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RESEARCH ARTICLE

A Data-Driven Knowledge Discovery Framework for Smart Education Management Using Behavioral Characteristics

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ABSTRACT Based on the characteristics of behavioral patterns, this paper constructs a data-driven knowledge discovery framework for smart education management. The aim is to realize automatic education effect evaluation using digital intelligent algorithms. The designed framework includes four parts: online course evaluation based on data mining, mining of association rules based on rough sets, dynamic adjustment of evaluation index weights, and the fuzzy comprehensive evaluation based on association rules. Their joint effect constructs a digital workflow, which realizes evaluation of both teaching effect of teachers and learning effect of students. In the simulation process, the designed framework is constructed based on the browser/server mode. Modeling tools such as business flow chart and unified modeling language are used to build the system logic model. The experimental results show that the performance of the education management framework based on 4 first-level indicators, 11 second-level indicators and 3 third-level indicators is stable. The testing case demonstrates an efficient method of evaluating perceived behavior patterns for intelligent educational management. From the perspective of system theory, the key elements of wisdom teaching in colleges and universities are summarized and refined; the behavioral model of wisdom teaching in colleges and universities is proposed, which deepens the understanding of the inner structure and laws of teaching and education practices in college classrooms.

INDEX TERMS Data mining, knowledge discovery, smart education management, behavioral characteristics.

I. INTRODUCTION

College network education is an important part of modern distance education, which provides conditions for people to continue learning [1]. With the continuous development of distance education, the research on the evaluation mode and evaluation method of the effect of online education has attracted increasing attention [2]. At present, the research on the effect of online education mainly focuses on the longitudinal analysis of the cost-benefit of online education [3]. while the horizontal integration of the distance education effect, resource utilization efficiency, graduate quality and other indicators among various educational institutions (online education colleges) are carried out [4]. Comparative evaluation studies are rarely mentioned [5]. Most of the related researches based on data and with teachers [6], [7]. The main body are mostly based on qualitative analysis of teachers, and lack of quantitative judgment [8]. The usefulness and reliability of the entire quantification system are verified [9].

In recent years, with the rapid development of Internet technology, the importance of data has attracted extensive attention of researchers in various industries [10]. Data has begun to penetrate into various industries in various fields, and intelligent data and machine learning have

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become popular [11]. It is widely used in various industries such as medical treatment, finance, entertainment and education [12], [13]. Education informatization has brought about a sharp increase in the amount of information and higher requirements for information extraction [14]. How to discover the rules and knowledge implicit in these data and assist in decision-making has become an urgent problem to be solved [15]. The emergence and development of data mining technology provides strong support for this [16]. Compared with traditional teaching [17]. The evaluation system of online teaching is not perfect [18]. Many online teaching systems do not provide teaching evaluation functions [19]. Even if corresponding functions are provided, the evaluation models used are often simple and solid, and cannot be replaced [20]. Not only is the maintainability poor and not universal, but the evaluation method is difficult to adapt to the requirements of modern society for evaluating students' comprehensive quality.

Generally elaborating the meaning of online learning behavior from the field of pedagogy, researchers have focused more on empirical research using observed, measured, and collected data on online learning behavior. In this study, online learning behavior is considered to be the sum of online learning traces produced by learners using different terminals as media and rich and diverse teaching resources to achieve certain learning purposes. Therefore, the final object of online learning behavior analysis is a series of learners' operations on online education platforms. Two of the most common applications of data mining models are behavioral segmentation and classification. In behavioral segmentation, clustering models are used to analyze customers' behavioral patterns and identify actionable groupings with differential characteristics. Classification models are used to predict the occurrence of events and estimate the propensity of events. Classification models are often used to optimize direct marketing campaigns to maintain and expand relationships with customers.

Based on the theory of perceived behavior mode, this paper constructs an evaluation model of intelligent education management [21]. The experiment uses the Delphi method to select corresponding indicators from four aspects: educational conditions, educational management, educational effects, and the construction of learning support service system. The remainder of this paper is organized as follows. In the next section, the related works will be shown in detail. In Section III, a data-driven knowledge discovery framework for smart education management is constructed. In Section IV, the simulation and experiments are carried out. In Section V, we discussed our works. Finally, some conclusions are drawn in Section VI.

II. RELATED WORK

Educational evaluation refers to the systematic investigation of educational activities by educators according to educational objectives and related standards to determine their value, strengths and weaknesses and adjust relevant activities accordingly [22]. Through the collected data and materials, the evaluation and measurement of various assessment indicators such as the learners' learning process, learning effect, understanding and mastery of knowledge and skills are realized [23].

