International Journal for Housing Science and Its Applications
Publish August 4, 2025. Volume 46, Issue 3 Pages 3069-3079

https://doi.org/10.70517/ijhsa463257

Construction and Organizational Effectiveness Enhancement of Enterprise Performance Management Optimization Model by Artificial Intelligence Technology

Tingliang Yan[1,2,*]
[1] Zhuhai College of Science and Technology, Zhuhai, Guangdong, 519041, China
[2] City University of Macau, Macau, 999078, China
Corresponding authors: (e-mail: jluzhsnow@163.com).

Abstract Performance evaluation is not only a reflection of the results of the enterprise's operational performance, but also an important reference for the optimization and improvement of enterprise performance management. This paper takes enterprise performance evaluation as an entry point, describes the design idea of enterprise performance management evaluation index system, and compares and analyzes the focus and shortcomings of two kinds of performance management tools, namely, balanced scorecard and key performance indicators. The uncertainty of the evaluated object in the process of performance management work is regarded as a random variable, and entropy is used to measure it. After completing the research preparation on the mathematical definition of entropy, the performance evaluation idea of CART decision tree algorithm is discussed by taking the example of R&D project of enterprise A. The performance evaluation model based on CART decision tree algorithm is constructed through three steps of defining variables, generating decision tree and pruning decision tree. Compared with similar modeling algorithms, the evaluation accuracy of the designed performance evaluation model on different performance data sets is stable at 95.00% and above, and up to 100.00%.

Index Terms cart decision tree algorithm, corporate performance management, performance evaluation model, balanced scorecard, key performance indicators

I. Introduction

In recent years, with the rapid development of artificial intelligence technology, enterprises have also begun to use artificial intelligence technology in performance management optimization [1], [2]. The application of artificial intelligence technology in performance management optimization can make the management of enterprises more intelligent and efficient, and help enterprises achieve comprehensive management and better performance [3], [4].

The application of artificial intelligence technology in enterprise performance management optimization has the following main effects. (1) Refined management, traditional performance management methods often require a large amount of human and material input, and there is a large error, while artificial intelligence technology can help enterprises to achieve automated data collection and analysis, in the development of performance management indicators, assessment of employee performance, monitoring processes, etc. greatly improve the efficiency and accuracy of management, to help enterprises to achieve more refined management [5]-[8]. (2) decision support, enterprise decision-making often need to consider many factors, and artificial intelligence technology can help enterprises realize comprehensive data collection and analysis in a short time, help enterprises objectively and scientifically formulate strategies and decisions, improve the accuracy and efficiency of decision-making [9]-[12]. (3) automated early warning, artificial intelligence technology can be in real-time monitoring of the business situation of enterprises, timely warning of potential risks and problems, and take the initiative to put forward solutions to help enterprises predict the future market dynamics, competitive pressure and other information, to improve the risk control and resilience of enterprises [13]-[16].

This paper firstly describes in detail the construction idea of enterprise performance evaluation index system, and the advantages and disadvantages of balanced scorecard method and key performance indicator method in performance management. Secondly, the uncertainty variable in performance management is measured and mathematically described as entropy and the related definition is explained. The CART decision tree algorithm is introduced again, and based on the R&D project of Company A, the theoretical framework of the performance evaluation model is designed as “data collection - data pre-processing - feature extraction - model construction”. At the same time, it discusses the construction process and steps of performance evaluation model under the CART decision tree algorithm. Finally, the overall performance of the model is evaluated by comparing the algorithms of similar models and integrating the features of executives. The practical application of the model is evaluated and analyzed with Company R as the research object.

II. Ideas for the construction of the indicator system and the selection of tools

II. A.Ideas for the construction of the indicator system

The first step is to define the company's strategic objectives. The second step is to use the four dimensions theory of the strategy map to analyze the four dimensions of finance, customers, internal business processes, and learning and growth in the context of the company's operations, and to locate the path of realization for each business dimension. Step 3: Determine company-level KPIs through the above analysis. The fourth step is to determine departmental performance indicators and job-level indicators by applying the theory of KPI decomposition and undertaking and combining the results of the four-dimensional analysis of the Balanced Scorecard. The idea of performance indicator construction is shown in Figure 1.

