the original data's information content. The formula for the variance contribution ratio of the common factors is shown in Equation (7).

$$M_{F_i} = \frac{\lambda_i}{\sum_{k=1}^{p} \lambda_k} (i = 1, 2, \ldots, p) \quad (7)$$

Equation (7), λ is the characteristic root of the correlation coefficient matrix. The cumulative contribution of public factors is calculated as in Equation (8).

$$N_{F_i} = \frac{\sum_{k=1}^{i} \lambda_k}{\sum_{k=1}^{p} \lambda_k} (i = 1, 2, \ldots, p) \quad (8)$$

By rotating the factors, the properties of these factors are reflected clearly. This helps to determine the degree of influence each factor has on the others, and subsequently identify which factors pertain to each other. After the factor variables are determined, the specific scores of each sample data in each different factor need to be calculated. By applying the FA method, the scores and rankings of each public factor can be computed to determine the factors that greatly influence the operation and management of the company. This ability to accurately pinpoint the entry point to enhance the operation and management of the company is extremely advantageous. The entropy weight method is one of the objective assignment methods, which can avoid the arbitrariness of manual subjective judgment. Firstly, the indicators are pre-processed to eliminate the gap between the indicators, and the standardization formula for the positive indicators is illustrated in Equation (9).

$$Y_{ij} = \frac{Xi_j - \min(X_{ij})}{\max(X_{ij}) - \min(X_{ij})} \quad (9)$$

The normalization formula for negative indicators is illustrated in Equation (10)

$$Y_{ij} = \frac{\max(Xi_j) - X_{ij}}{\max(X_{ij}) - \min(X_{ij})} \quad (10)$$

The fitness indicator's standardization is illustrated in Equation (11).

$$Y_{ij} = 1 - \frac{|X_{ij} - X_j|}{|\max(X_{ij} - X_j)|} \quad (11)$$

In Equation (11), X_j there are fixed values of the moderation criteria. The characteristic weight of the j-th indicator is calculated, i.e. contribution. The characteristic ratio of the i-th enterprise is calculated as shown in Equation (12).

$$P_{ij} = \frac{Y_{ij}}{\sum_{i=1}^{n} Y_{ij}} \tag{12}$$

For the j-th indicator, the entropy value is calculated as shown in Equation (13).

$$e_j = -\frac{1}{\ln n}\sum_{i=1}^{n} \ln(P_{ij}), 0 \le e_j \le 1 \tag{13}$$

The coefficient of variation is calculated by Equation (14).

$$g_j = 1 - e_j \tag{14}$$

The weights of the evaluation indicators are displayed in Equation (15).

$$W_j = \frac{g_j}{\sum_{i=1}^{m} g_j}, j = 1,2,...,m \tag{15}$$

4 Analysis of Evaluation Results and Comparison of Digital and Non-Digital Enterprises

For the 11 financial performance evaluation standards selected by the paper, the PCA method is applied. Seven indicators of profitability dimension are used as examples to start the analysis. Representative components are screened out. The selected indicators undergo multiple rounds of trial and error screening, supplemented by subjective judgment and selection, ultimately obtaining an ideal financial performance evaluation indicator system.

4.1 Analysis of the Screening Results of FPE Indicators based on PCA

On this basis, seven corporate profitability indicators are selected as examples and subjected to master meta-analysis. The 902 manufacturing companies on the main board of A-shares in Shanghai and Shenzhen are taken as the objects of this study. The indicators of return on assets, net profit margin on total assets, return on net assets, return on invested capital, operating profit margin, cost and expense margin, and earnings per share are expressed as X1, X2, X3, X4, X5, X6, X7. Using SPSS26.0 software, the correlation coefficient matrix R and its eigenvalues between the indicators are calculated. Table 1 displays the results.