Recently, educational researchers have also paid more and more attention to the ethics and security privacy issues related to student data in educational evaluation [24]. Due to the openness of the Internet, the privacy and security of student information is facing huge challenges. At present, the standards of ethics, privacy, and security issues related to the collection and use of student information are relatively lagging behind. It is necessary to establish a relatively complete and reliable student information management system. Cuartero and Role [25] believes that the results of educational activities in practice are unpredictable. In addition to some predictable results, there are often many unintended effects. Therefore, there are many limitations in the evaluation of only focusing on expected goals, and the focus of evaluation should be placed in educational practice, comprehensively collect the objective data and information of the educational process, so that the evaluation will not be interfered by the educational goals, and implement a comprehensive and objective evaluation. Chen and Zhong [26] believes that the above-mentioned educational evaluation tools and methods complement and complement each other. The development of information technology and the progress of teaching models are also pushing back the reform of educational evaluation methods. The evaluation of learners' core literacy has been accepted by more and more educators. A single educational evaluation tool can no longer meet the needs of comprehensive evaluation, it cannot evaluate learners' thinking development level and cognitive structure development, and there is no tool to effectively use data such as discourse and text in the teaching process.

Stepanova et al. [27] advocates the integration of evaluation and curriculum teaching, and believes that teaching activities are a series of behavioral activities based on educational goals, and the effectiveness of teaching activities is evaluated according to the degree of change in learners' behavior. Guided by educational goals, appropriate test tools are selected to measure the change of change of learners' behavior, and then to evaluate the achievement of learners' educational goals. Raudah et al. [28] believed that evaluation should not be limited to measurement tests, which only test memory ability, and should also consider comprehension, application, and synthesis capabilities, which to a certain extent compensated for the one-sidedness of traditional measurement and test evaluation, extending the scope of evaluation. It focuses on the classification of educational goals, and the evaluation implementation structure is relatively rigorous and standard, so the model is practical and easy to implement [29]. However, there are also many problems, such as the evaluation targets come from higher-level educational plans, curriculum planning, and lack of reasonable judgment of the goals in practical teaching; only evaluating the results

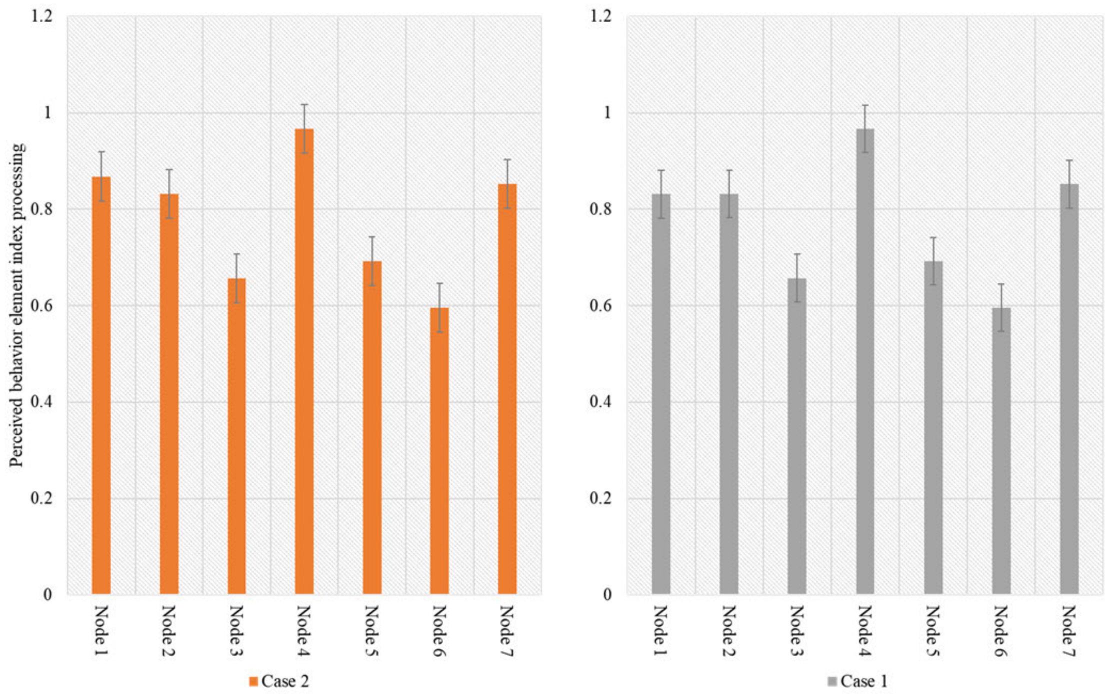

FIGURE 1. **Processing of indicators of perceived behavior elements.**

of students' specific learning behaviors may easily lead to one-sided and inconsistent evaluations [30]; goals in some domains such as emotion are difficult to specify; use of stylized evaluation criteria, lack of individualized evaluation of learners [31].

