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Design of Rule Extraction and Optimization Algorithms in Employee Performance Evaluation in Data Mining Environment

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ABSTRACT

In this study, a data-driven assessment framework integrating multi-criteria decision making, association rule mining and fuzzy clustering methods is proposed to address the scientific and objective needs of rule extraction and optimization in employee performance assessment. The TOPSIS model is improved by triangular fuzzy numbers to realize the objective ranking of business performance. The Apriori algorithm is improved to mine the association rules between competency and performance. The empirical results show that Employee 3 is ranked in the excellent grade with 101.32% task completion rate and 0.8323 relative proximity. The questionnaire results of competency quality had a significant impact on appraisal with a confidence level of 84.3%, while technical title and education were not sufficiently correlated with a confidence level of <30%. The fuzzy decision tree model generated 25 classification rules with a confidence level higher than 63.2%. And combined with the work attitude index with a weight of 0.2913 to complete the comprehensive performance assessment, the results show that the overall performance score of the employees in this enterprise is 0.81362, which is a good grade. This study makes the performance appraisal more objective, precise and efficient, and at the same time expands the application scope of data mining technology in enterprise management.

Keywords: employee performance evaluation, TOPSIS model, Apriori algorithm, association rule mining, fuzzy clustering

1. Introduction

Employee performance appraisal is a very important management task in the enterprise, which can

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help the enterprise to evaluate the work performance and performance of employees. Through performance evaluation, the enterprise can fully understand the employee's work ability, performance contribution, work attitude and development potential, provide targeted training and development opportunities for employees to help them improve their ability and performance, and at the same time, help the enterprise to better manage employees [1-4]. At the same time, performance evaluation is also an important basis for salary management, promotion and reward decisions, which can help enterprises allocate resources and rewards in a fair and just manner in order to better manage the enterprise and promote its long-term development [5-7]. However, with the development of enterprises and the upgrading of human resource management, the traditional performance evaluation system is no longer applicable. Firstly, over-emphasizing the completion of key performance indicators and indicating the overall performance of employees by the completion rate, ignoring the problem-solving ability of employees, whether they have innovative means, whether they expand and improve, and teamwork during the whole work process, which may lead to lopsided assessment results, affecting the authenticity and comprehensiveness of the assessment results [8-9]. Secondly, human assessment is susceptible to the interference of subjective factors of the assessor, such as personal preferences, prejudices and interpersonal relationships, which may lead to less than fair and accurate assessment results [10]. Meanwhile, in the case of job changes, company transformation, and project differences, the assessment rules are not updated in time, and obsolete rules are still used, or there is a lack of a complete performance system, which results in biased and unfair assessment results, and in serious cases, leads to talent loss [11-12]. In addition, the high cost of time and effort is a constraint, especially in large enterprises, which requires a lot of time and effort to conduct a comprehensive assessment, increasing the cost and burden of the enterprise. Finally, the existing performance appraisal methods are not very operable and are more inclined to assessing employees' performance and lack specific guidance and training for employees [13-14]. Therefore, it is necessary to overcome these limitations through innovative methods and techniques to improve the science and practicality of performance appraisal.

With the emphasis on data and digital transformation in various fields, human resource management has also begun to introduce data-supported management and decision-making, and employee performance evaluation, as an important part of human resource management, will be one of the main references for evaluating the performance of employees, such as daily email sending, document completion, video conferencing, voice calls, project feedback, and business trips in the work process [15-18]. However, the current assessment system has low utilization of data. Therefore, the application of data in employee performance assessment should be strengthened to realize an objective and intelligent assessment system, which requires good adaptability of assessment techniques and rules. On this basis, data mining technology is applied to employee performance assessment. Wang [19] used data mining technology as the basis and integrated information management and statistical analysis means to weaken the subjective factors in employee performance evaluation and strengthen other hidden factors in order to achieve a comprehensive, fair and objective evaluation method. Liang and Li [20] mined and created multiple input-output spatial network data in a cloud computing environment, and matched and classified the features of this data for identification under adaptive matched filtering method and back propagation neural network, so as to realize a distributed data mining employee performance evaluation method for wireless networks. Wang [21] introduced data mining and association rule algorithms to study the performance intelligent management system of construction enterprises and constructed a performance prediction model, but the prediction error of this model was only 41.18% of the prediction results at 5% and below. Yang et al [22] used a decision tree model designed using data mining techniques and inductive algorithms to analyze employee performance and identify the main factors from the many performance influencing factors as a way to provide a direction for improvement of performance evaluation criteria. Zheng [23] used data mining techniques to modify the ID3 solver in the decision tree algorithm as a way to build a model for employee performance evaluation, which possessed an accuracy rate of 95.3%. Chungade and Kharat [24] developed a virtual organization employee performance evaluation system, applied domain-driven data mining to identify and extract the indicators that did not appear in the employee performance evaluation, and applied sentiment analysis and fuzzy group decision support system to assess the complexity of the evaluation process with a single factor. The data in the above study are mostly structured data, which are not analyzed in combination with other data types, and still lack assessment comprehensiveness. Moreover, it is difficult to balance the accuracy and interpretability of the model, and it does not reflect the assessment rules in the dynamic environment, so it needs to be optimized. In recent years, optimization algorithms have been widely used in major strategies, such as genetic algorithms, differential evolutionary algorithms, ant colony algorithms, particle swarm optimization, etc., but these basic algorithms are lacking in high-dimensional data, dynamic environments, and global optimization, and it is difficult to achieve tripartite coordination among performance data, assessment rules, algorithm selection and application [25-28]. Based on this, multi-source data mining and improved optimization algorithms will become a new direction for employee performance evaluation.

Combining with data mining technology, this study proposes a systematic evaluation framework covering multi-criteria decision-making, association rule analysis and fuzzy clustering methods to enhance the scientific and objective nature of evaluation. To address the problem of business department performance ranking, the TOPSIS method is introduced to realize the superiority ranking by calculating the distance between the evaluation object and the ideal target. Considering the fuzzy nature of the indicator rubric, the improved TOPSIS method based on triangular fuzzy numbers is proposed to transform the expert evaluation into fuzzy number processing in order to better fit the actual decision-making scenario. The improved Apriori algorithm is used to mine frequent item sets and association rules from transactional data to reveal the causal relationship between competency indicators and performance results, providing data support for dynamic performance prediction. Aiming at the subjective characteristics of work attitude assessment, the mining model based on fuzzy clustering is constructed. Through fuzzy similarity matrix and transfer closure calculation, 360-degree appraisal data are transformed into fuzzy equivalence matrix, and combined with the horizontal intercept classification method, subjective bias is effectively smoothed to realize the fine grading of employee performance.

2. Rule Extraction and Optimization Algorithm Design for Employee Performance Evaluation

2.1. Methodology for evaluating operational performance

When companies conduct business performance evaluation, the focus of attention is on the ranking of personnel's strengths and weaknesses, which is essentially a multi-criteria decision-making problem. There are many methods for solving multi-criteria decision-making problems, such as the weighted sum method, the method of approximating the ideal point of ranking (TOPSIS method) and the ELECTRE method. Since the TOPSIS method can fully utilize the relevant information, the idea of solving is clear. Therefore, TOPSIS method will be used for ranking in performance evaluation.

2.1.1. Fundamentals of the TOPSIS methodology. The TOPSIS method evaluates the good and bad merits of evaluation objects by ranking their proximity to the desired goal.