Table 1. Matrix of correlation coefficients

	X1	X2	X3	X4	X5	X6	X7
X1	1	0.967	0.846	0.869	0.705	0.769	0.452
X2	0.967	1	0.879	0.883	0.721	0.778	0.425
X3	0.846	0.879	1	0.879	0.632	0.605	0.384
X4	0.869	0.883	0.879	1	0.571	0.608	0.340
X5	0.705	0.721	0.632	0.571	1	0.848	0.329
X6	0.769	0.778	0.605	0.608	0.848	1	0.639
X7	0.452	0.425	0.384	0.340	0.329	0.639	1

In Table 1, the seven preliminary evaluation indicators of each dimension of profitability have different focuses and are significantly different. The correlation coefficient between X1 and X2 is 0.967, indicating a highly positive correlation between them. Similarly, the correlation coefficient between X3 and X4 is 0.879, and the correlation coefficient between X5 and X6 is 0.848. However, the correlation between X7 and other dimensions is relatively low, with a maximum of only 0.639. The results of Bartlett's sphere test and KMO test are illustrated in Table 2.

Table 2. Bartlett spherical and KMO inspection results

Inspection category		Inspection results
KMO sampling		0.785
Bartlett sphericity	Approximate chi-square	9402.524
	Freedom	21
	Significance	0

In Table 2, there are significant differences in the profitability dimension of the seven primary indicators. The KMO test results in a score of 0.782, which is greater than 0.7 and suitable for FA. Bartlett spherical test of the test results are divided into three categories. The approximate chi-square is 9348.998, the degree of freedom is 21, and the significance is 0. This indicates that the sampling suitability of the sample is high, and the data fits well under the spherical assumption. The Principal Component Loadings Matrix and Score coefficient matrix are shown in Figure 7.

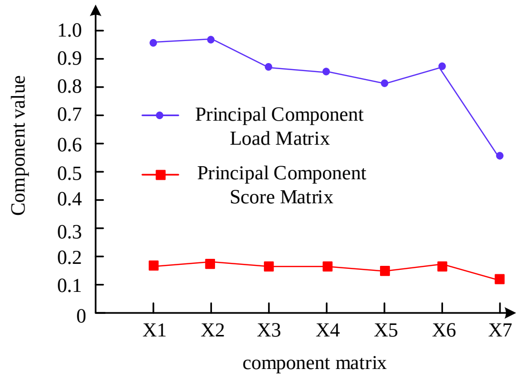

Fig. 7: Principal component load matrix and score coefficient

The principal components are represented by X_1, X_2, X_3, X_4, X_5, X_6. In terms of profitability, the study selects the above five financial indicators for the subsequent study. Then, following this procedure, the preliminary evaluation indicators of the other three dimensions are screened separately. Finally, the indicators to be selected for each dimension are combined and subjected to PCA analysis. According to the criterion of a cumulative variance contribution rate of 75% or more, this paper has screened out the final 11 indicators from the 27 preliminary indicators. The aim is to construct a financial performance evaluation index system for manufacturing enterprises.

4.2 Analysis of Financial Quality Results for Manufacturing Companies

The 11 financial performance evaluation criteria selected by the paper, are statically analyzed by calculating the observations, the mean, the median, the maximum, the minimum, and the standard deviation. Among them, the statistics of the indicators of the profitability dimension are shown in Figure 8.

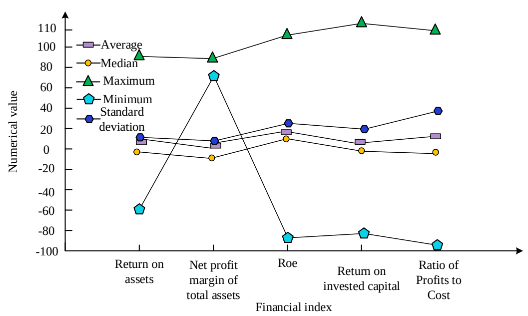

Fig. 8: Index statistics of profitability dimension

In Figure 8, the median of the overall return on assets, the median return on assets, the total asset net profit margin, and the cost expense profit margin of manufacturing enterprises are 4.78%, 3.5%, and 7.12%, respectively. These median values are all lower than the average of these three indicators, indicating that some companies perform poorly in terms of asset return, total asset net profit margin, and cost expense profit margin. This situation has led to the overall average of manufacturing enterprises being pulled down. This also indicates that some enterprises in the manufacturing industry are facing problems such as low profitability, low asset utilization efficiency, and poor cost management. The statistics of the indicators of the debt solvency dimension are shown in Figure 9.

