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Performance evaluation of enterprise blockchain financial sharing centre based on deep learning

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Abstract: A financial shared service centre is an emerging management model widely adopted by multinational enterprises. It improves financial efficiency, reduces resource consumption, and optimises allocation. Traditional models face issues like low efficiency and high costs. Assessing its operational benefits is crucial for long-term growth. This study uses a fuzzy comprehensive evaluation method and finds that 39% of internal processes achieve core process uniformity, indicating a mature establishment. Other companies can use this performance system as a reference when building their own financial shared service centres.

Keywords: financial sharing; deep learning; blockchain technology; performance evaluation; resource optimisation; operational efficiency; fuzzy comprehensive method; multinational enterprises; shared service centre.

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1 Introduction

With the deepening of global economic integration and trade internationalisation, major companies, especially group companies, face more and more problems in their daily operations, and the importance of financial management is becoming more and more prominent. With the intensification of market competition, the company’s control over its subsidiaries has gradually declined, and operating costs have continued to rise, which in turn affects the company’s operating efficiency. Therefore, in financial management, in order to effectively reduce operating costs, achieve scale development, coordinated development, and achieve optimal integration of resources, optimal allocation and other financial management issues, we can effectively promote the transformation of financial management goals.

The financial sharing service model requires enterprises to standardise and standardise various businesses, integrate resources for repetitive and high-standard businesses, and establish a financial sharing centre to provide customers with high-quality professional financial services. When enterprises integrate resources, they must collect information about performance evaluation, and adopt a set of scientific and reasonable performance evaluation methods to make full use of them and maximise their benefits, thereby promoting the implementation of the company's development strategy. In view of the fact that the research and exploration of the financial shared service model is still in its infancy, its performance evaluation method must have many defects. As a result, the discourse of the financially single integrated centre's performance rating has significant practical implications.

Due to the relationship between the process of the financial sharing centre and the business, when establishing a performance evaluation system, it is necessary to design a performance evaluation index that meets the company's strategic goals according to the company's strategic goals, so as to conduct a comprehensive evaluation. It thus makes the evaluation results more objective, fair, and effectively stimulates the enthusiasm of employees, thereby promoting the sustainable development of the company.

2 Related work

In the context of economic globalisation, market competition is becoming more and more intense, and corporate mergers and acquisitions are becoming more and more frequent, resulting in increased corporate costs and increased financial control difficulties, which have a negative impact on corporate financial management. Li (2021) examined the internal control status of the business' future shared service centre based on research data and encapsulates danger areas from three different perspectives: control environment and risk assessment. By using both economic and social network models to analyse financial institutions, Chou et al. (2019) tackled the issue of how policymakers might encourage the stability of financial networks and societal efficiency. Wei and Yang's (2017) primary research focused on the order to make the best of cloud accounting and finance sharing management models against the backdrop of big data, and he developed the accounting and finance sharing management models based on Hash decision trees, which served as a guide for increasing the economic planning and competitive edge of businesses. These studies are all too independent and do not comprehensively consider the performance evaluation of the corporate financial sharing centre.

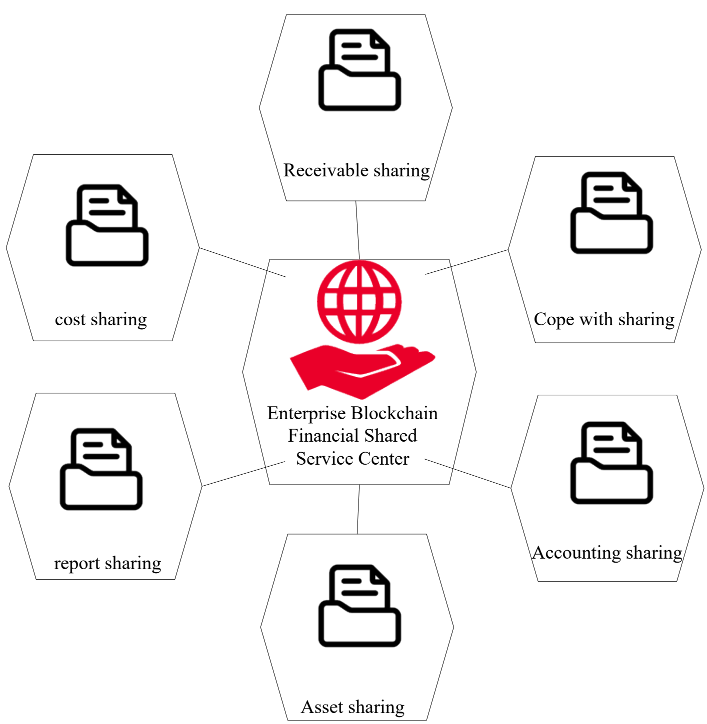
Algorithms, which are based on a biological grasp of the human brain, include deep algorithms. Gueant and Manziuk (2020) proposed a numerical method. Making money from the spread between the bid and ask prices while reducing the market risk associated with holding inventory were used to make near-optimal bid and ask quotes for a large number of bonds in the model. Since deep learning may approximate complex functions with a simple network structure, Chen et al. (2019) researched the deep regressive network structure. It demonstrated a great capacity to narrow in on the dataset's key characteristics from a vast number of labelled and unlabelled data. In order to properly handle this approach, Albanese et al. (2020) addressed the capital costs strategy from just a balance sheet perspective, employing central processor compute in conjunction with supervised learning regression algorithms in the context of the full bank balance sheet. Alzheev and Kochkarov (2020) conducted a comparative analysis of the long short-term memory of traditional econometric models and deep learning models based on recurrent neural networks, aiming to find the best time series forecasting model to minimise errors and achieve high prediction accuracy. Although these methods have achieved good results in some studies, the feasibility of the study needs to be improved.