III. METHODOLOGY

A. PERCEIVED BEHAVIORAL ELEMENTS

Perceptual behavior analysis can analyze data in a higher-dimensional space and visualize the information, which is convenient for users to understand and perceive data and the relationship and evolution process between data. Therefore, perceptual behavior analysis is easier than numerical statistics to convey the information contained in the data $r(a, b)$. The application of element visualization analysis $a(i, j)$ in the field of education can present a large amount of data accumulated in educational activities $x(t)$ in a suitable way.

$$r(a, b) = \sum_{i,j} a(i, j) - b(i, j) \tag{1}$$

$$\frac{t(i) - t(j)}{i - j}(x - 1) - \frac{1 - \sqrt{x(t)}}{1 - x(t)} = 0() \tag{2}$$

Teaching activities are a series of behavioral activities based on educational goals. The effectiveness of teaching activities is evaluated according to the degree of change in learners' behavior. During the implementation of educational evaluation, appropriate testing tools should be selected based on educational goals to measure learner changes in learning behavior $u(x)$, and then assess the degree $y(x)$ of achievement of learners' educational goals.

$$u(x)y(x)/\left[v(x)y'(x)\right] < 1 \tag{3}$$

$$[e(1), e(2), e(3), \ldots, e(n)] \in E(n, t) \tag{4}$$

The rubric $e(n)$ is a structured quantitative evaluation tool, which specifies the evaluation indicators in detail from multiple aspects related to the evaluation objective $E(n, t)$, and combines the advantages of qualitative evaluation and quantitative evaluation, with strong operability and high accuracy. Perceived behavior files are a set of materials collected according to a certain purpose, reflecting the students' learning process and final results. The students' learning process and works are recorded in digital form. Students can use these files to reflect, and teachers use these files to carry out evaluation $z(x)$.

$$z(x) = x_{\text{redirst}}^{i+j}(\theta(i, j)) - \theta(i - 1, j) \tag{5}$$

$$y_{\text{redirst}}^{i+j}(\beta(i, j)) = 1 - \text{reddi}(i, j) \tag{6}$$

In data analysis $x(i)$, visual analysis can first analyze data $y(i, j)$ in a higher dimensional space and discover more information $reddit(i, j)$ and laws than traditional methods. Secondly, visual analysis can visualize information to facilitate users to understand and perceive data and the relationship between data relationship, and even its evolution, so it is easier to convey connotative information than numerical values.

Since the absolute value of each index cannot be directly compared, it is necessary to process Figure 1 and then calculate, and finally obtain the index evaluation value. Calculating the index values of the evaluated network education colleges A, B, and C respectively, and finally obtain their respective comprehensive evaluation values. Since the calculation process is the same, the author only calculates the statistical data of Network Education College A here. Consistency check is also required for the total ordering of the hierarchy, and the test is still carried out layer by layer from high to low like the total ordering of the hierarchy. This is because although each level has been checked for consistency of single-level ordering, each pairwise comparison judgment matrix has a relatively satisfactory consistency. However, when comprehensively inspected, inconsistencies at all levels may still accumulate, resulting in serious inconsistencies in the final analysis results.

The Guizhou College evaluates the index system, and uses the analytic hierarchy process to determine the weight of each index. This scoring model selects the comment content of the tutor evaluation network for application, and sets up a number of comparative experiments to test the effectiveness of the tutor rating model. In terms of model training and model testing, five graduate students were invited to manually annotate part of the review data and test the reliability of the annotators. After the analysis of the labeling results, the Kendall harmony coefficient value is 0.873, and the reliability and consistency of the labeling results are strong. Then, the manual labeled data is used as the test standard of the classification result, and different word vector training methods and different sentiment classification methods are used for training. The system is put into use, and the operation is stable and reliable, which improves the efficiency of teaching evaluation management, reduces the cost of teaching management, and enables the platform to play its due efficiency, thereby ensuring the smooth progress of teaching and the effective realization of campus informatization goals.

B. FEATURES OF SMART EDUCATION

The intelligent education goal proposed model believes that evaluation should not be limited to the evaluation method that only tests memory ability, but also should consider the ability of understanding, application and synthesis, pay attention to the classification of educational goals, and the evaluation implementation structure is relatively rigorous and standard. The pattern is practical and easy to implement. Intelligent education can be defined as the method and philosophy of using artificial intelligence and other advanced technologies to improve the education and learning experience. It may include specific tools and applications such as personalized teaching, adaptive learning, virtual and augmented reality technology, automated assessment and feedback. When proposing intelligent education, its expected benefits for students and educators should be clarified, including improving learning efficiency, enhancing personalized learning, optimizing course content and evaluation, promoting innovation and critical thinking. At the same time, ethical and privacy issues that intelligent education may face should be considered, and the design and use of intelligent systems should comply with educational ethics and values.

After the features are encoded, the basic analysis unit and section of the analysis need to be determined. The basic analysis unit is the object to analyze the cognitive network structure $m(i, j)$, which can be a person, a concept $min1 - i, 1 - j$ or an object to be analyzed.

$$m(i, j) = \prod \min\{(1 - i)(1 + j)\} \tag{7}$$

Engage Network Analysis (ENA) is a new method for data visualization, which is used to identify and quantify elements in discourse data, simulate the connection structure between elements to generate dynamic network diagrams, and combine quantitative and qualitative analysis $w(t)$. It can realize the visualization of discourse data $w(i) - w(j)$ and text data.

$$w(t) = 1 - \overline{w(t)}/\sum_{i,j} w(i) - w(j) \tag{8}$$

$$1 - \sum_{i,j} \frac{a(i)w(i)}{1 - a(i)} - w(i) < a(i) \tag{9}$$

Any relatively small complex network $a(i)w(i)$ with fixed elements and dynamic connections can be modeled. The strength and composition $1 - a(i)$ of the cognitive framework of the model changes with time and activities. Data can be encoded according to certain rules. The connection relationship and strength between data elements are displayed in a dynamic network diagram $w(t, s)$, reflecting the cognitive level and level of learners.