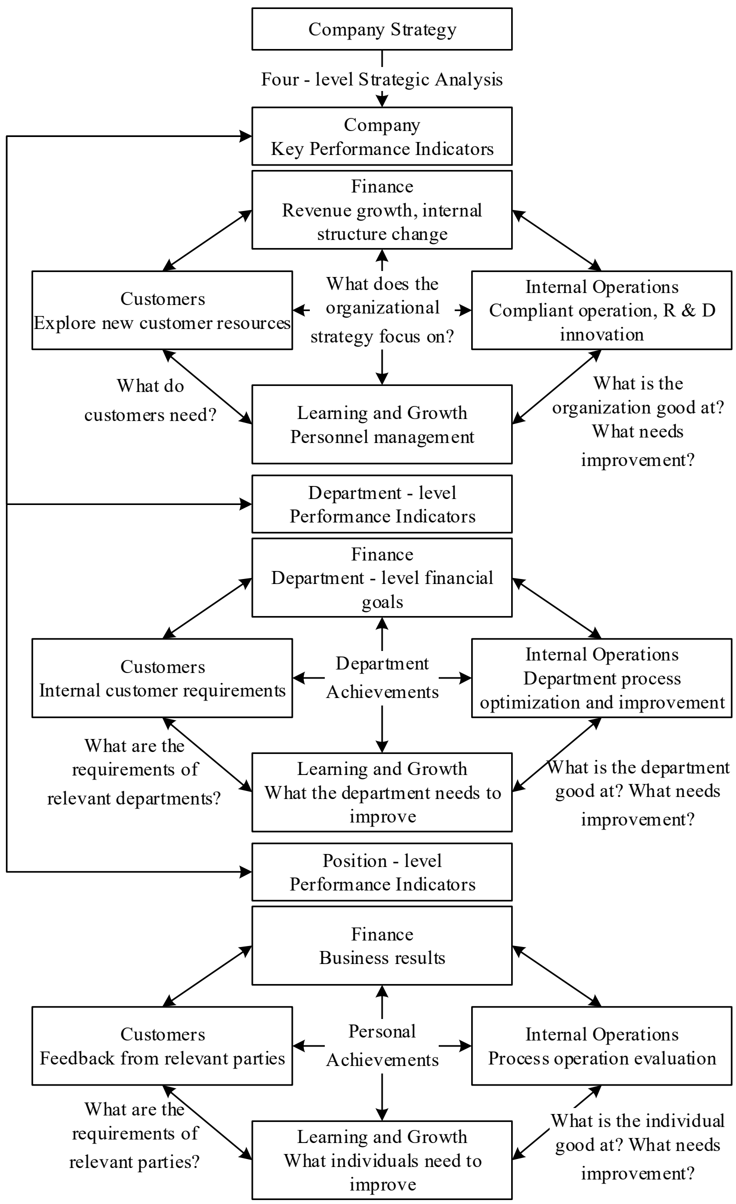

Figure 1: Ideas for constructing performance indicators

II. B.Tool selection

The BSC model, or Balanced Scorecard. It is a common performance management tool. It has the advantage of comprehensive consideration of business in corporate performance management, assessing corporate performance from four dimensions: finance, customers, internal processes and learning and growth, avoiding the limitations of a single indicator, and being able to reflect the operation of the enterprise more comprehensively. For the development of the company, it is necessary to break through the evaluation situation in which each business module is judged by financial and operational data, and focusing only on financial and operational indicators is not conducive to the long-term development of the organization. The introduction of other dimensional indicators can help enterprises diagnose their own development strengths and weaknesses, and guide management resources to focus on improving the disadvantaged items.

Key Performance Indicators (KPIs) are abbreviated as KPIs, and the implementation of KPI tools is based on the "two-eight principle", i.e., 20% of key factors will directly drive 80% of the economic output. The key to success in the field of performance management lies in pinpointing the 20% key factors, and through the reasonable design of indicators, it will help to improve the output of organizational performance.KPI has the advantages of clear value orientation and controllable management in the promotion of performance management. In terms of value orientation, KPIs are formulated to maximize the value of the enterprise's economic benefits, with a clear direction and closely aligned with the enterprise's value. When setting, it is easier to integrate the enterprise's strategic objectives with the department's business to ensure that the upper and lower levels share the same desire and goals are the same. In terms of controllable management, it is known from business practice that the measurement of work results is both objective and subjective, and the use of KPI focuses on the objectivity of the work results, and the subjective factors affecting the realization of the work are not included in the scope of KPI evaluation. This also makes KPI evaluation more concrete and objective.

The Balanced Scorecard and KPIs have their own advantages and disadvantages, among which the Balanced Scorecard is able to identify the indicators around the organization's strategic objectives, guided by the strategy and combining objective and subjective indicators, but it produces a large number of scattered indicators. In contrast, the Balanced Scorecard is able to accurately identify quantifiable and controllable granularity indicators with the organization's strategy at its core, but it also suffers from ambiguous strategic orientation, low indicator correlation, insufficient process control, and a lack of long-term leadership.

III. Performance evaluation model based on CART decision tree algorithm

III. A. Some definitions of entropy

In information theory and probability statistics, entropy is a measure that expresses the uncertainty of a random variable. The higher the entropy, the higher the degree of mixing and the greater the randomness.