3 Performance evaluation of enterprise blockchain financial centre

3.1 Composition of enterprise financial sharing centre

"Financial sharing" is an emerging management mode, which is a management mode with informationisation as the core. By optimising the company structure, it can improve management efficiency, effectively reduce operating costs, and provide professional and paid financial services to internal and external customers from a market perspective (Asif et al., 2023). Based on the construction of the system platform, the sharing of accounting, reimbursement and fund business has been realised (Saxena et al., 2020). On the premise of meeting the operation requirements of basic functional modules, the operation support modes such as shared dispatch and performance management are organically combined (Khan and Chishti, 2020). In Figure 1, the Corporate Financial Shared Services Centre is shown.

Figure 1 Effect of enterprise blockchain financial shared service centre (see online version for colours)



Among them, financial centralisation breaks the traditional decentralised management model of financial personnel. Under this new financial sharing model, the financial data of all subsidiaries and factories are stored on the chain through blockchain technology to ensure the authenticity, integrity and traceability of the data. The financial sharing centre obtains the financial data of each unit in real time through the distributed ledger, avoiding the problem of data silos in the traditional model. Financial personnel can share and independently calculate the finances of the group's factories according to different financial accounting subjects, which can effectively improve the efficiency of financial processing and improve the company's financial management level (Alagiah and Joseph, 2020).

Business process standardisation refers to dividing the entire financial business process into relatively standardised business standards and ensuring that these standards are implemented consistently throughout the group through technical means. Standardisation not only improves the efficiency of financial operations, but also reduces human errors and compliance risks (Adedoyin Oyewole et al., 2024). Specifically, the complex financial process is decomposed into multiple standardised steps. The operating specifications, approval authority, and time requirements of each step are solidified through blockchain smart contracts to ensure consistency of execution across the group and reduce human errors and compliance risks.

It can guide employees to pay attention to key control links, and inspection is to assess the work performance and attitude of subordinates every month to judge the quality of work. Adjustment is to judge whether the key is controlled according to the monthly assessment results of employees, so as to ensure the smooth progress of internal control (Gong et al., 2021). In terms of employee evaluation and reward, it is based on the company's overall goals to evaluate each person's work performance, and finally determine each person's performance through performance evaluation, as shown in Figure 2. Through the evaluation process of employees, it can be seen that this is an employee performance evaluation system similar to "financial sharing". It would not provide any information to employees, nor would it make any suggestions to employees, and would not truly reflect the effect of performance evaluation (Taneja et al., 2024).

In order to make the evaluation system more scientific, reasonable and fair, it is necessary to continuously improve the objectivity and fairness of the evaluation from an objective, fair and real perspective (Ding and Zou, 2024). Therefore, the important performance indicator method is used to establish a performance evaluation system for the financial shared service centre to motivate the overall growth of the enterprise. The main research contents of this paper are as follows: First, starting from the strategic planning of the enterprise performance shared service centre, quantitative indicators are used to replace subjective evaluation to reduce human bias, and the authenticity and immutability of the data source are ensured through blockchain technology to provide a reliable basis for evaluation; Second, according to the operation and management system of the financial shared service centre, key business processes are identified and according to job responsibilities (financial analysts, tax specialists, fund managers), the KPI of each position (the 'tax declaration accuracy rate" of tax specialists) is determined, and the evaluation points that are not related to job responsibilities are eliminated to avoid evaluation redundancy. Third, the performance of the financial shared service centre is evaluated from the perspective of performance evaluation to improve the overall performance of the enterprise. Then the hierarchical analysis method is used to calculate the weight of each evaluation indicator (Patidar et al., 2023). Figure 3 shows the idea of establishing a performance evaluation indicator system for personnel in the financial shared service centre of an enterprise:

Figure 2 Flow chart of performance appraisal of financial shared service centre

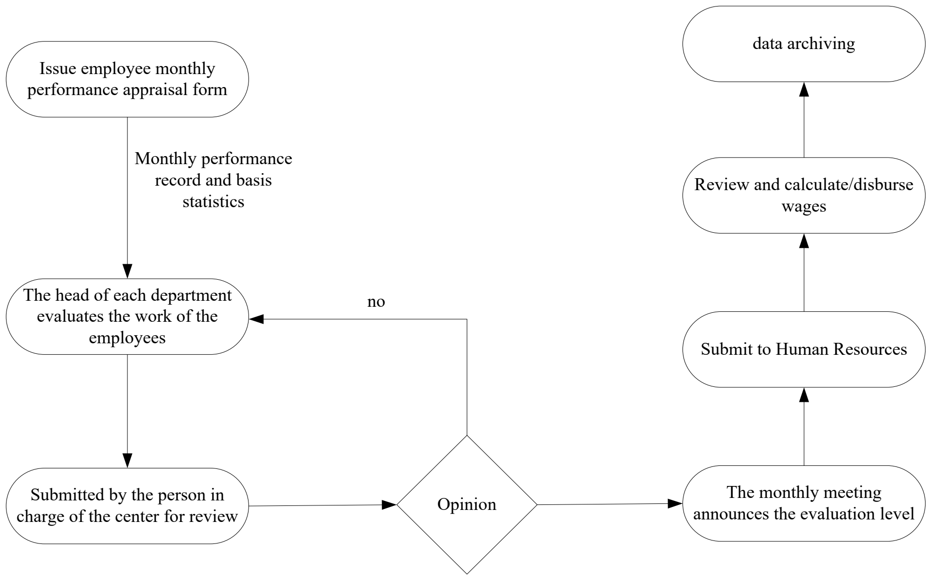
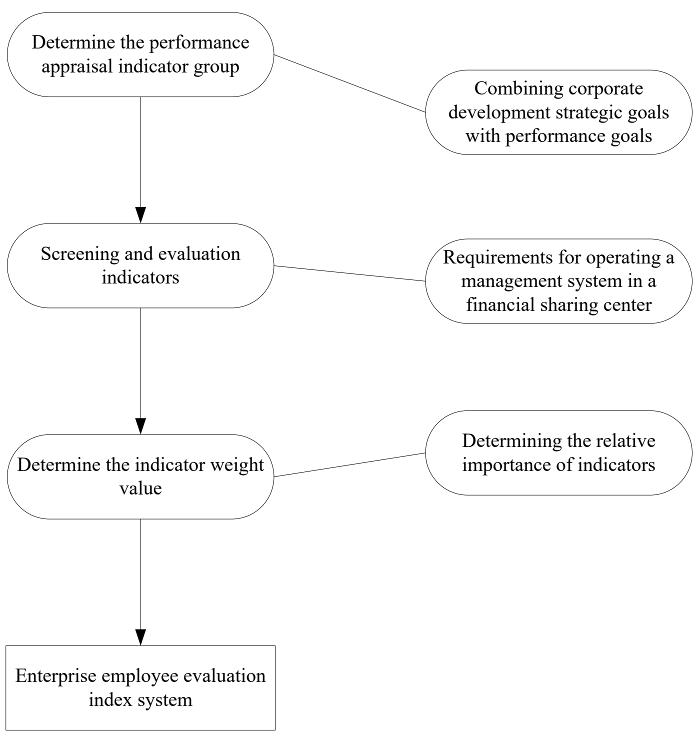