$$\begin{bmatrix} w(t, s) & 1 & 0 \\ 1 & w(t-1, s) & 1 \\ 0 & 1 & w(t, s-1) \end{bmatrix} \begin{bmatrix} a(i) \\ 1 - a(i) \\ i - a(i) \end{bmatrix} < w(t) \tag{10}$$

The stanza here is similar to the stanza in poetry, a stanza is a collection $1 - a(i)$ of discourse elements, discourse elements between different stanzas are not related, and discourse elements in the same stanza are related to each other. Figure 2 can divide discourse into multiple sections according to time series or activity sequence, for example, two unrelated discussion activities or data generated at two different times can be divided into two different sections.

The basic data sub-module mainly includes the basic data modification page editstafaddressin.asp and the display page stafpersoninf.asp. The mutual evaluation data collection sub-module mainly includes the mutual evaluation information display page hpchanginf.asp, the mutual evaluation authority setting page hpchanginfpopedom.asp, and the mutual evaluation information page addchanghp.asp. The learning works collection sub-module mainly includes the homework receiving page zyreturn.asp, the homework sending page sendzy.asp, the sent homework havesendzy and the homework management page sendzycontrol. The sub-module of reward and punishment record mainly includes adding reward and punishment information page, addjc.asp reward and punishment information display page icin.asp, and reward and punishment file editing authority setting page jcppedo.asp.

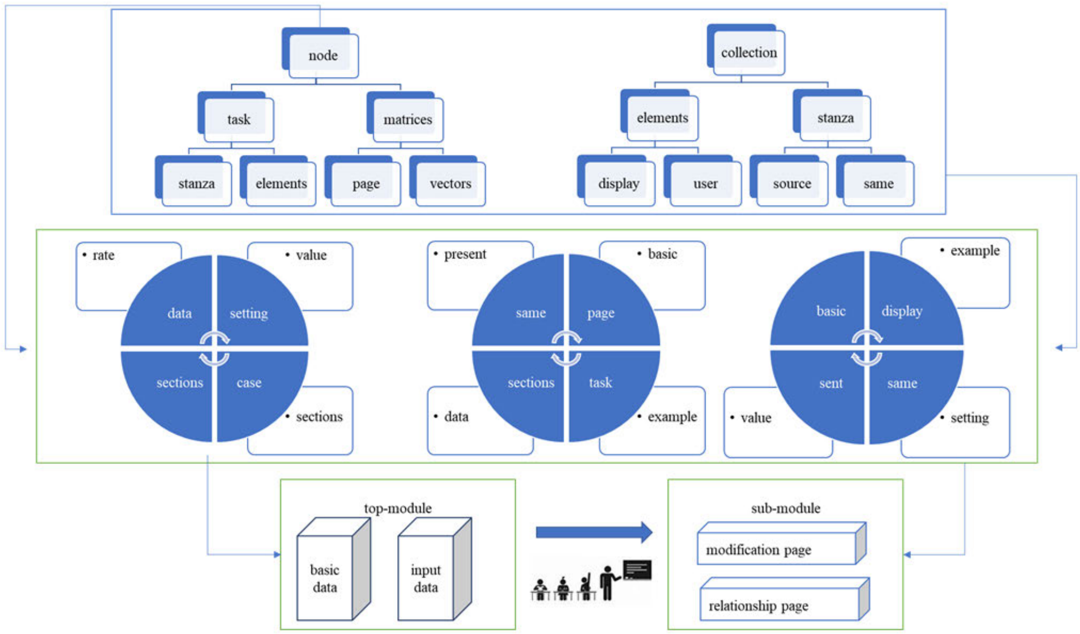

FIGURE 2. Distribution of educational feature patterns.

C. PATTERN HIERARCHY CONSTRUCTION

The user is only interested in the best set of schema hierarchies relevant to the processing task. Moreover, some users have a better understanding of the task. During the decision-making process, user may want to emphasize some attributes and include them in the final decision rule. Based on the dependencies between attributes, importance, and interaction with users, it is relatively easy and effective to find an optimal specification set or a minimum attribute set (called a user-defined minimum attribute set, which includes user-emphasized attributes and has the same resolving power as the original information table). ENA realizes the visualization of data through optimization algorithms, and displays the projection of the centroid of the coding element node and each analysis unit in the two-dimensional space orthogonal to the X dimension and the Y dimension, and the position of each centroid is determined by its own network structure. The weights of the connections are determined, and the Pearson correlation coefficient $c(n, m)$ and Spearman correlation coefficient $1 - n - m$ are used to test the fit of the formed network to the source data.