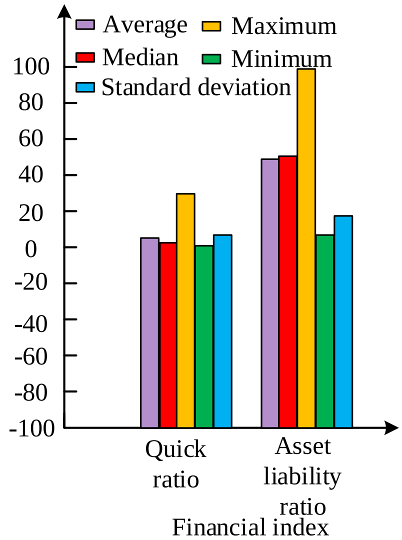

Fig. 9: Index statistics of debt repayment ability dimension

In Figure 9, the average levels of the quick ratio and asset-liability ratio are 1.55 and 44.25%, respectively. The asset-liability ratio is similar to its corresponding reasonable levels of 1 and 50%. The maximum value of the asset-liability ratio is 29.75. The minimum value is 0.07, and the standard deviation is 1.64. These results indicate that there are significant differences in asset-liability ratio and asset-liability ratio among listed companies in China. Among them, the maximum value of the asset-liability ratio is 98.21%, the minimum value is 1.43%, and the standard deviation is 18.41%. These data show the differences in financial conditions and changes in risk levels of listed companies. These differences may be caused by factors such as different industries, company sizes, and business strategies. Therefore, when assessing financial performance, it is necessary to take full account of these differences and to analyze and make judgments based on specific situations to develop appropriate financial management and asset allocation strategies for the company. The statistics of the indicators of development ability and operation ability dimension are shown in Figure 10.

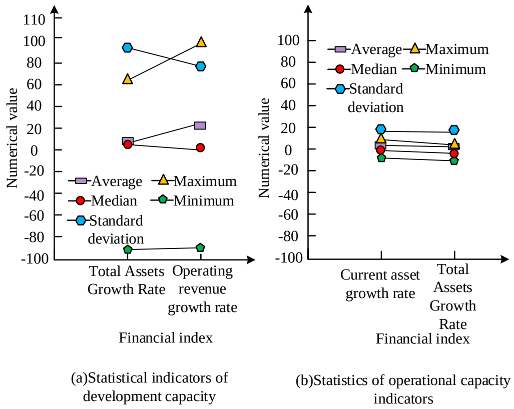

Fig. 10: Statistics of indicators for development and operational capacity dimensions

In Figure 10, the mean value of the total assets growth rate is 7.15 percent and the mean value of the operating income growth rate is 21.06 percent, with a standard deviation of 17.63 percent and 236.7 percent. There are significant differences between the maximum and the minimum values of these two indicators, which indicates that the average degree of dispersion of these two indicators is high. The mean value of the current assets turnover ratio and total assets turnover ratio are 1.41 and 0.64 respectively. The median is 1.15 and 0.62 respectively. The mean value is greater than the median, and the level of operational capacity of most enterprises is high. The maximum value is 6.12, 3.41. The minimum value is 0.05, 0.04. The standard deviation is 0.83, 0.34. Overall, the mean value of each indicator is larger than the median in the development capacity and operational capacity, which indicates that the overall level of development capacity and operational capacity of enterprises in the manufacturing industry is relatively strong. A comparison of the profitability of digitised and non-digitized companies is carried out for the period from 2014 to 2022.

In Figure 11, as a whole, the return on assets (ROA) of digitally transformed firms averages higher than the average of non-digitally transformed firms across all years. Over the period 2014-2023, the average return on equity (ROE) for digitally transformed firms is generally higher than the average ROE for non-digitally transformed firms, at 7.15 percent and 3.96 percent, respectively.