Definition 1 (Entropy): let X be a discrete random variable taking on a finite number of values and with a probability distribution of the form (1):

$$P(X = x_i) = p_i, i = 1, 2, \cdots, n \tag{1}$$

Then the entropy of random variable X is as in equation (2):

$$H(X) = -\sum_{i=1}^{n} p_i \log p_i \tag{2}$$

From the above definition, it is clear that the entropy of the random variable X is independent of its own value and is only related to its own distribution, so it is also written as equation (3):

$$H(p_i) = -\sum_{i=1}^{n} p_i \log p_i \tag{3}$$

Definition 2 (Conditional Entropy): have a random variable (X, Y) with a joint probability distribution of the form (4):

$$P(X = x_i, Y = y_j) = p_{ij}, i = 1, 2, \cdots, n; j = 1, 2, \cdots, m \tag{4}$$

Conditional entropy $H(Y \mid X)$ represents the uncertainty of random variable Y conditional on the known random variable X. The conditional entropy $H(Y \mid X)$ of a random variable Y conditional on a given random variable X is defined as equation (5):

$$H(Y \mid X) = \sum_{i=1}^{n} p_i H(Y \mid X = x_i) \tag{5}$$

where $p_i = P(X = x_i) = p_i$, $i = 1, 2, \cdots, n$, the information gain denotes the extent to which the uncertainty in the information of class Y is reduced, conditional on the information of feature X being known.

Definition 3 (Information Gain): the information gain $g(D, A)$ of feature A on the training dataset D is defined as the difference between the empirical entropy $H(D)$ of the set D and the empirical conditional entropy $H(D \mid A)$ of D the given conditions of feature A, i.e., equation (6):

$$g(D, A) = H(D) - H(D \mid A) \tag{6}$$

The difference between entropy $H(X)$ and conditional entropy $H(Y \mid X)$ is also known as mutual information. From equation (6), it can be seen that the information gain depends on the features, if the features are different, the information gain is generally different. Features with large information gain indicate that under the condition of known features X, the more the degree of uncertainty of class Y is reduced, so features with large information gain have stronger classification ability. However, the information gain is biased, that is, the more values of features, the greater the information gain of features, the information gain ratio can effectively solve this problem.

Definition 4 (Information Gain Ratio): the information gain ratio $g_R(D, A)$ of feature A to the training dataset D is defined as the ratio of its information gain $g(D, A)$ to the entropy $H_A(D)$ of the training dataset D with respect to feature A, i.e., Equation (7):

$$g_R(D, A) = \frac{g(D, A)}{H_A(D)} \tag{7}$$

which has the formula (8):

$$H_A(D) = \sum_{i=1}^{n} \frac{|D_i|}{|D|} \log_2 \frac{|D_i|}{|D|} \tag{8}$$

n is the number of values of feature A.

Definition 5 (Gini exponent): In a classification problem, assuming that there are K classes and the probability that a sample belongs to class k is p_k, the Gini exponent of the probability distribution is defined as equation (9):

$$Gini(p) = \sum_{k=1}^{K} p_k (1 - p_k) = 1 - \sum_{k=1}^{K} p_k^2 \tag{9}$$

If the set of samples D is partitioned into D_1 and D_2 depending on whether feature A takes a certain possible value a, i.e., equation (10):

$$D_1 = \{(x, y) \in D \mid A(x) = a\}, D_2 = D - D_1 \tag{10}$$

Then the Gini index of set D is defined as equation (11) under the condition of feature A:

$$Gini(D, A) = \frac{|D_1|}{|D|} Gini(D_1) + \frac{|D_2|}{|D|} Gini(D_2) \tag{11}$$

$Gini(D)$ denotes the uncertainty of set D, and $Gini(D, A)$ denotes the uncertainty of set D after partitioning by $A = a$. The larger the Gini index, the more mixed the sample set is and the greater the randomness.

III. B. Design Ideas for Performance Evaluation Based on CART Decision Tree Algorithm

Based on CART decision tree algorithm, A enterprise R&D project performance evaluation idea is mainly composed of five parts: data collection, data preprocessing, R&D project performance evaluation index extraction, model construction and result analysis. First of all, data collection is to obtain the project cost, project team member profiles, project progress and results and other relevant information involved in the R&D project performance evaluation indexes, followed by data preprocessing operations, and then feature extraction of the R&D project performance evaluation indexes, followed by the construction of the R&D project performance evaluation model based on the CART decision tree algorithm and training of the model, and finally the model results are analyzed. Analyze the model results are shown in Figure 2.