Assuming that there is p type of appraisal indicator, for the importance of each indicator, the weight vectors $W=\left(w_1,w_2,\cdots,w_p\right)$, $\sum_{i=1}^{p} w_i=1\left(w_1,w_2,\cdots,w_p\right)$, and $a_{ij}(i=1,2,\cdots,p;j=1,2,\cdots,q)$ are

used to represent the appraisal of the appraisal team members on the attributes of program j under indicator i. The steps of the TOPSIS method are:
1) Generate a normalized weighted decision matrix. Decision matrix vector is normalized:

$$d_{ij} = \frac{a_{ij}}{\sqrt{\sum_{j=1}^{q}\left(a_{ij}\right)^2}} (i = 1,2,\cdots,p; j = 1,2,\cdots,q) \tag{1}$$

Normalized weighted policy matrix

$$U = \left\{u_{ij}\right\} = \left\{w_1 \cdot d_{ij}\right\} (i = 1,2,\cdots,p; j = 1,2,\cdots,q) \tag{2}$$

2) Determine the positive ideal point U^+ and the negative ideal point U^-. Positive Ideal Point $U^+ = \left(u_1^+, u_2^+, \cdots, u_p^+\right)$

$$u_i^+ = \begin{cases} \max_j u_{ij} & Benefit\text{-}based\ indicators \\ \min u_{ij} & For\ \cos t\text{-}based\ indicators \end{cases}$$
$$(i = 1,2,\ldots,p; j = 1,2,\ldots,q) \tag{3}$$

Negative ideal point $U^- = \left(u_1^-, u_2^-, \cdots, u_p^-\right)$

$$u_i^- = \begin{cases} \min_j u_{ij} & Benefit\text{-}based\ indicators \\ \max_j u_{ij} & For\ \cos t\text{-}based\ indicators \end{cases}$$
$$(i = 1,2,\ldots,p; j = 1,2,\ldots,q) \tag{4}$$

3) Calculate the distance measure. Distance from Option j to the positive ideal point

$$S_j^+ = \sqrt{\sum_{i=1}^{p}\left(u_{ij} - u_i^+\right)^2}\ j = 1,2,\cdots,q \tag{5}$$

Distance from Option j to the negative ideal point

$$S_j^- = \sqrt{\sum_{i=1}^{p}\left(u_{ij} - u_i^-\right)^2}\ j = 1,2,\cdots,q \tag{6}$$

4) Relative proximity of Scenario j to the ideal point

$$G_j = \frac{S_j^-}{S_j^- + S_j^+} 1,2,\cdots,q \tag{7}$$

The magnitude of the relative closeness allows for the ranking of the scenarios.

2.1.2. Triangular fuzzy number based approach. In the performance evaluation system of the business sector, most evaluation indicators are difficult to quantify, and in applying the TOPSIS method, it is necessary for the experts of the evaluation team to score each indicator. Considering the fuzzy nature of people's awareness and evaluation, the correspondence between the triangular fuzzy number and the indicator rubric is established, the triangular fuzzy number is utilized for scoring and evaluation, and the traditional TOPSIS method is improved, and the TOPSIS method based on the triangular fuzzy number will finally be used for evaluation.

The steps of TOPSIS method based on triangular fuzzy number are as follows:

1) Generate a normalized weighted fuzzy decision matrix. There are p kinds of assessment indicators, and for the importance of each indicator, the weight vector $W=\left(w_1,w_2,\cdots,w_p\right)$, $\sum_{i=1}^{p} w_i=1\left(w_1,w_2,\cdots,w_p\right)\tilde{x}_{ij}=\left(x_{ij}^{(l)},x_{ij}^{(m)},x_{ij}^{(u)}\right)(i=1,2,\cdots,p;j=1,2,\cdots,q)$ is used to represent the fuzzy evaluation of the attributes of the program j under the indicator i by a single member of the assessment team, where $x_{ij}^{(m)}$ is the most probable evaluation, $x_{ij}^{(l)}$ is the most conservative evaluation, and $x_{ij}^{(\mu)}$ is the most optimistic evaluation.

$$\tilde{Y}=\left(\tilde{y}_{ij}\right)_{pq} \tag{8}$$

where $\tilde{y}_y=\left(y_{ij}^{(l)},y_y^{(m)},y_{ij}^{(w)}\right)(i=1,2,\cdots,p;j=1,2,\cdots,q)$, and

$$y_{ij}^{(l)}=\frac{x_{ij}^{(l)}}{\sqrt{\sum_{j=1}^{q}\left(x_{ij}^{(i)}\right)^2}},\; y_{ij}^{(m)}=\frac{x_{ij}^{(m)}}{\sqrt{\sum_{j=1}^{q}\left(x_{ij}^{(m)}\right)^2}},\; y_{ij}^{(u)}=\frac{x_{ij}^{(u)}}{\sqrt{\sum_{j=1}^{q}\left(x_{ij}^{(i)}\right)^2}} \tag{9}$$

Normalized Weighted Fuzzy Decision Matrix

$$\tilde{Z}=\left\{\tilde{z}_{ij}\right\}=\left\{w_i\cdot\tilde{y}_{ij}\right\}(i=1,2,\cdots,p;j=1,2,\cdots,q) \tag{10}$$

2) Determine the positive ideal point $\tilde{Z}^+$ and the negative ideal point $\tilde{Z}^-$. Positive Ideal Point $\tilde{Z}^+=\left(\tilde{z}_1^+,\tilde{z}_2^+,\cdots,\tilde{z}_p^+\right)$

$$\tilde{z}_i^{(i)+}=\begin{cases}\max_j z_{ij}^{(i)} & Benefit\text{-}based\ indicators\\ \min z_{ij}^{(i)} & For\ \cos t\text{-}based\ indicators\end{cases}$$
$$t=l,m,u;i=1,2,\ldots,p \tag{11}$$

Negative ideal point $\tilde{Z}^-=\left(\tilde{z}_1^-,\tilde{z}_2^-,\cdots,\tilde{z}_p^-\right)$

$$\tilde{z}_i^{(t)-}=\begin{cases}\min_j z_{ij}^{(1)} & Benefit\text{-}based\ indicators\\ \max_j z_{ij}^{(t)} & For\ \cos t\text{-}based\ indicators\end{cases}$$
$$t=l,m,u;i=1,2,\cdots,p \tag{12}$$

Negative ideal point $\tilde{z}^-=\left(\tilde{z}_1^-,\tilde{z}_2^-,\cdots,\tilde{z}_p^-\right)$

$$\tilde{z}_i^{(1)-}=\begin{cases}\min_j z_{ij}^{(t)} & Benefit\text{-}based\ indicators\\ \max_j z_{ij}^{(t)} & For\ \cos t\text{-}based\ indicators\end{cases}$$
$$t=l,m,u;i=1,2,\cdots,p \tag{13}$$

3) Calculate the distance measure. Distance from Option j to the positive ideal point

$$S_j^+=\sqrt{\sum_{i=1}^{p}d^2\left(\tilde{z}_{ij},\tilde{z}_i^+\right)}j=1,2,\cdots,q \tag{14}$$

where $d\left(\tilde{z}_{ij},\tilde{z}_i^+\right)=\sqrt{\left[\left(\tilde{z}_{ij}{}'-\tilde{z}_i^{l+}\right)^2+\left(\tilde{z}_{ij}{}^m-\tilde{z}_i^{m+}\right)^2+\left(\tilde{z}_{ij}{}^M-\tilde{z}_i^{M+}\right)^2\right]/3}$