The ROE for non-digitally transformed companies is 6.91 percent, while the ROE for non-digitally transformed companies is 4.95 percent. After 2020, digital transformation companies tend to be more profitable than non-digital transformation companies due to their expertise in digital technology and their efficient cost management.

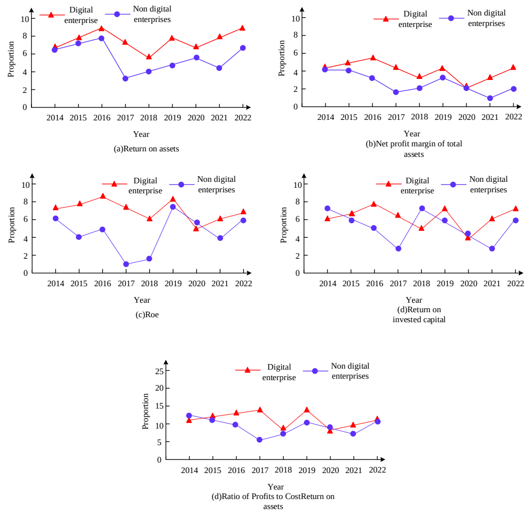

Fig. 11: Comparison of profitability between digital and non-digital enterprises from 2014 to 2022

5 Conclusion

As a part of the real economy, manufacturing is crucial in economic development. Every country in the world has realized that the DT of enterprises has become the inevitable choice of the times, and combining the new generation of digital technology with the traditional advantages of manufacturing enterprises is a realistic need for the future progress of enterprises. Under strong support for the digital economy, traditional manufacturing enterprises have started to utilize digital technology for business transformation. In the digital economy, whether digital transformation can bring new development for enterprises, the changes in financial performance before and after the transformation of manufacturing enterprises are worth exploring. The study employed the PCA method to select initial indicators within the FPE index system for manufacturing enterprises. After a thorough screening, it constructed a financial performance evaluation index system that suited the analysis of digitally transformed enterprises. The paper examined the differences in financial performance before and after digital transformation and carried out a comprehensive evaluation and comparative analysis of financially transformed and non-digitally transformed enterprises. The results indicated that digitally transformed enterprises yielded a mean return on net assets at a higher rate compared to non-digitally transformed enterprises, specifically 7.15% and 3.96%, respectively. Furthermore, digitally transformed enterprises appeared to boast greater advantages and operational adaptability in the digital arena when compared to their non-digitally transformed counterparts. Digitally transformed companies achieved superior financial performance in comparison to their non-digitally transformed counterparts. The stress capacity of firms that have undergone digital transformation was consistently higher than that of non-digitally transformed firms across all years. However, the study has some limitations. It is important to approach all forms of evaluation methods objectively and not excessively depend on them in future research.

References:

[1] Li D, Chen Y, Miao J, Does ICT create a new driving force for manufacturing? -Evidence from Chinese manufacturing firms, *Telecommunications Policy*, Vol.46, No.7, 2021, pp. 1029-1042.

[2] Jing S, Feng Y, Yan J, Path selection of lean digitalization for traditional manufacturing industry under heterogeneous competitive position, *Computers and Industrial Engineering*, Vol.161, No.2, 2021, pp. 1631-1648.

[3] Jafari S V, Garcia A, Candelo E, Couturier J, Exploring the impact of digital transformation on technology entrepreneurship and technological market expansion: the role of technology readiness, exploration and exploitation, *Journal of Business Research*, Vol.124, No.1, 2021, pp. 100-111.

[4] Long G, Li C, Li S, Xu T, Nonlinear characteristics of the effect of manufacturing servitization on consumer business performance, *Mathematical Problems in Engineering*, Vol.2021, NO.49, 2021, pp. 41-52.

[5] Li J P O, Liu H, Ting D S J, Jeon S, Chan R V P, Kim J E, Digital technology, tele-medicine and artificial intelligence in ophthalmology: a global perspective, *Progress in Retinal and Eye Research*, Vol.82, No.3, 2020, pp. 25-86.