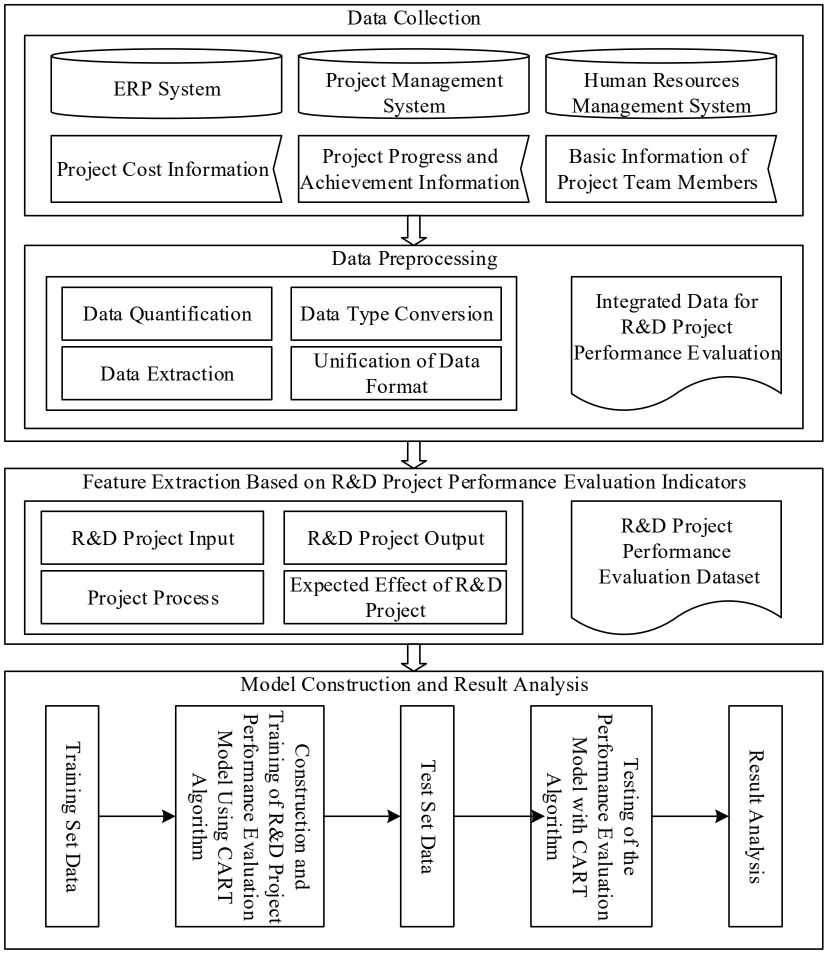

Figure 2: The performance evaluation idea of R&D projects based on CART algorithm

As shown in Figure 2, the idea of R&D project performance evaluation first needs to complete the preparation of data, including data collection and pre-processing operations. Collect data from ERP system, project management system and human resource system related to R&D project performance evaluation, such as project cost and expenditure details, project progress information, project expected results information and basic information of project team members. Then SQL statements are applied to the data for data type conversion, data format unification, data quantification and other data cleaning and data conversion operations, and then through the extraction of data, and then get the data table of R & D project performance evaluation integration.

Finish the data processing work and enter the work of feature engineering. The data involved in R&D project performance evaluation indicators are mainly feature extracted through four dimensions: R&D project input, R&D project process management, R&D project output and R&D project expected effect, and the R&D project performance evaluation dataset is established at the same time. In order to test the effectiveness of the model, the dataset is divided into training set and test set here.

Finally, the R&D project performance evaluation model based on CART algorithm is constructed, and the Gini index is selected for feature selection. In order to optimize the results obtained from the model, it is necessary to use a large amount of data to train the R&D project performance evaluation model. Then substitute the test set of data into the model for verification, reduce the error to the minimum range, and finally obtain the relative importance of the factors affecting the results of R&D project performance evaluation feature ranking, which provides a reference for the weight setting of R&D project performance evaluation.

III. C. Performance evaluation model construction based on CART decision tree algorithm

The CART algorithm adopts a technique of binary recursive partitioning, and the final decision tree generated is a binary tree. After obtaining the data of A enterprise's R&D project performance evaluation, the R&D project performance evaluation model based on CART algorithm is constructed through three steps: defining variables, decision tree generation, and decision tree pruning, as follows:

(1) Defining variables

The specification of variables is the groundwork for decision tree modeling. First, the output variables in the analyzed object are defined as target variables, also called dependent variables. Second, the factors that have an impact on the results are defined as input variables, also called independent variables. In this paper, the performance evaluation level of R&D projects of A enterprises is designated as the target variable, and 11 indicators, such as timely completion rate, cost saving rate, funding rate, and filing rate of project documents, are selected as input variables.