Distance from Program j to the negative ideal point

$$S_j^- = \sqrt{\sum_{i=1}^{p} d^2\left(\tilde{z}_{ij}, \tilde{z}_i^-\right)} j = 1, 2, \cdots, q \tag{15}$$

where $d\left(\tilde{z}_{ij},\ \tilde{z}_i^-\right) = \sqrt{\left[\left(\tilde{z}_{ij}{}' - \tilde{z}_i^{l-}\right)^2 + \left(\tilde{z}_{ij}{}^m - \tilde{z}_i^{m-}\right)^2 + \left(\tilde{z}_{ij}{}^\mu - \tilde{z}_i^{u-}\right)^2\right]/3}$

4) Relative closeness of Scheme j to the ideal point

$$G_j = \frac{S_j^-}{S_j^- + S_j^+} 1, 2, \cdots, q \tag{16}$$

2.2. Ability quality association rule analysis based on improved Apriori algorithm

After completing the evaluation of business unit performance based on TOPSIS method and triangular fuzzy number, the potential association rules between employee competency and performance performance need to be further explored, for this reason, the improved Apriori algorithm will be introduced in this section for association analysis.

2.2.1. Competency assessment and association rule Apriori model analysis. Competency indicators are reflections of the employee's knowledge system, skill level, work experience, etc. The collection of raw data for these indicators is simple and clear. For example, the skill level can be obtained by recording the skill level certificates obtained by the employees, and the work experience can be obtained by calculating the difference between the employee's entry time and the current time. However, these data do not directly reflect the actual performance level of employees in the future work. Therefore, it is necessary to use the correlation analysis method of data mining to analyze the causal association between competence and performance, so as to come up with a more scientific performance prediction. As the quality of ability will grow with the growth process through the acquisition of knowledge and accumulation of experience, it is a continuous process; therefore, in the data mining of this type of indicator, it is often analyzed and evaluated at a point in time or a period of time, and the real-time evaluation function cannot be realized.

Data mining correlation analysis can discover hidden laws from a large amount of data, and derive causal rules such as “the occurrence of certain events causes the occurrence of some other events”, of which the Apriori algorithm is one of the most commonly used and well-known methods in correlation analysis. Currently, almost all parallel data mining algorithms for efficiently discovering association rules are based on the Apriori method.

2.2.2. Steps of Apriori model construction. Consider a transaction database represented by $database$ for $\{T_1, T_2, T_3, \ldots, T_n\}$, where each T is an instance of a transaction. All individual items in the transaction database constitute the set $\{I_1, I_2, I_3, \ldots, I_m\}$, where T is a scale item. An association rule is defined as an implication of the form $x \Rightarrow y$, where x is the antecedent, y is the consequent, and x and y are disjoint. Transactional support and confidence are key evaluation metrics to assess the effectiveness of association rules. Transactional support reflects the probability that an item set occurs in all transactions, while confidence indicates the relative probability that a consequent y occurs under the condition that the antecedent x occurs.

Definition 1 (Transactional Support Degree) The transactional support degree of an itemset x, denoted as $Sup(x)$, is the frequency with which the itemset x is transacted in the database D.

$$Sup(x) = \frac{|x|}{|D|} \tag{17}$$

where $|x|$ denotes the number of times itemset x appears in all transactions of the database and $|D|$ denotes the total number of transactions.

Definition 2 (Confidence) The confidence level of association rule $x \Rightarrow y$ is denoted as $conf(x \Rightarrow y)$ and is calculated by dividing the size of the set of transactions containing itemsets x and y by the size of the set of transactions containing only itemset x.

$$conf(x \Rightarrow y) = \frac{|x \cup y|}{|x|} \tag{18}$$

where $|x \cup y|$ is the number of transactions that contain both x and y itemsets, and $|x|$ is the number of transactions that contain only itemset x.

Property 1 If the itemset is frequent, then all its non-empty subsets will also be frequent.

Property 2 For any infrequent itemset, all its supersets are equally infrequent.

Theorem 1 If an element occurs less than k times in a frequent $k-$term set, it will not occur in any frequent $(k+1)$ -term set.

Theorem 2 If the number of frequent itemsets in the set of frequent $k-$itemsets is less than $k+1$, the frequent itemset is the maximum frequent itemset.

The flow of Apriori algorithm is shown in Fig. 1:

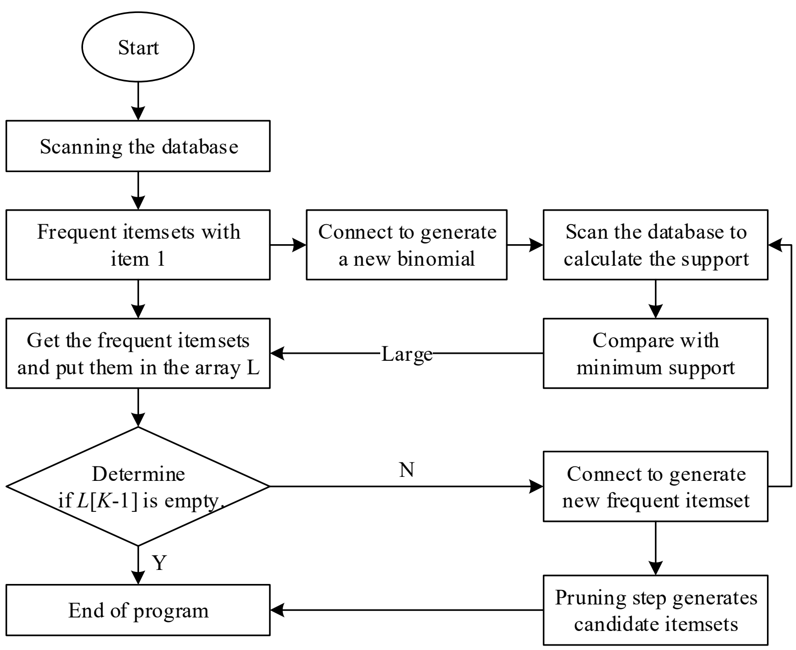

Fig. 1. Flow of the Apriori algorithm

2.3. *Mining models for work attitude assessment*

After clarifying the correlation between competence quality and performance, how to quantify the highly subjective work attitude indicator becomes another key issue. In this section, we will combine the fuzzy clustering method to construct an objectivized mining model for work attitude assessment.

2.3.1. Work Attitude Assessment and Fuzzy Cluster Mining Model Analysis. Work Attitude Assessment Indicator: A kind of feedback to the employee's work attitude in the work process, which is a kind of supplement to the work result. Some employees may have low work output due to experience and other reasons, but we can not erase his (her) efforts in the work, the process of this effort may be the accumulation of future performance improvement. Therefore, through the evaluation of work attitude, it is an important part of the reasonable and perfect performance appraisal system to make the staff's efforts evaluated accordingly. This type of evaluation is very subjective, because there is no uniform standard, and it is more difficult to accurately distinguish between good and bad attitudes. In order to make up for this evaluation data in the collection process is too subjective characteristics, this paper adopts the 360-degree performance appraisal method, that is, by the employee's coworkers, supervisors and other interpersonal relationships related to the employee scoring; and in the evaluation and analysis of the introduction of the "fuzzy similarity matrix" as a tool, through the formation of fuzzy sets of judgment matrix. Thus, the deviation caused by subjectivity is smoothed out, making the evaluation result more objective and real. Since the evaluation of professional ethics is similar to work attitude, this paper includes it in the analysis of work attitude evaluation indexes.