$$c(n, m) = \text{ lameda } (n) - n/1 - n - m \tag{11}$$

$$\frac{r(i) - r(j)}{i - j} < (x - 1)(i + j)/x(i - j) \tag{12}$$

The adjacency matrices from the same analysis unit $r(i) - r(j)$ are then accumulated, and the accumulated adjacency matrices are normalized and transformed into an adjacency vector $\mathrm{x}(i - j)$ in the high-order space, this adjacency vector contains the co-occurrence times of all coded elements. To interpret and visualize these adjacency vectors, ENA uses a singular value decomposition (SVD) algorithm to reduce the dimension of the high-dimensional space (the singular value decomposition algorithm is similar to principal component analysis, but the difference is that it does not recalculate the data), and in this way, the information contained in the source data can be preserved as much as possible, so that the loss $u(i)$ of data features is minimized, and it is convenient to present the data $x(i - 1)$ and distinguish the differences between different networks.

$$(x - 1)^{T-1}\{x(i), x(i - 1), \ldots, x(i - j)\} < i \tag{13}$$

$$\max E(i) = {}^{u(i)w(i-1)/\sqrt{1-w(i)-w(i-1)}} \tag{14}$$

The connections between nodes in the network graph $maxE(i)$ represent the co-occurrence of two codes at the same time or activity $w(i - 1)$, quantifying the domain knowledge, thinking habits, and cognitive elements of a person (or team) at a certain point in time in discourse data $1 - w(i - 1)$. The way in which they connect to each other, the way and strength of their connections change over time, to characterize the development and connection process between their domain-specific professional thinking elements in solving complex problems. In this way, Figure 3 simulates the evolution of individuals' cognitive frameworks over time, and in turn quantifies and assesses their ability to think and work in their respective domains.

First of all, we create a table in the MySQL database according to the data returned by different interfaces, and use the Navicat terminal tool to operate the database MySQL. When creating a table, the table name of each table is the interface name, and the column name of each table is the description of the return type of the interface.

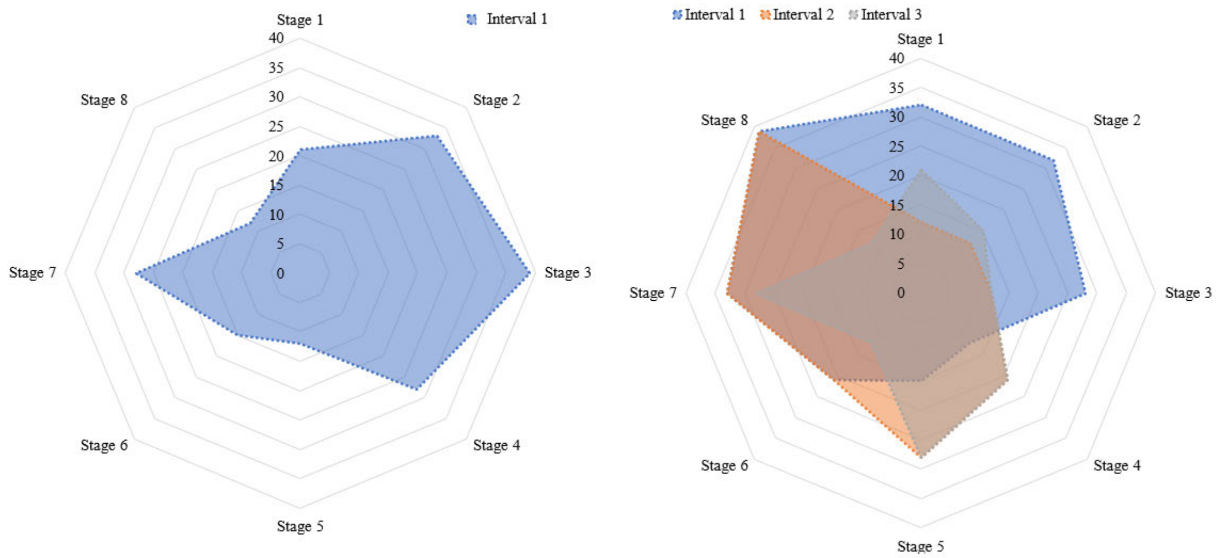

FIGURE 3. Comparison of pattern hierarchy information.

Then, the information returned by different interfaces is stored in the MySQL database, and the information required for the research is obtained through multi-table association. Finally, the obtained data is sorted out to facilitate subsequent statistics and analysis. This module is mainly composed of four parts: administrator login module, evaluation information query module, learning evaluation basis display module and comprehensive evaluation module. The administrator enters the evaluation background through a certain account and password, enters the evaluation information query module, and enters the student's name and the relevant course name. The learning evaluation basis related to the input information, including the original materials, are all displayed on the evaluation basis display page, based on the collected basis, the administrator can make a comprehensive assessment of the students' learning process.

D. MANAGEMENT EVALUATION DATA COLLECTION

The experiment distributed the management evaluation data of 400 online courses in the Guizhou College of Finance and Economics of online education of the university. 259 copies were effectively recovered, involving a total of 6 online courses, and the amount of data is far from enough to mine effective association rules. Therefore, this section takes data as an example to illustrate the basic method of mining association rules in online course evaluation. Through this example, we conclude that three attributes of course content, instructional design and technology are necessary to determine the final rating, and we have excavated four association rules that can be used to assist decision-making. This page displays a reduction of the initial data table. The largest characteristic root $D = 3$, $CI = 0$, then $CR = 0 < 0.1$, the consistency check is passed. Then the weights of the three-level indicators that constitute the amount of substitute lessons are $W2 = [0.2500, 0.2500, 0.5000]$. At this point, the weight construction of the teaching contribution and its sub-indicators is completed. The public service index consists of three secondary indicators: cultural and sports public activities, being invited or participating in academic reports, and participating in academic conferences.