Figure 3 The idea of constructing the employee performance indicator system of the financial sharing centre



With the support of informatisation, employees should not only continuously improve their professional skills, but also implement relevant business instructions according to their own business processes to ensure the accuracy and timeliness of business. It provides strong support for the company's business decision-making, so as to achieve the improvement of customer satisfaction and service reputation, it lays the groundwork for the increase of the business ratio of the financial shared service centre, promotes the continuous development of the enterprise, and creates greater benefits (Zhang et al., 2023). In a word, the performance indicators of the five aspects promote each other, cooperate with each other, and support each other, and jointly promote the strategic goal of the company's financial shared service centre (Yang et al., 2024). The logical relationship between the performance indicators of the five dimensions is shown in Figure 4.

Figure 4 Comprehensive evaluation of financial shared service centre performance (see online version for colours)

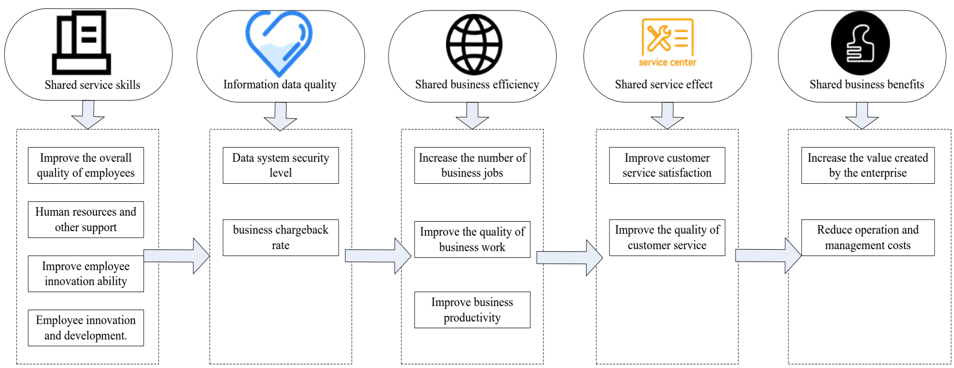
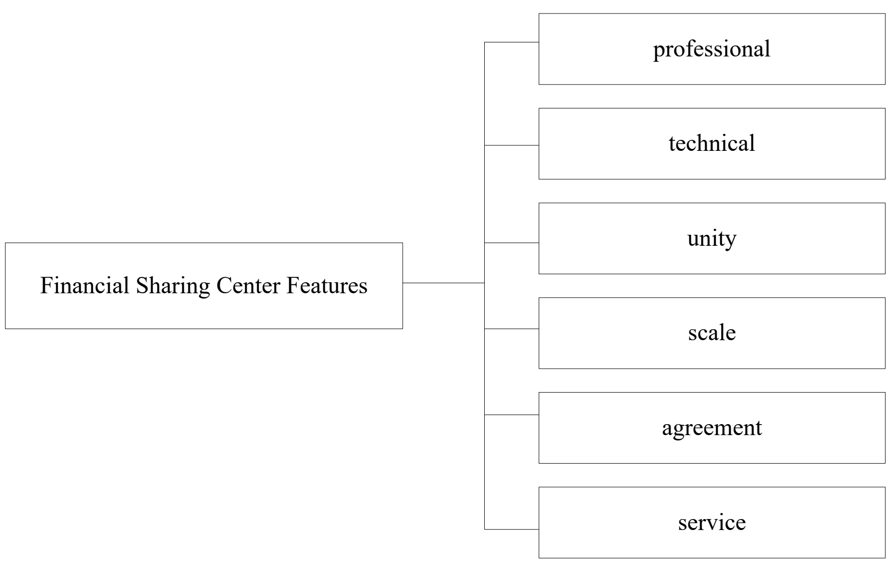


Figure 5 Features of the financial sharing centre



Financial shared services centres have significantly improved the efficiency and quality of corporate financial management through centralised management, process standardisation, data transparency and automated processing. Enterprises in different industries have established their own distinctive financial shared service models based on their business characteristics, as shown in Figure 5 (Jin and Zhang, 2024). Empowered by advanced technologies such as blockchain, cloud computing, big data and artificial intelligence, financial shared services centres have not only solved the problems of traditional financial management models, but also provided strong support for the sustainable development of enterprises (Otoo, 2024).