2.3.2. Data mining model construction for fuzzy clustering:

1) Initialization of raw data for this type of performance indicator. The raw data may have different judgment results because of different weights when setting. For example, "compliance with rules and regulations" is more important, and the full score is set to 20 points, while employee motivation as a more detailed branch is set to 10 points.

The data are initially processed so that each judgment item is distributed in the range of [0, 1]. In this paper, we use the original data and the full score for the initialization of the adjustment. After initialization of the employee performance indicators can constitute a data matrix in the range of [0, 1], to facilitate the formation of the corresponding affiliation function.

2) Calibration of performance indicators to form a fuzzy similarity matrix. Set the optimal performance of the employee's indicator value of $V_1(X_{11}, X_{12}, \ldots, X_{1n})$, n for the assessment of an employee used in the number of indicators; the corresponding good, general, poor indicator value of $V_2(X_{21}, X_{22}, \ldots, X_{2n})$, $V_3(X_{31}, X_{32}, \ldots, X_{3n})$, $V_4(X_{41}, X_{42}, \ldots, X_{4n})$, respectively, to be evaluated by the employee V_0 volume value of $(X_{01}, X_{02}, \ldots, X_{0n})$, according to the above vectors listed in the fuzzy relationship matrix, see equation (19):

$$R = \begin{array}{c} \begin{matrix} V_1 & V_2 & V_3 & V_4 & V_5 \end{matrix} \\ \begin{bmatrix} 1 & X_{12} & X_{13} & X_{14} & X_{10} \\ & 1 & X_{23} & X_{24} & X_{20} \\ & & 1 & X_{34} & X_{30} \\ & & & 1 & X_{40} \\ & & & & 1 \end{bmatrix} \end{array} \tag{19}$$

3) Normalization of matrix elements by rows. The matrix elements can be normalized in two ways, the min-max method as shown in Eq. (20), and the Z-score method as in Eq. (21):

$$X^* = \frac{X - \min}{\max - \min} \tag{20}$$

$$X^* = \frac{X - \mu}{\sigma} \tag{21}$$

If the matrix elements are not normalized, the subsequent calculations will be difficult to converge, resulting in too many invalid calculations thus leading to data mining failure.

In this paper, the min-max method is selected in the study.

4) Calculate the fuzzy equivalence matrix. The fuzzy similarity matrix obtained in step (2) only satisfies the self-inversion and symmetry, and does not satisfy the transferability. To obtain the fuzzy equivalence matrix with transfer relationship, the fuzzy similarity matrix needs to be deformed and calculated. There are many ways to compute the fuzzy similarity matrix, among which the method of obtaining the transfer closure $R(t)$ and thus forming the fuzzy equivalence matrix by the flat method is the most common.

The method of obtaining the transfer closure $R(t)$ of R by the flat method:

$$\begin{aligned} & R \times R = R^2 \\ & R^2 \times R^2 = R^4 \\ & \ldots \\ & R^k \times R^k = R^{2k} \end{aligned} \tag{22}$$

After a finite number of operations, there must be a case of $R^{2k} = R^{2k+1}$, so the closure $R(t) = R^{2k} = R^{2k+1}$ is passed; the result at this point is the fuzzy equivalence matrix, i.e., the matrix of the affiliation function, see equation (23).

$$R^* = \begin{array}{c} \begin{array}{ccccc} V_1 & V_2 & V_3 & V_4 & V_5 \end{array} \\ \begin{bmatrix} 1 & Y_{12} & Y_{13} & Y_{14} & Y_{10} \\ & 1 & Y_{23} & Y_{24} & Y_{20} \\ & & 1 & Y_{34} & Y_{30} \\ & & & 1 & Y_{40} \\ & & & & 1 \end{bmatrix} \end{array} \tag{23}$$

5) Evaluate the employee's performance based on the passing closure. λ Take values progressively from 1 to 0 to get different level cutoffs and hence different classifications.

Let $\lambda_1 = 1$, $\lambda_1 > \lambda_2 > \lambda_3$.

When $\lambda = \lambda_1$ is taken, all the positions of the elements in the fuzzy equivalence matrix that are less than λ_1 are replaced with 0, and all the positions that are greater than λ_1 are replaced with 1. At this time, the matrix level cutoffs are divided into 5 categories, which are $\{V_1\}$, $\{V_2\}$, $\{V_3\}$, $\{V_4\}$, and $\{V_0\}$, which do not account for the problem.

When $\lambda = \lambda_2$ is taken, the level intercepts are divided into 4 categories, including $\{V_i, V_0\}$ as one category and each of the rest into one category. The level of performance of the evaluated subject is precisely stated, as $\{V_2, V_0\}$ indicates that the evaluated subject is closest to the performance result labeled as good, and the employee's performance evaluation result can be approximated as good.

When $\lambda = \lambda_3$ is taken, the level intercepts are divided into 3 categories, including $\{V_i, V_j, V_0\}$ as one category and the rest are each grouped into one category. This further describes the employee's performance level, for example, $\{V_2, V_3, V_0\}$ indicates that the employee's performance level is in the upper middle of the range, between good and average. Of course in this paper, only the case of $\lambda = \lambda_2$ is considered in the process of performing the model implementation, and no refinement is performed to analyze the level cutoff set at $\lambda = \lambda_3$.

In addition, due to the characteristics of the performance appraisal, the gap between excellent and good is small, while the gap between general and good is large, such as general excellent for 90 points, good for 80 points, general for 60 points and unqualified for 40 points, etc., which may result in the level cutoff set of $\{V_i, V_j\}$ as a category, while $\{V_0\}$ is a separate category of the situation. This situation indicates that the subject of the evaluation is far from the calibrated performance standard, i.e., the level of performance is also too far from the set failing line, and should fall into the category of exceptionally poor level of performance.

3. Realization of Employee Performance Appraisal Model and Case Study

In Chapter 2, we systematically constructed a performance assessment rule extraction framework based on TOPSIS method, improved Apriori algorithm and fuzzy clustering. In order to further verify the practical application effect of these methods, this chapter will combine with specific business scenarios to develop data mining design and implementation of three types of appraisal indexes, namely, work performance, ability quality and work attitude, and verify the effectiveness and operability of the model through empirical analysis.

3.1. Design and implementation of data mining for work performance appraisal indicators

Combined with the previous research on the work performance assessment indicators and TOPSIS model, the module is programmed with a sequential structure, which is illustrated in the following by the telemarketing records of some of the employees of the target company in a certain month, and the marketing data is extracted from the work performance of the marketing department in the database of the daily operation and management subsystem, which is shown in Table 1.

Table 1. Monthly sales records of employees in Marketing Department

Employee	Total number of calls made	Number of marketing customer successes	Number of complaints	Complete the tasks of each month
Employee1	3817	2446	84	97.84%
Employee2	3753	2366	70	94.64%
Employee3	3676	2533	23	101.32%
Employee4	3502	2398	79	95.92%
Employee5	3200	2333	55	93.32%
Employee6	3072	2329	126	93.16%
Employee7	2729	1202	60	48.08%
Employee8	3480	1535	35	61.40%
Employee9	4009	3017	74	120.68%
Employee10	2906	2231	17	89.24%

3.1.1. Establishment of a standardization matrix. In Table 1, “the total number of calls made, the number of successful marketing customers, the number of complaints, and the completion of this month's tasks” corresponds to the performance appraisal secondary indicators “workload, work efficiency, work quality, and task completion progress”.