According to the database analysis in Figure 4, it is now necessary to analyze the system administrators, educational administrators, examination administrators, test question administrators, teaching teachers, question-setter teachers, test-setting teachers, marking teachers, and students. E-R (Entity-Relationship Model)modeling is carried out on entities such as exams, rules for setting papers, questions, knowledge points, and subjects. After analyzing the above entities, it is not difficult to find exam administrators, question administrators, and teachers. These entities can be abstracted into one entity: Teacher User entity, so the above entities can be simplified as: System Administrator, Academic Administrator, Teacher User, Student, Exam. There are 10 entities, such as class, test paper rule class, test paper class, test question class, knowledge point class, and subject class. Because the student entity has class and major information, considering the redundancy, it can be expanded into three entities: student, class and major, and the E-R model can be drawn in combination with the examination entity.

E. EVALUATION INDEX DISTRIBUTION

For the overall evaluation index object of the research, first put forward an assumption that the overall population obeys a normal distribution, and then rank the samples with a sample size of n in order of size. For the corresponding coefficient n, the test statistic w is calculated according to a specific formula. Finally, we check the specific normality boundary value table and compare their sizes. If the

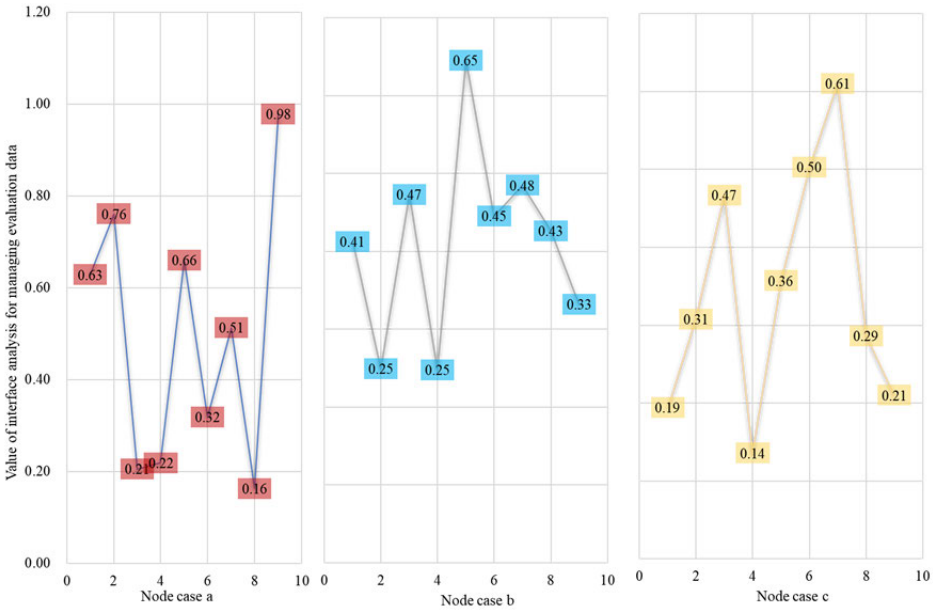

FIGURE 4. Analysis of management evaluation data.

conditions are met, the hypothesis is accepted and the population is considered to obey the normal distribution. Otherwise, the hypothesis is rejected and the population is considered not to obey the normal distribution. Using SPSS software to carry out statistical analysis to get the results, the statistical data of the six courses can achieve good reliability at different levels of significance. Each time the most important attribute is selected and added to the attribute set, after the forward selection of the step is completed, the attribute set has already included some important attributes. And it does not change the degree of dependence between the original attribute set and the decision attributes. Attributes are removed one by one from the attribute set in ascending order of importance. If removing the attribute will cause a change in the degree of dependency, restore the attribute, otherwise remove the attribute. The last remaining set of attributes is the Onga reduction set or the user-defined minimum set of attributes. In summary, the annotation results of the five postgraduates are highly credible, that is, the annotators can accurately judge the sentiment scores of postgraduate comments, so they can be used as the annotation data for subsequent model training and testing.

The internal consistency coefficient in Table 1 also reflects the correlation between the items of each item. The coefficient is preferably above 0.80, and the range between 0.70 and 0.80 is also acceptable: when the number of items is less than 6, the reliability coefficient is also preferably 0.60 or more to ensure data reliability. Otherwise, revising the scale or changing the terms should be considered. The overall internal consistency coefficient of the scale $a = 0.709$, that is, Cronbach $a > 0.70$, indicating that the reliability of the scale is acceptable. The internal consistency coefficients

TABLE 1. Description of evaluation indicators.