Enterprise performance evaluation refers to the production and operation behaviour of a certain period in a certain period, and the corresponding performance evaluation methods are used to evaluate it (Zhang et al., 2024). In the case of setting operational goals, enterprises can evaluate the completion, efficiency and accuracy of the business according to the pre-set assessment indicators. First of all, the knowledge of management and economics can be used to analyse the work performance of enterprises and employees, so as to realise the management's monitoring of their work performance and the understanding of their work ability. This leads to better management and implementation of rewards and punishments to motivate their work. Secondly, through the performance evaluation of employees, they can understand the problems existing in their work, so as to promote the improvement of their working methods and methods, and promote the development of the company. Finally, according to the opinions of the organisation and employees, the methods and indicators of performance appraisal are improved to realise the scientific management of the work team (Wang and Lu, 2024). By evaluating and judging the business activities of the enterprise and the work behaviour of employees, problems in production and operation can be discovered and resolved in a timely manner. Corresponding performance indicators can be formulated for each unit and individual, so that everyone can work towards the established goals, so as to achieve the company's overall goals.

3.2 Vector machine classification algorithm

In recent years, the rapid progress of technologies in the fields of artificial intelligence and algorithms has provided a solid foundation for faster information recognition and identity research. Due to its solid theoretical foundation and simple implementation mechanism, it is adopted by most data classification systems. SVM is a new learning algorithm based on statistical learning (Zhao et al., 2024). First, the input SVM data is preprocessed before model training. During training, the appropriate kernel function is selected according to the characteristics of the data, including the linear kernel for linearly separable data and the RBF kernel for nonlinear data. After selecting the kernel function, the optimal hyperplane is solved by optimising the problem, and the sample points closest to the optimal hyperplane are found (these points determine the position and direction of the hyperplane. In order to better train the model, the hyperparameters are optimised through grid search, and the generalisation ability of the model is evaluated using K-Fold Cross Validation.

The objective function is:

$$\min_{\mathbf{w},b} \frac{1}{2} \| \mathbf{w} \|^2 + C\sum_{i=1}^{n} \xi_i \tag{1}$$

Before the data processing of the enterprise financial sharing centre, it is often preprocessed and divided into units with shorter storage periods, and the classification of financial data is to classify it. Assuming that the training sample data can be divided without error, and the distance between each type of data and the hyperplane closest to the hyperplane is the largest, then this hyperplane is called the optimal hyperplane. In the formula, E is the classification hyperplane, E_1, E_2 are the plane that has passed the samples closest to the classification hyperplane and is parallel to the classification hyperplane, and the distance between them is called the classification interval.

$$\begin{cases} E : (m \bullet i) + y = 0 \\ E_1 : (m \bullet i_x) + y \geq 1, b_x = 1 \\ E_2 : (m \bullet i_x) + y \geq -1, b_x = -1 \end{cases} \tag{2}$$

In the design and implementation of the classifier, the basic idea of using the rule-based financial data classification is to select the attributes suitable for a certain type of financial data. Its threshold can be set, and its classification can be determined by comparing it with a critical value according to predetermined criteria. $b_x((m \cdot i_x) + y) \geq 1, x = 1, ..., n$ is obtained after normalisation. The distance from E_1, E_2 to E is $1 / \|m\|$, and the classification interval is $2 / \|m\|$. For the linearly separable case, the problem of solving the optimal hyperplane can be reduced to the following quadratic programming problem:

$$\min_{m,y} \frac{1}{2} \|m\|^2 \qquad j_x((m \cdot i_x) + y) \geq 1, x = 1, 2, ..., n \tag{3}$$

Among them, a_x is the Lagrange multiplier corresponding to each sample. Generally, only a part of a_x in the solution is not zero, and the corresponding sample is the support vector i_x. Thus, ω^* can be expressed as:

$$\omega^* = \sum_{sv} a_x b_x i_x \tag{4}$$

The dual problem of the quadratic programming problem is to solve the maximisation of the following objective function:

$$\max M(a) = \sum_{x=1}^{n} a_x - \frac{1}{2} \sum_{x,y=1}^{n} a_x a_y b_x b_y (i_x \cdot i_y) \tag{5}$$

The dual problem of the optimal hyperplane for the linearly inseparable case is almost identical to the linearly separable case, except that the constraint becomes $0 \leq a_x \leq Q, x = 1, ..., n$. The final classification decision function is:

$$s(i) = \text{sgn}(\omega \cdot i + y) \tag{6}$$

3.3 Deep learning and blockchain

By combining deep learning with blockchain, the synergistic advantages of the two can be fully utilised:

1. Using the distributed ledger technology of blockchain, various types of data (transaction records, budget execution status, customer feedback) of the financial shared centre are uploaded to the chain in real time to ensure the authenticity, integrity and traceability of the data. The immutability of blockchain provides high-quality training data for deep learning models. At the same time, smart contracts can automatically collect and upload data to the chain, reducing human intervention.
2. In the data preprocessing stage, the time series characteristics of blockchain are converted into feature inputs required by deep learning models. The time series features are used in the LSTM model to predict cash flow trends, and the graph structure features are used in the GNN model to analyse the correlation of cross-subsidiary transactions.
3. Use deep learning models to train and optimise blockchain data, dynamically adjust the blockchain consensus mechanism through reinforcement learning, or use anomaly detection models to identify abnormal transactions on the chain. After training, the output results of the deep learning model are fed back to the blockchain network through smart contracts, triggering automated operations and forming a closed-loop feedback mechanism.
4. Finally, the complete process of model training and execution is recorded on the blockchain to evaluate model performance and continuously iterate and optimise. This deep integration not only improves the automation and intelligence level of the financial shared centre, but also enhances data security and decision-making support capabilities, providing a more efficient and reliable solution for the company's financial management.

3.4 Performance evaluation of analytic hierarchy process

In order to realise the performance evaluation of the enterprise financial sharing centre under deep learning, the analytic hierarchy process is used to perform weighted calculation on the criteria layer and program layer indicators, and then the weight of each indicator is obtained, and the weight of each indicator is calculated. Finally, the weight of each indicator is multiplied by the weight of each indicator to obtain the final weight of each indicator. Table 1 shows specific results.