First of all, the data of “total number of calls, successful number of marketing customers, number of complaints, and completion of this month's tasks” are used to establish a matrix, which is shown in equation (24).

$$\begin{vmatrix} 3817 & 2446 & 84 & 0.9784 \\ 3753 & 2366 & 70 & 0.9464 \\ 3676 & 2533 & 23 & 1.0132 \\ 3502 & 2398 & 79 & 0.9592 \\ 3200 & 2333 & 55 & 0.9332 \\ 3072 & 2329 & 126 & 0.9316 \\ 2729 & 1202 & 60 & 0.4808 \\ 3480 & 1535 & 35 & 0.6140 \\ 4009 & 3017 & 74 & 1.2068 \\ 2906 & 2231 & 17 & 0.8924 \end{vmatrix} \tag{24}$$

Because the "number of complaints" indicator is significantly different from the other three indicators, it is a "very small indicator", also known as "efficiency indicator", that is, the lower the number of complaints, the better the marketing The lower the number of complaints, the higher the quality of the marketing staff's work. Therefore, before using the TOPSIS algorithm, the third column of the matrix (84, 70, 23, 79, 55, 126, 60, 35, 74, 17) need to be assimilated. The method used in the isotropization process is the difference method: using the maximum value of the elements of the column in order to go and the elements of the column to do the difference, to do the difference between the results of the original replacement of the original data in the column in situ.

The matrix of equation (24) is homogenized, and the result is shown in equation (25).

$$\begin{vmatrix} 3817 & 2446 & 42 & 0.9784 \\ 3753 & 2366 & 56 & 0.9464 \\ 3676 & 2533 & 103 & 1.0132 \\ 3502 & 2398 & 47 & 0.9592 \\ 3200 & 2333 & 71 & 0.9332 \\ 3072 & 2329 & 0 & 0.9316 \\ 2729 & 1202 & 66 & 0.4808 \\ 3480 & 1535 & 91 & 0.6140 \\ 4009 & 3017 & 52 & 1.2068 \\ 2906 & 2231 & 109 & 0.8924 \end{vmatrix} \tag{25}$$

The matrix after isotropic processing needs to be normalized to form a standardized matrix, and the purpose of the normalization process is to eliminate the influence of the scale of different performance indicators on the results of the model algorithm. The normalization method is shown in equation (26).

$$z_{ij} = x_{ij} \Big/ \sqrt{\sum_{i=1}^{n} x_{ij}^2} \tag{26}$$

Where z_{ij} - the elements of the i-th row and j-th column in the normalization matrix;

x_{ij} - elements of the jth column of the ith row in the homogenization matrix;

n - the number of rows of the homogenization matrix.

The normalization matrix is normalized according to Eq. (26) to obtain the normalized matrix, see Eq. (27).

$$\begin{vmatrix} 0.3562 & 0.3452 & 0.1878 & 0.3450 \\ 0.3504 & 0.3338 & 0.2505 & 0.3337 \\ 0.2964 & 0.2868 & 0.4605 & 0.3868 \\ 0.3268 & 0.3383 & 0.2101 & 0.3382 \\ 0.2986 & 0.3291 & 0.3174 & 0.3288 \\ 0.2866 & 0.3286 & 0 & 0.3286 \\ 0.2547 & 0.1696 & 0.2950 & 0.1696 \\ 0.3248 & 0.2166 & 0.4068 & 0.2165 \\ 0.3742 & 0.4256 & 0.2325 & 0.4256 \\ 0.2712 & 0.3148 & 0.4873 & 0.3147 \end{vmatrix} \tag{27}$$

3.1.2. Determination of ideal and worst solutions. The maximum and minimum values of each column of the normalized matrix are taken as the ideal and worst solutions for each attribute value, forming the ideal solution U^+ criterion vector and worst solution U^- criterion vector, respectively, $U^+ = |0.3742\ 0.4256\ 0.4605\ 0.4256|, U^- = |0.2547\ 0.1696\ 0\ 0.1696|$.

3.1.3. Calculating distances between vectors. According to equations (5) and (6), the distance between each solution set (appraised employee) vector in the standardized matrix and the ideal solution $\tilde{z}^+$ criterion vector S^+ and the worst solution $\tilde{z}^-$ criterion vector S^- are calculated respectively, and the distances between each solution set in the standardized matrix and the criterion vectors are shown in Table 2.

Table 2. The distance between each scheme set in the matrix,the criterion vector

Employee	The distance of the ideal solution U^+ the criterion vector	The distance of the worst solution U^- criterion vector
Employee1	0.2209	0.3274
Employee2	0.1995	0.3694
Employee3	0.1129	0.5604
Employee4	0.1062	0.3532
Employee5	0.1851	0.4133
Employee6	0.446	0.3299
Employee7	0.5653	0.2941
Employee8	0.4023	0.3069
Employee9	0.1527	0.4554
Employee10	0.2018	0.4453

3.1.4. Calculate and rank relative proximity. According to equation (7), the relative proximity G of each scheme set is calculated, and the relative proximity is sorted from large to small, and the "mandatory proportion method" is used to set the proportion of 10%, 20%, 60% and 10% as the cut-off points of "excellent", "good", "average" and "unqualified" performance appraisal results, and the data mining results based on performance appraisal are shown in Table 3.

Table 3. Monthly performance appraisal results of Marketing Department employees

Employee	Total	Number of	Number of	Complete	Proximity	Assessment

	number of calls made	marketing customer successes	complaints	the tasks of each month		result
Employee1	3817	2446	84	97.84%	0.5971	Normal
Employee2	3753	2366	70	94.64%	0.6493	Normal
Employee3	3676	2533	23	101.32%	0.8323	Excellent
Employee4	3502	2398	79	95.92%	0.7688	Good
Employee5	3200	2333	55	93.32%	0.6907	Normal
Employee6	3072	2329	126	93.16%	0.4252	Normal
Employee7	2729	1202	60	48.08%	0.3422	Below standard
Employee8	3480	1535	35	61.40%	0.4327	Normal
Employee9	4009	3017	74	120.68%	0.7489	Good
Employee10	2906	2231	17	89.24%	0.6881	Normal

Analyze the results of work performance appraisal using TOPSIS model: Employee 3 is located in the top 10% of the total ranking after algorithmic sorting, and from the perspective of its “total number of dialed subscribers, the number of successful marketing customers, the number of complaints, and the completion of this month's task” assessment indicators, Employee 3 is ranked in the top, after using TOPSIS sorting. The result is in line with certain objective facts, the same way to analyze other assessed employees, its TOPSIS analysis results and expectations are basically the same, so the use of TOPSIS model for job performance assessment is more appropriate.

3.2. Data Mining Design and Realization of Aptitude Assessment Indicators

After the work performance appraisal model based on TOPSIS method verifies the objectivity of performance ranking, this section will turn to the analysis of employee competence quality assessment index. Through the improved Apriori algorithm, this section aims to mine the potential association rules between competence quality and performance results to provide data support for dynamic performance prediction.