Evaluation node	Dimension x		Dimension y	
Training ratio	T<0.05	0.34773 0.86624	P<0.05	0.08976 0.4872
Relationship coefficient	T<0.1	0.37169 0.85891	P<0.1	0.73963 0.27844
Consistency coefficient	T<0.5	0.68593 0.31174	P<0.2	0.27722 0.95686

under the dimensions are $a1 = 0.630$ and $a2 = 0.629$, indicating good reliability. Then the weights of the two secondary indicators of the teaching contribution degree are $W3 = [0.6667, 0.3333]$. The secondary indicators in the teaching contribution degree are composed of the number of courses taught, the total number of class hours and the number of students.

The 1,000 comments randomly selected for this study are used as the test set, and the sentiment scores are manually scored. According to the text of the comments, the graduate student's score on the six dimensions of his supervisor is judged. Then, Figure 5 uses the scoring model to score the test set by the mentor, and compares the scoring result of the mentor scoring model with the actual score to test the validity of the scoring model. When determining the weight of the first-level index, the four dimensions of the first-level index are compared in pairs, and the results are presented in the form of a matrix, and the calculation process is carried out with the help of the mathematical software MATLAB. The relative weights of the amount of substitute courses and the years of substitute courses in the evaluation system of college teachers' ability are 0.6667 and 0.3333. For the three

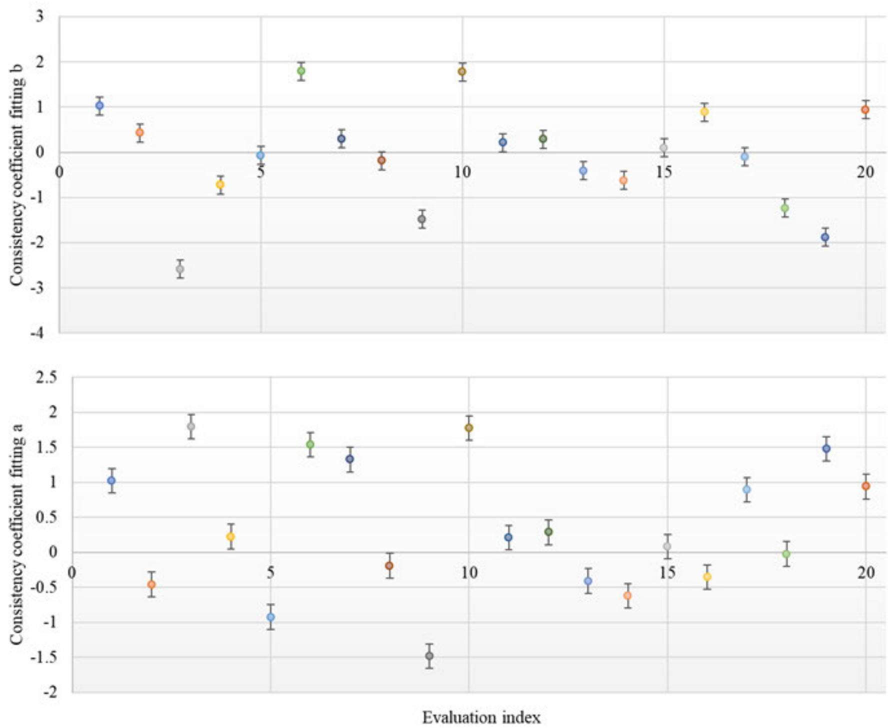

FIGURE 5. Fitting of the consistency coefficient of the evaluation index.

three-level indicators of the three-level indicators of teaching contribution, the relative weights of the number of classes, the total number of class hours and the number of students, the weights are 0.25, 0.25 and 0.5.

There are five steps to determine the weight of indicators through it, which are: establishing a clear hierarchical structure, constructing a judgment matrix, calculating the weights of indicators, and checking the consistency of hierarchical ordering and weighting value determination. The value obtained at this time does not have any alignment relationship and needs to be orthogonalized. The values of the academic index, scientific research index, teaching contribution, and public service index are added together to obtain a weighted sum. This sum is then normalized to generate a priority vector represented by the weights assigned to each of the indices, thereby indicating their relative importance in the overall assessment. Then, the consistency ratio test is carried out according to the largest characteristic root of the judgment matrix constructed by the four indicators. Only when the value of CR is less than 0.1 can it be considered that there is good consistency, and the weight distribution can be considered reasonable; otherwise, it is necessary to reconstruct the judgment matrix if and only if the value of CR is less than clock stop.

IV. SIMULATION AND ANALYSIS

A. PERCEPTUAL BEHAVIOR PATTERN RECOGNITION

The validity of the Perceived Behavioral Patterns Questionnaire refers to the closeness of the object to be measured in the research to the measured result. Like reliability, the validity of the questionnaire is an important criterion to reflect the measurement effect of the questionnaire [32]. Due to the indirectness of the validity verification method, a single validity index often cannot fully prove the validity of the test. In actual research, multiple validity indicators are often used to verify the validity of the questionnaire. This study will be effective on the surface of the questionnaire. The scientific research index is composed of 4 second-level indicators, the teaching contribution is composed of 2 second-level indicators and 3 third-level indicators, and the public service index is composed of 3 third-level indicators. The coordination coefficient test showed significant ($p = 0.017 < 0.05$), which means that the annotation results of the annotators have a certain correlation, and that the annotation results in Figure 6 are consistent.