(2) Decision Tree Generation

Decision tree generation is the process of inputting training set data, setting parameter conditions, and finally outputting a binary tree.The CART algorithm uses the Gini index as a node splitting evaluation criterion for feature selection when constructing a classification tree. The Gini index can be used to quantify the degree of confusion of the data, indicating the probability that the randomly selected samples in the sample set are divided into the wrong samples, the larger the Gini index indicates that the probability of the randomly selected samples in the data set appearing to be divided into the wrong samples is the higher, which also indicates that the degree of confusion of this data set is high and the data is impure, and vice versa, the degree of confusion of the data is lower and the purity of the data is higher. Assuming that the number of all samples in the set is m class, P_m represents the probability that the m class of samples is selected, the formula for calculating the Gini index is shown in equation (12):

$$Gini(p) = \sum_{m=1}^{M} P_m (1 - P_m) \tag{12}$$

(3) Decision tree pruning

Decision tree is a complex tree generated by considering all the data points, if the structure of the tree is too complex, indicating that there is a greater likelihood of overfitting, which in turn reduces the accuracy of the model, at this point it is necessary to set the stop conditions for its pruning process, so that the structure is simplified, otherwise the decision tree branches will continue to grow, which is not conducive to the classification of data. The pruning method is divided into pre pruning and post pruning, this paper selects the post pruning method for pruning. The process of post pruning is to first input the validation set data to the decision tree algorithm to generate a fully grown decision tree, and then from the bottom up to the pruning operation, and finally through the loss function to determine at which nodes for pruning, the form of the loss function in the form of equation (13):

$$C_\alpha(T) = C(T) + \alpha |T| \tag{13}$$

$C(T)$ indicates how well the decision tree model fits the training dataset, $|T|$ is the number of leaf nodes in the subtree, which indicates the complexity of the model, and α is a parameter that weighs the two. A large α makes the model training process tend to choose decision trees with simple structure and a large penalty for model complexity, and conversely, a sufficiently small α means that the model training process tends to choose more complex trees and a smaller penalty for model complexity.

IV. Testing of the performance evaluation model

This chapter focuses on the designed performance evaluation model, performance evaluation on overall operational performance, analysis of actual application performance, and performance evaluation based on executive characteristics.

Table 1: Comparison of Model evaluation effect

	Model	U1(%)	U2(%)	U3(%)
S1	M1	96.16	2.45	5.42
	M2	88.47	7.33	16.23
S2	M1	100.00	0.00	0.00
	M2	89.28	0.00	18.76
S3	M1	97.18	1.88	3.78
	M2	88.69	5.67	16.99

IV. A. Operational performance evaluation of the model

IV. A. 1) Comparison of evaluation effectiveness

Comparing (M1) the algorithmic model of this paper with (M2) the BP neural network model, the results of (U1) correctness rate, (U2) misjudgment rate, and (U3) probability of committing the first type of error of the evaluation results on (S1) the training sample set, (S2) the test sample set, and (S3) the overall sample are shown in Table 1.

Both for (S1) training sample set, (S2) test sample set and (S3) overall sample, the correct rate of (M1) model of this paper's algorithm is significantly higher than that of (M2) BP neural network model, which is stabilized at 95.00% and above and reaches 100.00% in (S2) test sample set. While (U2) misjudgment rate and (U3) probability of committing the first type of error are significantly lower than (M2) BP neural network model, and as low as 0.00% in (S2) test sample set. Therefore, for the performance evaluation study of private listed companies, (M1) algorithmic model of this paper is better than (M2) BP neural network model.

IV. A. 2) Importance of indicator variables

In the performance evaluation study of private listed companies, there are many financial indicators involved, and analyzing the importance of the indicator variables to the performance of listed companies can not only provide suggestions for company decision makers to improve the company's operating environment, but also provide guidance for market investors and government decision makers to find companies with investment support value. In this regard, the model of this paper gives the following 15 indicator variables in the dimension of financial performance: net assets per share, gearing ratio, operating index, inventory turnover ratio, EBITDA, weekly asset turnover ratio, return on assets, working capital ratio, working capital, cash ratio of operating income, price-to-book ratio, cash ratio, equity-to-debt ratio, retained earning-to-asset ratio, and return on net assets, which are listed in the order of No.1, 2, 3...13, 14, 15 for numbering. The importance analysis of the variables based on the model of this paper is shown in Figure 3.

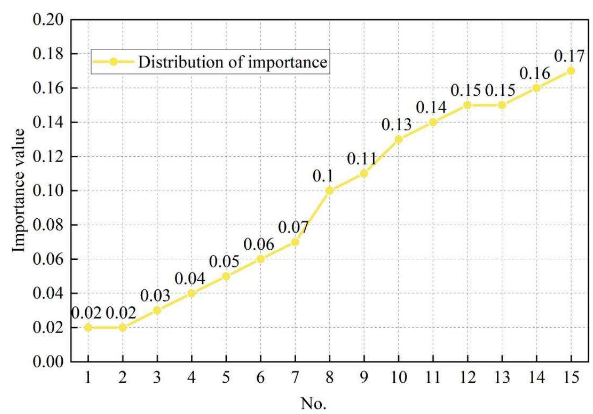

Figure 3: Variable importance analysis based on the model of textual

Two indicator variables, No.14 Retained Earnings Assets Ratio and No.15 Return on Net Assets, have the greatest importance at 0.16 and 0.17, respectively, which shows that shareholders' profitability and profitability have a great impact on the company's performance.