3.2.1. Data categorization and pre-processing of competency indicators. Ability to assess the quality of the four aspects of business knowledge, skill level, education and culture, job age, which business knowledge data from the results of the skills assessment questionnaire, skill level by the employee information in the technical title information to provide, education and culture and job age are derived from the information provided by the employee's personal data.

The following to the target company's R & D department part of the staff's ability to quality information to illustrate, the employee's skills title, academic qualifications and the recent quarterly assessment results have been categorized, only need to job seniority and assessment questionnaire results indicators to be categorized, the classification rules are shown in Table 4.

Table 4. Job seniority,assessment questionnaire results index classification basis

Post seniority	Category	Questionnaire result	Category
More than 20 years	Expert	90-100	Excellent
11-19 years	Journeyman	80-89	Good
6-10 years	Mastery	70-79	Normal
3-5 years	Dexterity	60-69	UP standard
0-2 years	Beginner	0-59	Below standard

3.2.2. Association rule analysis based on improved Apriori algorithm. After the Apriori algorithm operation, the value of the minimum support and the minimum confidence are constantly adjusted to screen the association rules, and the minimum support and the minimum confidence are finally set to 0.2 and 0.6, respectively, according to the actual results of the operation. Minimum support that is, the frequency of the rule appears, this value is set too low, the screened rule appears too few times, the rule does not have a general first, minimum confidence that is, the conditional probability of the appearance of the rule, the minimum confidence is set too low, the screened rule is not credible.

Because the association rule is oriented by the assessment results, the frequent item set must contain the "latest quarterly assessment results", which also leads to the fact that the minimum support degree cannot be set too high, and the setting is too high, for example, 0.3, then a rule may not be filtered out, according to the above competency assessment index and the frequent item set search rules in the Apriori model study, the frequent item set search results are shown in Table 5.

Table 5. Frequent item set search results

Frequent item set	Frequent item	Support degree
Frequent item set 1	Assessment is excellent	0.1
	Assessment is good	0.2
	Assessment is normal	0.525
	Assessment is failed	0.1
Frequent item set 2	The result of the questionnaire is normal The assessment is normal	0.3
	Assistant Engineer The assessment is normal	0.325
	Graduate students The assessment is good	0.125
	Mastery The assessment is good	0.1
	Journeyman The assessment is good	0.3
	Junior college The assessment is normal	0.3
	Undergraduate The assessment is normal	0.4
	Beginner The assessment is normal	0.5
	The result of the questionnaire is good The assessment is normal	0.5
Frequent item set3	Mastery Graduate students The assessment is good	0.3
	Assistant Engineer Beginner The assessment is normal	0.2
	Undergraduate Beginner The assessment is normal	0.225
	The result of the questionnaire is good Beginner The assessment is normal	0.125

According to the analysis of association rules based on the improved Apriori algorithm, the association rules that satisfy the minimum confidence are obtained as shown in Table 6. Because of the small sample data, only 3 association rules are screened out, which is also related to the minimum support and minimum confidence threshold, when these two thresholds are small, the effective rules will increase, of course, so that the screened out rules "interest" will be reduced, and the value of the rules is no longer obvious. Therefore, in practice, the need for artificial search process according to the frequent item set to adjust the minimum support and minimum confidence, when the choice is appropriate, you can filter out the desired rules.

Table 6. Association rule result

Association rule	Confidence degree
Mastery Graduate students The assessment is good	0.663
Assistant Engineer Beginner The assessment is normal	0.798
Undergraduate Beginner The assessment is normal	0.695
The result of the questionnaire is good Beginner The assessment is normal	0.843

From the above part of the employee data screening rules can be inferred: technical title, education and culture and the final assessment results have no obvious correlation, only based on the subjective assessment of the employee's academic qualifications and titles is unfair.

When using Apriori algorithm to screen the association rules for the whole company's data, no matter how to set the minimum confidence degree and minimum support degree, can not get the comprehensive assessment rules, so that from the side to draw a strong conclusion: technical title, education and culture have no obvious correlation with the final assessment results, and it is undesirable to only based on the subjective appraisal of the staff's academic qualifications and job titles.

In order to be able to carry out the assessment of employee competence quality in a fair way, and at the same time combining the results of the above correlation rules, the assessment rules of employee competence quality are set as shown in Table 7 below.

Table 7. Employee ability,quality assessment association rules

Assessment basis		**Assessment result**
Questionnaire result	**Score**	
Excellent	**90-100**	**The assessment is excellent**
Good	**75-89**	**The assessment is good**
Normal	**61-74**	**The assessment is normal**
Below standard	**0-60**	**The assessment is failed**

Employee's ability to assess the quality of the basis is set: assessment questionnaire 90 ~ 100 results for the assessment of excellence, assessment questionnaire 75 ~ 89 results for the assessment of good, assessment questionnaire 61 ~ 74 results for the assessment of the general, assessment questionnaire 60 and the following results for the assessment of the unqualified, exclude the technical title, education, culture and job seniority and performance appraisal of the linkage.

3.3. Work attitude evaluation model construction based on fuzzy decision tree

After delving into the knowledge related to fuzzy decision trees, we then applied this algorithm to the performance appraisal module.

3.3.1. Work Attitude Assessment Indicators and Data Collection. This study develops a corresponding assessment index of work attitude of employees in enterprises. The final evaluation score of work attitude is determined through a comprehensive assessment of five indicators:

employees' sense of responsibility and dedication, positive initiative, teamwork and communication, discipline and compliance awareness, adaptability and willingness to learn.

Comprehensive assessment of the above, a large number of data form of assessment information has been accumulated, we are randomly selected from the data form of assessment information, 20 employees percentage assessment results for testing, 20 employees work attitude numerical assessment data as shown in Table 8.

Table 8. Numerical assessment data of 20 employees

ID	Responsibility and engagement	Proactive	Teamwork and communication	Sense of discipline and compliance	Adaptability and willingness to learn
1	74	73	68	80	81
2	89	100	78	76	80
3	98	57	89	89	59
4	79	67	67	73	54
5	64	92	96	86	85
6	74	72	56	74	63
7	74	97	63	75	56
8	66	64	62	89	57
9	97	84	79	78	88
10	86	84	91	93	75
11	71	96	78	93	72
12	81	92	60	62	91
13	92	86	58	87	79
14	71	76	92	68	76
15	55	60	66	57	67
16	77	73	82	64	75
17	89	80	55	75	61
18	81	99	59	90	90
19	89	56	89	66	66
20	55	95	68	64	65

From the data collected, the data are now precise, not conducive to performance evaluation, because performance evaluation is a fuzzy categorization problem, so now we need to convert the percentage data in this table into grade evaluation results. We are in accordance with corporate requirements are divided into grade results in this way. Provides 85 $\leqslant$ excellent $\leqslant$ 100, in the table as A; 75 $\leqslant$ good $\leqslant$ 84, in the table as B; 65 $\leqslant$ pass $\leqslant$ 74, in the table as C; 0 $\leqslant$ fail $\leqslant$ 64, in the table as D.

3.3.2. Data fuzzification. In order to further analyze the data, we have to transform the distribution information of the data into the degree of fuzziness of the data. Fuzzifying the raw data with an affiliation function will better apply the numerical features in this example to calculate the degree of affiliation for each example.