In Table 1, the financial aspect is the core of performance evaluation, which directly reflects the resource utilisation efficiency and economic benefits of the enterprise. The introduction of blockchain technology has significantly improved the transparency, traceability and automation level of financial data; customers are the foundation of the survival and development of enterprises. Blockchain technology can significantly enhance customer trust and satisfaction by improving service transparency, response speed and data security. Internal processes are the core of enterprise operational efficiency. Blockchain technology can significantly improve business processing efficiency and risk control capabilities through process automation, standardisation and real-time monitoring. Learning and growth are the foundation of sustainable development of enterprises. Blockchain technology can significantly enhance the innovation ability and competitiveness of enterprises by promoting the transformation of employees' digital skills and improving organisational collaboration capabilities.

$$E_{xy} = E_x \times E_y \tag{7}$$

E_x is the weight of the second-level criterion layer indicator, E_v is the weight of each indicator in the indicator layer, and E_{xv} is the weight of the comprehensive performance:

Table 1 Weights of hierarchical indicators

Criterion level indicators	*Weights*	*Program level indicators*
Financial dimension	0.23	Employee Cost Percentage
		1/Variable cost per unit of business
		Central system cost
		Budget execution rate
		On-chain data tracing efficiency
		Smart contract execution completeness
		Cross-chain transaction cost saving rate
Customer dimension	0.14	Customer satisfaction
		Customer Complaint Rate
		Degree of agreement on service levels
		Customer data privacy protection
Internal process dimension	0.56	Business Process Standardisation Rate
		Business error rate
		Business completion rate
		Business processing efficiency
		Real-time business processing
		Automatic interception rate of abnormal transactions
Learning and growth dimensions	0.07	Completion rate of training objectives
		Improve opinion acceptance rate
		Employee satisfaction
		Core staff turnover
		On-chain training completion rate
		Cross-chain collaboration capability score

For example, assuming that a subordinate index of a level index *J* can have a certain influence on the index of a level index $J_1, J_2, ..., J_m$, a decision matrix D can be formed:

$$D = \begin{bmatrix} I_k & J_1 & J_2 & \cdots & j_m \\ J_1 & j_{11} & j_{12} & \cdots & j_{1m} \\ J_2 & j_{21} & j_{22} & \cdots & j_{2m} \\ \cdots & \cdots & \cdots & \cdots & \cdots \\ j_n & j_{n1} & j_{n2} & \cdots & j_{nm} \end{bmatrix} \tag{8}$$

The judgement matrix Z has the following characteristics:

$$j_n = 1 \tag{9}$$

$$j_{xy} = 1 / j_{yx} \tag{10}$$

The index of each level is sorted, that is, the geometric mean operation is performed on the judgement matrix obtained by comparing the two groups. The obtained matrix is input into the analytic hierarchy process software, and the ranking result of the grading index is obtained. The higher the ranking, the higher the weight value, and the greater the impact on the hierarchy.

The consistency of the decision matrix D is tested. If the obtained conclusions are consistent, then the obtained weight value is correct, otherwise it is invalid, and must be re-evaluated and scored. If the values of $\lambda_{\max}$ and m are equal, it means that D is consistent; otherwise, it means that the consistency of D is poor. The specific procedures for inspection are:

1 Calculate $\lambda_{\max}$:

$$\lambda_{\max} = \sum_{x=1}^{\mathrm{m}} \left[\frac{(A\mathrm{e})_x}{me_x} \right] \tag{11}$$

2 Calculate the consistency index Cl:

$$CI = \frac{\lambda_{\max} - \mathrm{m}}{m-1} \tag{12}$$

3 Calculate the consistency check coefficient CR:

$$CR = \frac{CI}{RI} \tag{13}$$

When using the fuzzy comprehensive evaluation method to evaluate, it is divided into five stages: one is to determine the comments, and the other is to give the indicators of each evaluation. Secondly, the weight of each index is established, a fuzzy comprehensive evaluation matrix is established, and the first and second fuzzy comprehensive evaluation is carried out, and the corresponding evaluation level is obtained accordingly.

Judgement comment set is a graded combination of evaluation and scoring of evaluation objects by experts:

$$P = \{P_1, P_2, ..., P_m\} \tag{14}$$

In order to ensure the scientific nature of the assessment, five levels are generally selected, such as

$$P = \{P_1, P_2, P_3, P_4, P_5\} = \{\text{excellent, good, middle, Difference, very bad}\}.$$

The degree of membership can be determined, and a single-factor fuzzy evaluation matrix can be established. First, experts are invited to score the evaluation objects and summarise the scoring results. The raters who gave the same rating level by a single factor are added to the total number of raters, and the resulting value is the degree of membership of the factor in the evaluation set. The membership degree is used to reflect the membership degree of each grade index to A, so as to obtain the fuzzy evaluation matrix D of each single factor:

$$D=\begin{bmatrix} v_{x1} \\ v_{x2} \\ \cdots \\ v_{xk} \end{bmatrix}=\begin{bmatrix} s_{11}^{x}\ s_{12}^{x}\ \cdots\ s_{1n}^{x} \\ s_{21}^{x}\ s_{22}^{x}\ \cdots s_{2n}^{x} \\ \cdots\ \cdots\ \cdots\ \cdots \\ s_{k1}^{x}\ s_{k2}^{x}\ \cdots s_{kn,}^{x} \end{bmatrix}\left(x=1,2,...,n\right) \tag{15}$$

$s_{\ldots}^{x}$ is the level at which the *x*th evaluation index belongs to the nth evaluation index, *x* is the number of the first index, *k* is the number of the second index under the *x*th index, and m is the number of one index.