IV. B. Practical application and assessment

IV. B. 1) Employee Performance Measurement

Taking the 500-employee scale R enterprise as the research object, using the key performance indicators as the evaluation tool, adopting the designed performance evaluation model to realize the enterprise performance appraisal system in the employee performance evaluation level and personal assessment coefficient. Since the model algorithm in this paper is mainly used in the enterprise employee evaluation link, the implementation efficiency and computational efficiency of the model algorithm in this paper meets the clustering analysis of larger samples for this implementation of the performance appraisal system, and the design of employee performance evaluation data dimensions in R. There are a total of seven dimensions, including (A) sense of responsibility, (B) teamwork, (C) implementation ability, (D) communication ability, (E) work performance, (F (E) work performance, (F) work efficiency, and (G) integrity, and each dimension adopts a 10-point scale.

From the 500 sets of assessment data, 10 sets of representative data were selected for rationality verification, and the assessment data of the 10 R enterprise employees are shown in Fig. 4. Among the 10 sets of data, there are the 8th and 9th employees who perform better, with the scores of all dimensions at 4.00 and above, which is one of the goals of enterprise performance management.

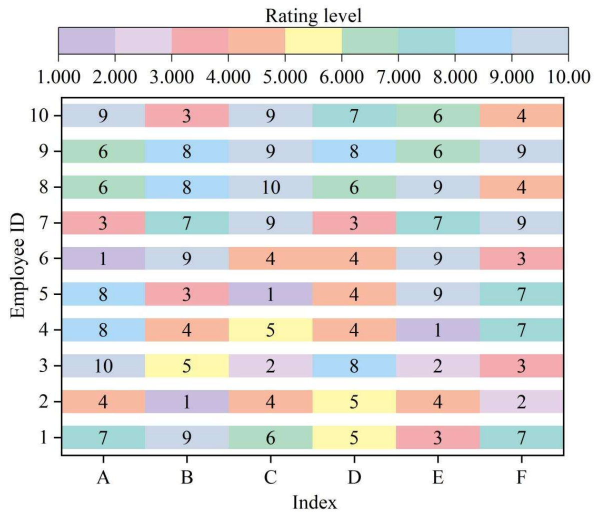

Figure 4: Evaluation data of 10 employees

IV. B. 2) Employee appraisal results of the performance appraisal system

Using the performance evaluation model designed in this paper to conduct the performance evaluation of a total of 500 employees in R. 12 employees of the company were selected according to the departments and positions (job numbers in order: 036, 066, 081, 122, 136, 179, 222, 238, 312, 359, 401, 423) as the results of the experimental data are shown in Figure 5.

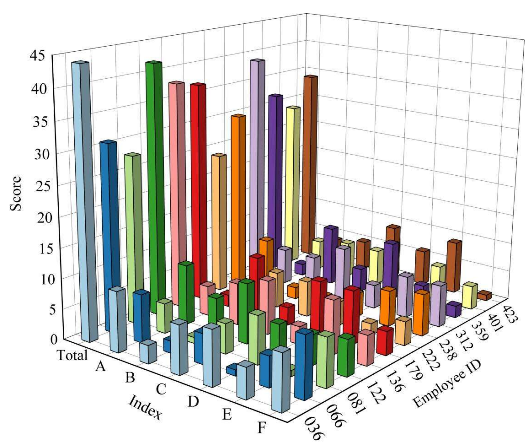

Figure 5: Performance assessment data of 12 employees

IV. B. 3) Comparison of performance evaluation results

According to the results of the above departmental performance evaluation dimensions and employee assessment, the model generates the final performance evaluation results for output processing, calculated by the model of this paper generated (V1) departmental performance evaluation indicators, (V2) personal assessment coefficients and (V2) employee assessment scores results are shown in Table 2.

Comparing the performance scores calculated by the model of this paper with the internal performance evaluation scores of Company R, there is not much difference in the performance evaluation results, but the performance results calculated by the model of this paper reflect a more comprehensive and integrated evaluation, and after the examination and approval of the appraisal and management committee of Company R, the accuracy of the data is within a reasonable range, and the resulting data has applicability.

IV. C. Model Evaluation Based on Executive Characteristics

Corporate executives, as the core of strategic decision-making and information processing, have a non-negligible role in influencing the overall corporate performance. This section further validates the feasibility of the model in performance evaluation by analyzing the precision, recall and F1 value performance of the designed performance evaluation model when facing the executive team.