In the following, using the fuzzy logic workbox in Matlab software, the raw data example samples are fuzzified according to the affiliation function, and the fuzzification results are obtained as shown in Table 9:

Table 9. Fuzzy processing results

	Adaptability and willingness to learn				Adaptability and willingness to learn				Adaptability and willingness to learn				Adaptability and willingness to learn				Adaptability and willingness to learn			
	A	B	C	D	A	B	C	D	A	B	C	D	A	B	C	D	A	B	C	D
1	0	0.25	0.75	0	0	0.25	0.75	0	0	0	0.75	0.25	0	1	0	0	0	1	0	0
2	1	0	0	0	1	0	0	0	0	1	0	0	0	0.625	0.375	0	0	1	0	0
3	1	0	0	0	0	0	0	1	1	0	0	0	1	0	0	0	0	0	0	1
4	0	0.625	0.375	0	0	0	0.75	0.25	0	0	0.75	0.25	0	0.25	0.75	0	0	0	0	1
5	0	0	0.125	0.875	0	1	0	0	0	1	0	0	0.625	0.375	0	0	0.75	0.25	0	0
6	0	0.25	0.75	0	0	0	0	0	1	0	0	1	0	0.25	0.75	0	0	0	0.25	0.75
7	0	0.25	0.75	0	0	1	0	0	0	0	0.25	0.75	0	0.375	0.625	0	0	0	0	1
8	0	0	0.75	0.25	0	0	0.125	0.875	0	0	0.125	0.875	1	0	0	0	0	0	0	1
9	1	0	0	0	0.875	0.125	0	0	0	0	1	0	0	1	0	0	1	0	0	0
10	0.625	0.375	0	0	0.875	0.125	0	0	1	0	0	0	1	0	0	0	0	0.875	0.125	0
11	0	0	1	0	1	0	0	0	0	1	0	0	1	0	0	0	0	0	1	0
12	0	1	0	0	1	0	0	0	0	0	0	1	0	0	0.25	0.75	1	0	0	0
13	1	0	0	0	0	0.625	0.375	0	1	0	0	1	0.875	0.125	0	0	0	1	0	0
14	0	0	1	0	0	0	0.625	0.375	1	0	0	0	0	0	0.75	0.25	0	0.75	0.25	0
15	0	0	0	1	0	0	0	0	0	0	0.75	0.25	0	0	0	1	0	0	1	0
16	0	0.875	0.125	0	0	0	0.125	0.875	0	1	0	0	0	0	0.375	0.625	0	0.875	0.125	0
1	0.	0.	0	0	0	0	1	0	0	0	0	1	0	0.	0.	0	0	0	0	1

7	875	125												75	25					
18	0	1	0	0	0	1	0	0	0	0	0	1	1	0	0	0	1	0	0	0
19	0.875	0.125	0	0	0	0	0	0	1	0	0	0	0	0	0.75	0.25	0	0	0.75	0.25
20	0	0	0	1	0	1	0	0	0	0	0.75	0.25	0	0	0.125	0.875	0	0	0.625	0.375

3.3.3. Fuzzy clustering model and rules for work attitude evaluation. According to the above fuzzy processing results about the work attitude of 20 employees in the enterprise, the fuzzy decision tree about the evaluation of employees' work attitude was constructed as shown in Figure 2.

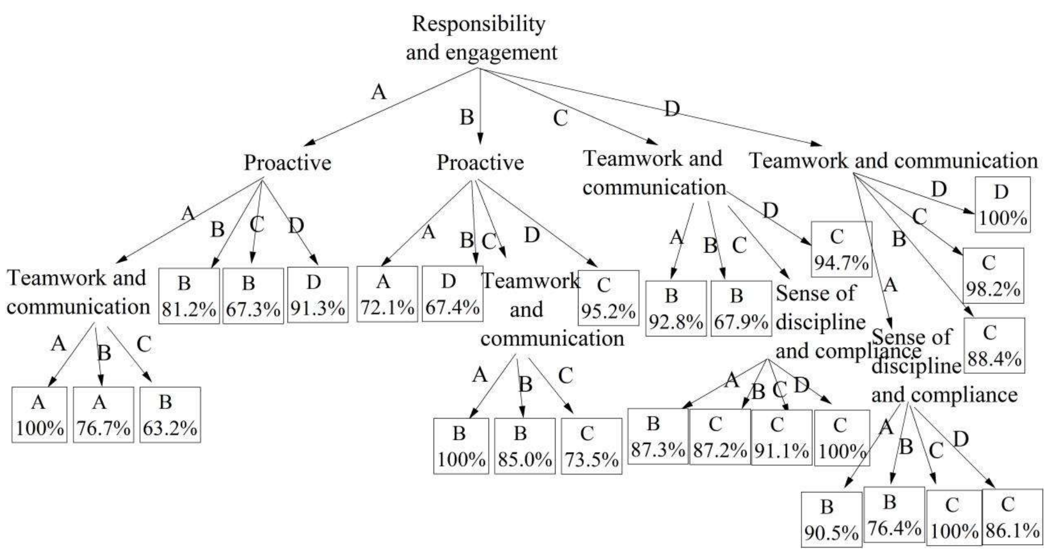

Fig. 2. Evaluation of work attitude fuzzy decision tree

The corresponding rule set from Figure 2 is:

1) If Responsibility and Dedication = A, Positive Initiative = A, Teamwork and Communication = A, then Adaptability and Willingness to Learn is A with Confidence Level CF = 100%;

2) If Responsibility and Dedication = A, Proactivity = A, Teamwork and Communication = B, Adaptability and Willingness to Learn is B, Confidence Level CF = 76.7%;

3) If Sense of Responsibility and Dedication = A, Positive Initiative = A, and Teamwork and Communication = C, then Adaptability and Willingness to Learn is D, with a Confidence Level CF = 63.2%;

4) If Sense of Responsibility and Dedication = A and Positive Initiative = B, then Adaptability and Willingness to Learn is B with a Confidence Level CF = 81.2%;

5) If Responsibility and Dedication = A and Positive Initiative = C, the Adaptation and Willingness to Learn Confidence Level is B, Confidence Level CF = 67.3%;

6) If Responsibility and Dedication = A and Positive Initiative = D, the Adaptability and Willingness to Learn confidence level is D with a confidence level CF = 91.3%;

7) If Responsibility and Dedication = B and Positive Initiative = A, Adaptability and Willingness to