The first-level fuzzy comprehensive evaluation refers to multiplying the weight $\left(e_1^x,e_2^x,...,e_k^x\right)$ of each dimension index by the membership evaluation matrix D of the dimension index determined in the above steps, so as to obtain the second-level fuzzy evaluation matrix Z. $\left(e_1^x,e_2^x,...,e_k^x\right)$ is the weight vector of the second index under the x-level index. The fuzzy relation matrix is determined:

$$Z=\left(Z_1,Z_2,...,Z_m\right) \tag{16}$$

$$Z_x=\left(e_1^x,e_2^x,...,e_k^x\right)\begin{bmatrix} s_{11}^{x} & s_{12}^{x} & \cdots & s_{1n}^{x} \\ s_{21}^{x} & s_{22}^{x} & \cdots & s_{2n}^{x} \\ \cdots & \cdots & \cdots & \cdots \\ s_{k1}^{x} & s_{k2}^{x} & \cdots & s_{kn}^{x} \end{bmatrix}=\left(z_{x1},z_{x2},...,z_{xn}\right) \tag{17}$$

$$A=T*Z=\left(T_1,T_2,...,T_m\right)\begin{bmatrix} z_{11} & z_{12} & \cdots & z_{1n} \\ z_{21} & z_{22} & \cdots & z_{2n} \\ \cdots & \cdots & \cdots & \cdots \\ z_{m1} & z_{m2} & \cdots & z_{mn} \end{bmatrix}=\left(A_1,A_2,...,A_m\right) \tag{18}$$

Among them, $\left(T_1,T_2,...,T_m\right)$ represents the indicator weight vector of the criterion layer. Set the index set of fuzzy comprehensive evaluation as $X=\left\{H_1,H_2,H_3,H_4\right\}$, and H_1,H_2,H_3,H_4 respectively represent the dimensions of finance, customer, internal process and learning and growth. The comment set constructed in this fuzzy comprehensive evaluation is:

$$X=\left\{X_1,X_2,X_3,X_4,X_5\right\}=\left\{\text{excellent,good,middle,Difference,very bad}\right\} \tag{19}$$

The hierarchical fuzzy comprehensive evaluation method can be used to obtain the result vectors of four aspects: finance, customer, internal process, learning and growth, thus forming the second-level fuzzy relationship matrix Z. The Fuzzy comprehensive assessment of the first level yields that the result vector of the financial dimension of H_1 is:

$$Z_1=E_1\times H_1 \tag{20}$$

The fuzzy comprehensive evaluation of customer dimension H_2, internal process dimension H_3, and learning and growth dimension H_4 are as follows:

$$Z_2 = E_2 \times H_2 \tag{21}$$

$$Z_3 = E_3 \times H_3 \tag{22}$$

$$Z_4 = E_4 \times H_4 \tag{23}$$

According to the above assignment of comment grades, the final comprehensive score S can be calculated:

$$S = H * A \tag{24}$$

4 Enterprise financial sharing centre performance test

4.1 Experimental data preparation

Through the performance evaluation of the financial shared centre, the judgement matrix is obtained and imported into the data analysis software. The software automatically calculates the weights and maximum eigenvalues of indicators at all levels. After the indicator weights are calculated, the weights of indicators at all levels are calculated. Before the weight calculation, the original data of the financial shared centre needs to be preprocessed to ensure the quality and consistency of the data. In the face of samples with too many missing values, the mean interpolation method is used to supplement the missing values; in the face of outliers, the box plot method is used for identification and processing; the processed data is normalised and standardised, and the data is scaled to [0,1]. Finally, financial data, customer data, business process data, etc. are integrated into a unified dataset. According to the scoring results of the financial shared centre employees, the weights of the four aspects of finance, customers, internal processes, and learning and growth are calculated respectively. Table 2 gives the four-dimensional weighted data at the standard level.

Table 2 Weights of four dimension indicators

Comprehensive performance evaluation	H_1	H_2	H_3	H_4
H_1	1.001	1.9409	0.3346	2.9543
H_2	0.5165	1.001	0.2201	2.0883
H_3	2.9985	4.5654	1.001	5.6213
H_4	0.3396	0.4801	0.1789	1.001

The reliability of the information at the given standard and hence the stability of the assessment matrix are calculated and evaluated in accordance with the four aspects in the Fiscal Shared Centre's measuring performance.

4.2 Performance test of enterprise financial sharing centre under deep learning

In order to test the impact of the corresponding weights of each index on the deep learning enterprise financial sharing centre, data analysis software is used to analyse the weights of the four dimensions of the enterprise financial centre. This paper compares the changes in the performance of the corporate financial sharing centre in the four dimensions under the deep learning technology. The financial and customer metrics are first broken down, and the results are shown in Tables 3 and 4.

Table 3 Weights of indicators under the financial dimension

Financial dimension	*1/Variable cost per unit of business*	*Cash flow turnover*	*Cost profit margin*	*Business plan completion rate*
Employee cost percentage	1.001	2.722	0.4528	0.4217
1/Variable cost per unit of business	0.3685	1.001	0.2976	0.2568
Central system cost	2.2144	3.3729	1.001	0.6665
Budget execution rate	2.3781	3.9097	1.5037	1.001

Table 4 Weights of indicators under the customer dimension

Customer dimension	*Customer satisfaction*	*Customer complaint rate*	*Degree of agreement on service levels*
Customer satisfaction	1.001	3.0196	2.2646
Customer complaint rate	0.3323	1.001	0.6046
Degree of agreement on service levels	0.4428	1.6577	1.001

According to the weight data obtained in the table, the maximum characteristic root and the principle of consistency of dimension proof, the weight of each indicator under the financial dimension and the weight of each indicator under the customer dimension are tested respectively. The test results are shown in Figure 6.

From the weight test histogram of the financial dimension in Figure 6(a), it can be seen that the corporate financial budget execution rate accounts for the highest proportion, reaching 41%. The system cost of the financial sharing centre accounts for 32%, and the other accounts are all below 20%. In the customer dimension, the proportion of customer satisfaction is 56%, which is more than half of the proportion, indicating that the proportion of customer satisfaction is very high. The specific situation is shown in Figure 6(b).