Before examining the issue of the relationship between executive characteristics and corporate performance, it is important to ensure that the model used has validity, the model is invalid research everything is meaningless, so this paper first made a 3D visualization that can evaluate the validity of the model is shown in Figure 6.

Table 2: Employee individual performance appraisal score data

ID	Textual model			Offline assessment			Changing value
	V1	V2	V3	V1	V2	V3	
036	0.7	1	0.7	0.8	1	0.8	0.8
066	0.9	1	0.9	0.9	1	0.9	0.9
081	0.8	0.9	0.72	0.8	0.9	0.8	0.72
122	0.7	0.8	0.56	0.7	0.8	0.7	0.56
136	0.7	1	0.7	0.7	1	0.7	0.7
179	0.9	0.9	0.81	1.0	0.9	1	0.9
222	0.9	0.8	0.72	0.9	0.8	0.9	0.72
238	0.9	1	0.9	0.8	1	0.9	0.9
312	0.8	1.2	0.96	0.9	1.2	0.9	1.08
359	0.7	0.8	0.56	0.8	0.8	0.7	0.56
401	0.8	0.9	0.72	0.9	0.9	0.9	0.81
423	0.8	0.9	0.72	0.8	0.9	0.8	0.72
437	1.1	1.0	1.1	1.2	1.0	1.2	1.2

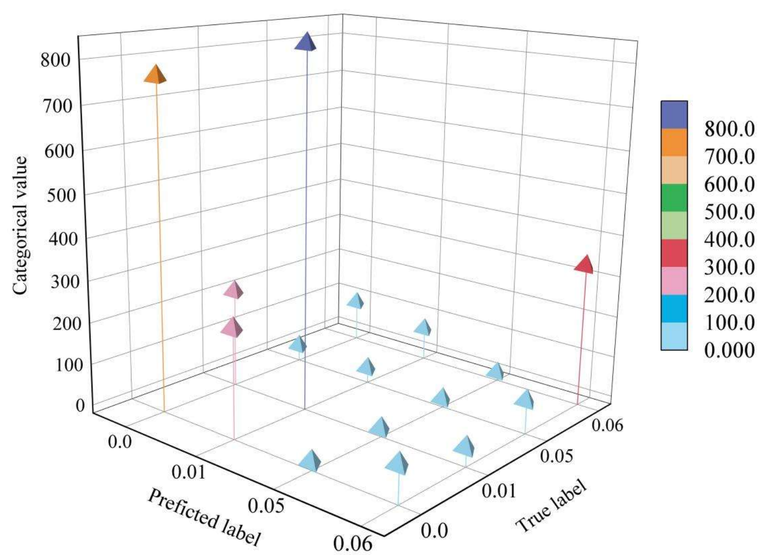

Figure 6: Visualization of model evaluation

The visualization of model validity enables a more intuitive evaluation of the accuracy of the model. Demonstrate the number of predicted value categories that are right and wrong. Diagonal lines in the YZ plane indicate elements whose predicted value is equal to the expected value, and off-diagonal values indicate elements that the classifier predicted incorrectly. The predicted label in the graph indicates the true classification value and the truelabel indicates the experimental predicted classification value, which is the final classification result formed after many superimpositions.The value of the Z axis indicates the range of the Tobin's Q value. Tobin's Q is a commonly used indicator to measure the market performance of enterprises, and its calculation formula is market price/replacement cost.

When Tobin's Q is equal to 0.0 761 is TP true positive. 305 is FN true negative and 318 is FP false positive. At this time precision precision=100*TP/(TP+FP)=0.7053, recall recall=100*TP/(TP+FN)=0.7139, other values according to the formula, in turn, can be derived from the results of the model evaluation is shown in Table 3.

Table 3: Model evaluation value based on executive characteristics

Tobin Q value	Precision	Recall	F1-score	Support
0.01	0.7054	0.7138	0.7096	1067
0.02	0.7266	0.7745	0.7506	1078
0.06	0.000	0.000	0	94
0.07	0.6843	0.6975	0.6909	467
Accuracy			0.7107	2706
Weighted	0.6859	0.7107	0.6978	2706

Generally the higher the precision, recall and F1 value the better the model effect, from the table it can be seen that the Tobin's Q value in equal to 0.02 the model effect is the best, in equal to 0.01 and equal to 0.07 the effect is about the same. When evaluating the model as a whole, the accuracy is 0.7107, and the precision and sensitivity are also around 0.7, and since F1 is a combination of recall and precision, it can also be seen that the model effect is very good from the effect of F1. Where the total number of samples is 2706, to assess the overall function of this model recognition system, it is necessary to look at the overall integrated prediction performance of the different categories of the Tobin's Q value takes the value of the weighted avg method, this method assigns different weights to the different categories, which is generally determined by the weight based on the proportion of true distribution of the category, and each category needs to be multiplied by the weights and then summed up, and the method takes into account the category unbalance balanced situation. From the table, we can see that when Tobin's Q value is taken as the value of four categories, the precision, recall and F1 value under the weighted avg method are all around 0.7, which is a relatively high overall performance and a reasonable model.