Learn is A with a Confidence Level CF = 72.1%;
8) If Responsibility and Dedication = B and Positive Initiative = B, Adaptability and Willingness to Learn is D with Confidence CF = 67.4%;
9) If Sense of Responsibility and Dedication = B, Positive Initiative = C, and Teamwork and Communication = A, then Adaptability and Willingness to Learn is B, with a Confidence Level CF = 100%;
10) If Responsibility and Dedication = B, Proactivity = C, Teamwork and Communication = B, Adaptability and Willingness to Learn is C, Confidence Level CF = 85.0%;
11) If Responsibility and Dedication = B, Positive Initiative = C, and Teamwork and Communication = C, then Adaptability and Willingness to Learn is D, with a Confidence Level CF = 73.5%;
12) If Sense of Responsibility and Dedication = B and Positive Initiative = D, then Adaptability and Willingness to Learn is C with a Confidence Level CF = 95.2%;
13) If Responsibility and Dedication = C and Teamwork and Communication = A, Adaptability and Willingness to Learn is B with a Confidence Level CF = 92.8%;
14) If Responsibility and Dedication = C and Teamwork and Communication = B, Adaptability and Willingness to Learn is B, Confidence Level CF = 67.9%;
15) If Responsibility and Dedication = C, Teamwork and Communication = C, and Teaching Attitude = A, then Adaptability and Willingness to Learn is B, Confidence Level CF = 87.3%;
16) If Responsibility and Dedication = C, Teamwork and Communication = C, and Teaching Attitude = C, then Adaptability and Willingness to Learn is C with a Confidence Level CF = 91.1%;
17) If Responsibility and Dedication = C, Teamwork and Communication = C, and Teaching Attitude = D, then Adaptability and Willingness to Learn is C with a Confidence Level CF = 100%;
18) If responsibility and dedication = C, teamwork and communication = D, adaptability and willingness to learn is C with a confidence level CF = 94.7%;
19) If Responsibility and Dedication = D, Teamwork and Communication = A, and Teaching Attitude = A, Adaptability and Willingness to Learn is B, with a Confidence Level CF = 90.5%;
20) If Responsibility and Dedication = D, Teamwork and Communication = A, and Teaching Attitude = B, then Adaptability and Willingness to Learn is B with a Confidence Level CF = 76.4%;
21) If Responsibility and Dedication = D, Teamwork and Communication = A, and Teaching Attitude = C, then Adaptability and Willingness to Learn is C with a Confidence Level CF = 100%;
22) If Responsibility and Dedication = D, Teamwork and Communication = A, and Teaching Attitude = D, then Adaptability and Willingness to Learn is C with a Confidence Level CF = 86.1%;
23) If responsibility and dedication = D and teamwork and communication = B, adaptability and willingness to learn is C with a confidence level CF = 88.4%;
24) If Responsibility and Dedication = D and Teamwork and Communication = C, Adaptability and Willingness to Learn is C with a Confidence Level CF = 98.2%;
25) If Responsibility and Dedication = D and Teamwork and Communication = D, Adaptability and Willingness to Learn is D with Confidence Level CF = 100%.

4. AHP-based comprehensive performance assessment model and empirical analysis

In order to further integrate the three types of indicators of business performance, competence and work attitude, Chapter 4 will construct a comprehensive performance evaluation model based on fuzzy clustering to form a comprehensive employee integrated performance appraisal system. Based on the fuzzy clustering results and weight allocation, this chapter will design a multilevel evaluation model and verify its feasibility.

4.1. *Comprehensive Employee Performance Appraisal Indicators*

This section will assess three aspects: business performance, competence and work attitude. Through the assessment of workload, work efficiency, work quality, task completion progress of these secondary indicators assessment score as the final score of employee performance assessment. Through the comprehensive assessment of the employee's business knowledge, skill level, education and culture, job seniority and other secondary indicators to calculate the quality of the employee's ability; through the comprehensive assessment of the employee's sense of responsibility and dedication, initiative, teamwork and communication, discipline and compliance awareness and adaptability and willingness to learn five secondary indicators to determine the final evaluation of the work attitude score.

The constructed employee performance evaluation indicators and their weights are shown in Table 10.

Table 10. Employee performance evaluation index and its weight

Target	Primary index	Secondary index	Weight
A: Employee performance evaluation indicators	B1: Business performance 0.3319	C1: Workload	0.0745
		C2: Work efficiency	0.0773
		C3: Quality of work	0.0729
		C4: Task completion progress	0.1072
	B2: Ability and quality 0.3368	C5: Business knowledge	0.0983
		C6: Skill level	0.0787
		C7: Academic culture	0.0974
		C8: Post seniority	0.0624
	B3: Work attitude 0.3313	C9: Teaching workload	0.0726
		C10: Teaching document preparation	0.0614
		C11: Teaching process	0.0637
		C12: Teaching attitude	0.0615
		C13: Practical teaching	0.0721

From Table 10, each weight vector is given as

A = {0.3319 0.3368 0.3313}

B1 = {0.0745 0.0773 0.0729 0.1072}

B2 = {0.0983 0.0787 0.0974 0.0624}

B3 = {0.0726 0.0614 0.0637 0.0615 0.0721}

4.2. *Application of fuzzy comprehensive evaluation model and analysis of results*

After clarifying the performance evaluation indicators and their weights, the evaluation data need to be quantified through a fuzzy matrix.

In the assessment process, first of all, to assess the subject's superiors, peers, subordinates and the subject's own evaluation, after the statistics of the subject's assessment of each assessment factor and assessment scores, also according to the "85 $\leqslant$ excellent $\leqslant$ 100, A; 75 $\leqslant$ good $\leqslant$ 84, B; 65 $\leqslant$ pass $\leqslant$ 74, C; 0 $\leqslant$ failing $\leqslant$ 64, D". Then the appraisal fuzzy evaluation matrix is established against the appraisal 1-point quantitative scale. The following continues to establish the fuzzy matrix as an example of enterprise employee performance appraisal as shown in Table 11.

Table 11. Fuzzy matrix of university teacher performance

	A	B	C	D
C1	0.25	0.35	0.15	0.25
C2	0.4	0.35	0.2	0.05
C3	0.35	0.3	0.15	0.2
C4	0.15	0.3	0.35	0.2
C5	0.2	0.35	0.3	0.15
C6	0.25	0.45	0.25	0.05
C7	0.3	0.5	0.15	0.05
C8	0.1	0.35	0.35	0.2
C9	0.15	0.55	0.25	0.05
C10	0.25	0.35	0.2	0.2
C11	0.3	0.25	0.35	0.1
C12	0.4	0.5	0.05	0.05
C13	0.35	0.35	0.15	0.15
C14	0.2	0.4	0.25	0.15

Calculated according to the vector of weights {0.0745 0.0773 0.0729 0.1072 0.0983 0.0787 0.0974 0.0624 0.0726 0.0614 0.0637 0.0615 0.0721} for each indicator of employee performance, it results in a composite rating of performance of the 20 employees of the enterprise of 0.81362, which is a good Grade.

5. Conclusion

This study constructs a multidimensional employee performance evaluation framework based on data mining technology, and realizes the objective and precise evaluation of enterprise employee performance through TOPSIS model, improved Apriori algorithm and fuzzy decision tree method.

For the performance evaluation of enterprise employees, after the TOPSIS model combined with triangular fuzzy numbers to deal with subjective indicators, the results of employee performance ranking are highly consistent with business performance. For example, Employee 9 is ranked in the good grade with a task completion rate of 120.68% and a relative proximity of 0.7489, and its high task completion rate and low number of complaints (74) verify the robustness of the model to extreme data. In addition, the improved Apriori algorithm found that questionnaire results had a significant impact on appraisal with a confidence level of 84.3% while the correlation between technical title and education and culture was lower than 30% when mining the association rules of competence quality, which further supported the scientific validity of the questionnaire-centered dynamic evaluation rules. The fuzzy decision tree model generated 25 classification rules with a confidence level higher than 63.2%. For example, the rule "Sense of responsibility and dedication = A, positive initiative = A, teamwork and communication = B → adaptability and willingness to learn is A (confidence level 100%)" reveals the intrinsic connection between key indicators. The final comprehensive performance score of the enterprise's employees is 0.81362, of which the contribution of work attitude indicators accounts for 33.13%, reflecting the balance of multidimensional indicators.

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