[6] Lim M K, Xiong W, Wang C, Cloud manufacturing architecture: a critical analysis of its development, characteristics and future agenda to support its adoption, *Industrial Management and Data Systems*, Vol.121, No.10, 2021, pp. 2143-2180.

[7] Li J, Saide S, Ismail M N, Indrajitr R E, Exploring IT/IS proactive and knowledge transfer on enterprise digital business transformation (EDBT): a technology-knowledge perspective, *Journal of Enterprise Information Management*, Vol.35, No.2, 2021, pp. 597-616.

[8] Chen W, Zhang L, Jiang P, Meng F, Sun Q, Can digital transformation improve the information environment of the capital market? Evidence from the analysts' prediction behavior, *Accounting and Finance*, Vol.62, No.2, 2021, pp. 2543-2578.

[9] Anthony Jnr, B., Petersen S A, Helfert M, Guo H, Digital transformation with enterprise architecture for smarter cities: a qualitative research approach, Digital Policy, *Regulation and Governance*, Vol.23, no.4, 2021, pp. 355-376.

[10] Sia S K, Weill P, Zhang N, Designing a future-ready enterprise: the digital transformation of DBS bank, *California Management Review*, Vol.63, No.3, 2021, pp. 35-57.

[11] Dilek C K, Babak A, Understanding the role of employees in digital transformation: conceptualisation of digital literacy of employees as a multi-dimensional organizational affordance, *Journal of Enterprise Information Management*, Vol.34, No.6, 2021, pp. 1649-1672.

[12] Laghi E, Marcantonio M D, Cillo V, Paoloni N, The relational side of intellectual capital: an empirical study on brand value evaluation and financial performance, *Journal of Intellectual Capital*, Vol.23, No.3, 2020, pp. 479-515.

[13] Cremers K J M, Fulkerson J A, Riley T B, Benchmark discrepancies and mutual fund performance evaluation, *Journal of Financial and Quantitative Analysis*, Vol.57, No.2, 2021, pp. 543-571.

[14] Jahangir M, Mokhtari R, Mousavi S A, Performance evaluation and financial analysis of applying hybrid renewable systems in cooling unit of data centres-a case study, *Sustainable Energy Technologies and Assessments*, Vol.46, NO.8, 2021, pp. 32-46.

[15] Meng Q, Zhou Y, Enterprise economic performance evaluation based on 5G network and embedded processing system, *Microprocessors and Microsystems*, Vol.80, No.2, 2021, pp. 61-65.

[16] Mousavi M M, Lin J, The application of PROMETHEE multi-criteria decision aid in financial decision making: case of distress prediction models evaluation, *Expert Systems with Applications*, Vol.159, No.11, 2020, pp.

3438-3458.
[17] Wang H, Feng J, Zhang H, Li X, The effect of digital transformation strategy on performance: the moderating role of cognitive conflict, *International Journal of Conflict Management*, Vol.31, No.3, 2020, pp. 441-462.
[18] Zhu L, Li M, Metawa N, Financial risk evaluation z-score model for intelligent IoT-based enterprises, *Information Processing and Management*, Vol.58, No.6, 2021, pp. 102-111.
[19] Birskyte L, Mingelaite D, Government financial support: does it improve the performance of small and medium-sized enterprises in Lithuania? *International Journal of Entrepreneurship and Small Business*, Vol.43, No.1, 2021, pp. 142-163.
[20] Choudhuri S, Adeniye S, Sen A, Distribution alignment using complement entropy objective and adaptive consensus-based label refinement for partial domain adaptation, *Artificial Intelligence and Applications*, Vol.1, No.1, 2023, pp. 43-51.

Contribution of Individual Authors to the Creation of a Scientific Article (Ghostwriting Policy)

The author contributed in the present research, at all stages from the formulation of the problem to the final findings and solution.

Sources of Funding for Research Presented in a Scientific Article or Scientific Article Itself

No funding was received for conducting this study.

Conflict of Interest

The authors have no conflict of interest to declare.