Taking a comprehensive look at the model, it can be said that the effect of the model is good, so the designed performance evaluation model can well demonstrate the extent of the influence of executive characteristics on the performance of the company.

V. Conclusion

This paper adopts entropy to measure the uncertainty variables in enterprise performance evaluation, and constructs an evaluation model of enterprise performance based on the CART decision tree algorithm. Compared with similar modeling algorithms, the accuracy of this model on a variety of different datasets is stabilized at 95.00% and above, up to 100.00%, with a misclassification rate as low as 0.00%. In terms of financial dimension, the model is able to propose two important indicators (retained earnings to assets ratio and return on net assets ratio) based on the company's situation. In practical application, the performance evaluation scores given are similar to the actual offline evaluation scores. In the evaluation of the model based on executive characteristics, the precision, recall and F1 value are all around 0.7.

The designed performance evaluation model not only has good and stable system performance, but also shows more professional evaluation ability in both financial and management dimensions of performance management evaluation. By applying artificial intelligence technology to the evaluation and management of enterprise performance, it can assist in the optimization of enterprise performance and the enhancement of enterprise organizational productivity.

References

[1] Khan, A. N., Mehmood, K., & Ali, A. (2024). Maximizing CSR impact: Leveraging artificial intelligence and process optimization for sustainability performance management. Corporate Social Responsibility and Environmental Management, 31(5), 4849-4861.

[2] Ding, W. (2022, January). Enterprise Performance Management Optimization Based on Big Data. In International Conference on Decision Science & Management (pp. 3-10). Singapore: Springer Nature Singapore.

[3] Rožman, M., Oreški, D., & Tominc, P. (2022). Integrating artificial intelligence into a talent management model to increase the work engagement and performance of enterprises. Frontiers in psychology, 13, 1014434.

[4] Fu, H. (2021). Optimization study of multidimensional big data matrix model in enterprise performance evaluation system. Wireless Communications and Mobile Computing, 2021(1), 4351944.

[5] Nyathani, R. (2023). AI in performance management: Redefining performance appraisals in the digital age. J. Artif. In tell. Cloud Comput. SRCIJAICC-146, 134, 2-5.

[6] Varma, A., Pereira, V., & Patel, P. (2024). Artificial intelligence and performance management. Organizational Dynamics, 53(1), 101037.

[7] Gui, X. (2020). Performance appraisal of business administration based on artificial intelligence and convolutional neural network. Journal of Intelligent & Fuzzy Systems, 39(2), 1817-1829.
[8] Han, S., Zhang, D., Zhang, H., & Lin, S. (2025). Artificial Intelligence Technology, Organizational Learning Capability, and Corporate Innovation Performance: Evidence from Chinese Specialized, Refined, Unique, and Innovative Enterprises. Sustainability (2071-1050), 17(6).
[9] Zhao, Y. (2022). Decision support system for economic management of large enterprises based on artificial intelligence. Wireless Communications and Mobile Computing, 2022(1), 9453580.
[10] Guo, J., & Wang, D. (2021). An empirical study on artificial intelligence technology based on big data to assist enterprise management decision. The International Journal of Electrical Engineering & Education, 0020720920983547.
[11] Sun, Q., Chen, G., & He, S. (2022, October). Enterprise Development Decision Support System Based on Artificial Intelligence Technology. In 2022 International Conference on Artificial Intelligence of Things and Crowdsensing (AIoTCs) (pp. 245-249). IEEE.
[12] Liu, C. (2024). Research on the Influence of Artificial Intelligence on Enterprise Management Decision-making. Academic Journal of Business & Management, 6(1), 108-112.
[13] Han, H. (2023, November). Research on Financial Risk Early Warning System Based on Computer Artificial Intelligence. In 2023 3rd International Signal Processing, Communications and Engineering Management Conference (ISPCEM) (pp. 558-562). IEEE.
[14] Tang, M., Zhao, T., Hu, Z., & Li, Q. (2023). Research on risk prediction and early warning of human resource management based on machine learning and ontology reasoning. Tehnički vjesnik, 30(6), 2036-2045.
[15] Seo, B. G., & Park, D. H. (2017). Development on early warning system about technology leakage of small and medium enterprises. Journal of Intelligence and Information Systems, 23(1), 143-159.
[16] Chohan, M. A., Li, T., Ramakrishnan, S., & Sheraz, M. (2025). Artificial Intelligence in Financial Risk Early Warning Systems: A Bibliometric and Thematic Analysis of Emerging Trends and Insights. International Journal of Advanced Computer Science & Applications, 16(1).