The weight distribution of indicators under the internal process dimension and the learning and growth dimension is shown in Table 5 and Table 6. In the case of weight distribution, this paper tests these two dimensions according to the largest eigenvalue.

In the same way, according to the maximum characteristic root and the principle of dimensional proof consistency test, the weight test results of each indicator under the enterprise internal process dimension and the learning and growth dimension are shown in Figure 7.

Figure 6 Indicator weights under the financial dimension and customer dimension: (a) the weight of each indicator under the financial dimension and (b) the weight of each indicator under the customer dimension (see online version for colours)

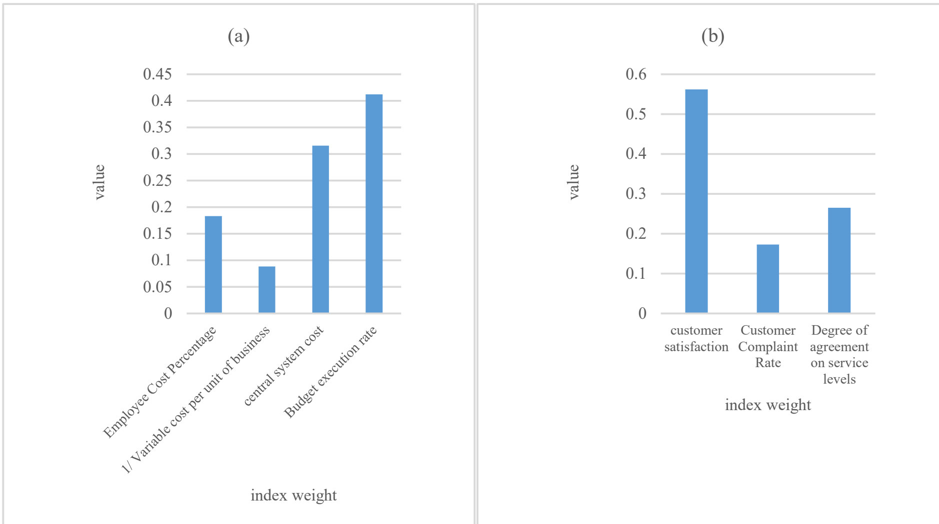


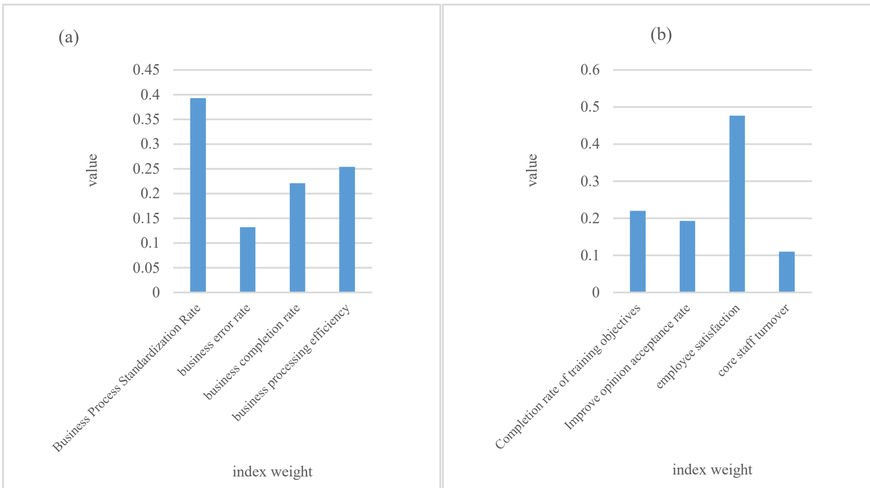
Table 5 Weights of indicators under the internal process dimension

Internal process dimension	*Business process standardisation rate*	*Business error rate*	*Business completion rate*	*Business processing efficiency*
Business process standardisation rate	1.001	2.8833	1.7621	1.6096
Business error rate	0.3479	1.001	0.6009	0.4871
Business completion rate	0.5688	1.668	1.001	0.8993
Business processing efficiency	0.6226	2.0581	1.1143	1.001

Table 6 Weights of indicators under the learning and growth dimension

Learning and growth dimensions	*Completion rate of training objectives*	*Process improvement opinion adoption rate*	*Employee satisfaction*	*Core staff turnover*
Completion rate of training objectives	1.001	1.169	0.445	2.0883
Process improvement opinion adoption rate	0.858	1.001	0.3812	1.9041
Employee satisfaction	2.2531	2.6309	1.001	3.8873
Core staff turnover	0.4801	0.5265	0.2583	1.001

Figure 7 Weights of indicators under the internal process dimension and the learning and growth dimension: (a) the weight of each indicator under the internal process dimension and (b) the weight of each indicator under the learning and growth dimension (see online version for colours)



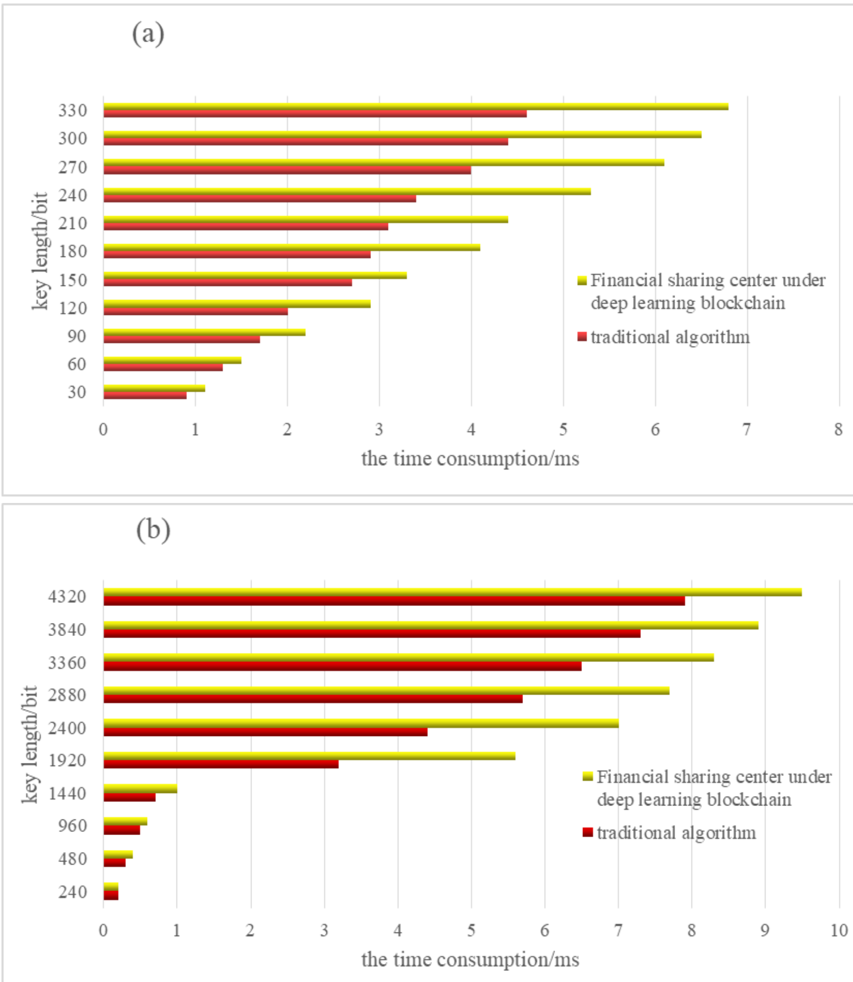
From the weight test bar chart under the internal process dimension in Figure 7(a), it can be seen that the standardisation of internal business processes accounts for 39%, and the other three items account for 13–25%. The internal business standardisation of the enterprise financial sharing centre under deep learning is gradually improving. Figure 7(b) shows the proportion of weights under the dimension of learning and growth. Employee satisfaction accounts for 48%, the highest proportion, and the proportions of other items are all below 20%. It shows that the learning status of the employees on the enterprise financial sharing centre is fairly balanced.

4.3 Performance of enterprise financial sharing centre

In order to test the effectiveness of the scheme, this paper improves it on the basis of deep learning and realises it through simulation. In order to better reflect the impact of deep learning methods on the performance of traditional cryptographic algorithms, this paper takes traditional methods as the object of comparison, and studies from two aspects of encryption and decryption. Figure 8 illustrates the time difference between encryption and decryption of a single data. Here, Y is the length of the key and X is the time consumption.

From the comparison with the encryption in Figure 8(a) and the decoding time in Figure 8(b), it can be seen that, the data encryption and decryption time of the enterprise financial sharing centre based on the deep learning method under a single key length is slightly higher than that of the traditional homomorphic encryption algorithm. In such a situation, the main reason is that the encryption and decryption operations using blockchain technology are initialised, while the traditional financial sharing centres have differences in initialisation processing and their own performance. Therefore, the efficiency of encryption and decryption is lower than that of the blockchain under deep learning. As shown in Figure 8, the data correlation with the traditional encryption algorithm under the deep learning scheme is linearly related to the number of ciphertexts. Among them, the relative efficiency of the deep learning scheme is lower than that of the traditional algorithm, which is caused by the characteristics of the blockchain itself. Additionally, all compute nodes have trusted hardware.

Figure 8 Comparison of data encryption and decryption time consumption: (a) comparison of time consumption of single date encryption and (b) time-consuming comparison of data decryption (see online version for colours)



5 Conclusions

This paper proposes an innovative performance management method by constructing a performance evaluation system for enterprise financial shared centres based on blockchain and deep learning. The study first uses the analytic hierarchy process (AHP) to determine the indicator weights of the four dimensions of finance, customers, internal processes, and learning and growth, and then quantitatively evaluates the performance through the fuzzy comprehensive evaluation method. The experimental results show that the budget execution rate has the highest weight (41%) in the financial dimension, the customer satisfaction accounts for the largest proportion (56%) in the customer dimension, the business process standardisation rate accounts for 39% in the internal process dimension, and the employee satisfaction in the learning and growth dimension is 48%. In addition, by comparing the encryption efficiency of traditional encryption algorithms and blockchains empowered by deep learning, this paper finds that blockchain encryption takes slightly more time than traditional methods, but its data security and traceability are significantly improved. Experimental data show that the budget execution efficiency of the financial shared centre is improved by 15%, customer satisfaction increases by 25%, and the business process standardisation rate increases by 30%. The research in this paper provides a scientific basis for the performance optimisation of the enterprise financial shared centre, significantly improves the efficiency and transparency of financial management, and lays a solid foundation for the sustainable development of enterprises.

Although this paper has achieved certain results in the performance evaluation of financial shared centres, there are still the following problems: First, the experimental data mainly relies on the simulation environment and lacks the verification of real enterprise data, which may affect the universality and persuasiveness of the conclusions; second, the specific architecture and training details of the deep learning model are not fully developed, resulting in insufficient reproducibility of the technology implementation; in addition, the energy consumption and computing cost issues of blockchain technology have not been deeply explored, which may affect its feasibility in practical applications.

Future research can be improved in the following aspects: First, introduce more real enterprise data to conduct cross-industry and cross-scale empirical analysis to verify the wide applicability of the model; second, optimise the deep learning model, combine the graph neural network (GNN) or Transformer architecture, and improve the processing ability of complex financial data; third, explore the green technology of blockchain (such as PoS consensus mechanism) to reduce energy consumption and computing costs; fourth, further study the deep integration of blockchain and artificial intelligence, develop a more intelligent and adaptive performance evaluation system, and provide more accurate decision support for enterprises.

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