Similarly, when calculating the teaching contribution degree and the public service index, the Java language is used for programming calculation. The calculated teacher teaching contribution degree and public service index can also be stored in the data structure of TreeMap to ensure that it is arranged according to the teacher's job number to facilitate the availability of the verification system in the following text. This platform introduces the concept of attribute importance in rough set theory into the weight determination process in online course evaluation, and proposes to combine the weight given by decision makers' prior knowledge with the attribute importance determined by rough set theory as the final determination of online course evaluation.

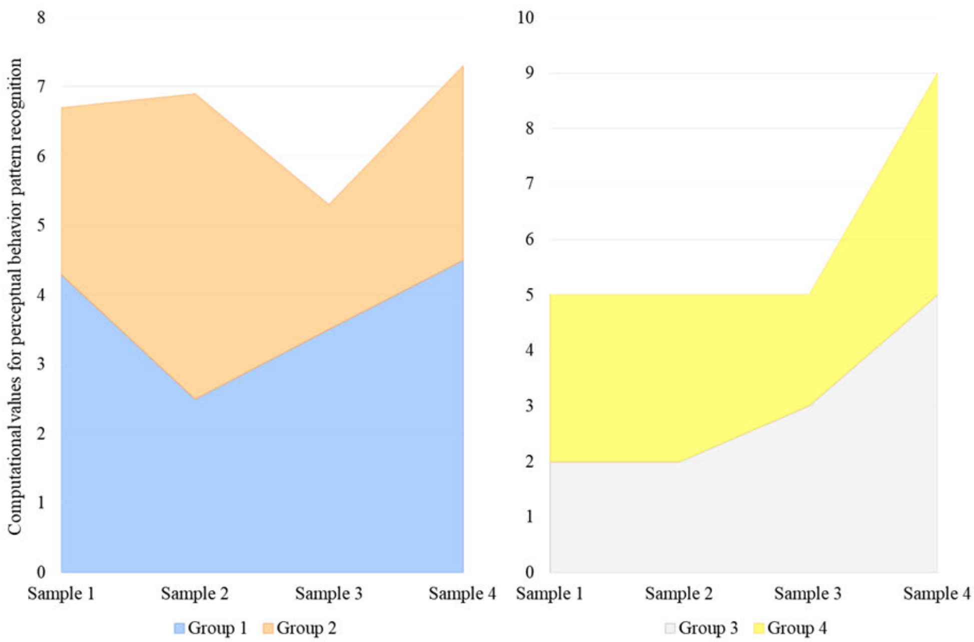

FIGURE 6. Perceptual behavior pattern recognition calculation.

The method of index weight is to combine the objective attribute importance determined by a large amount of historical data with the attribute weight determined by subjective prior knowledge to determine the final comprehensive weight, so as to realize the unity of subjective prior knowledge and objective situation. The data to be collected in this module include self-assessment data (log data), mutual assessment data, learning result data and teacher evaluation data. The content of the self-assessment data includes the learner's learning plan, learning summary and learning characteristics; the mutual-assessment data includes the evaluation of learning methods, learning attitudes, learning effects and collaborative learning abilities (the specific evaluation indicators can be changed according to the evaluation purpose); learning results include homework and works; teachers' evaluation mainly includes records of rewards and punishments.

B. SIMULATION OF SMART EDUCATION MANAGEMENT EVALUATION

In the education management evaluation index system, the dimension of each attribute is different, and the orientation of the attribute may also be different, so they cannot be compared. It is necessary to normalize the attribute value. Dimensionless refers to eliminating the influence of the original variable dimension through a certain mathematical transformation. The indicators selected in this paper have different dimensions. There are original data in units of time, value, percentage, and number of people. The meanings of each indicator are different, and the indicators cannot be simply added together. Therefore, before the comprehensive processing of the indicators, the indicators must be processed without dimension. Such evaluation indicators include the evaluation of course teaching quality, the evaluation of online learning effectiveness, the satisfaction level of curriculum setting, the evaluation of curriculum effectiveness, the effectiveness of examination evaluation and testing, and the satisfaction of teaching support for online tutoring and online communication.

The basis for collecting learning evaluation is mainly reflected in the ability to collect data according to the customized learning documents or learning forms. Figure 7 classifies and organizes the information to be collected, and provides online editing, document import and document upload. The format of the collected information mainly includes pictures, videos, sounds and so on. The user can upload the useful learning evaluation basis to the specified directory through different clients through the IE page. The online learning evaluation is based on the real-time monitoring system of the acquisition system, which can monitor the uploaded documents in time. The management of learning evaluation basis is mainly reflected in the ability to classify and manage the learning evaluation basis according to the system, organize the collected learning evaluation basis, and also formulate the collection task plan and the process review of the collection of learning evaluation basis. The e-learning evaluation basis collection system can uniformly classify and save the e-learning evaluation criteria collected from different sources and formats, which is convenient for management

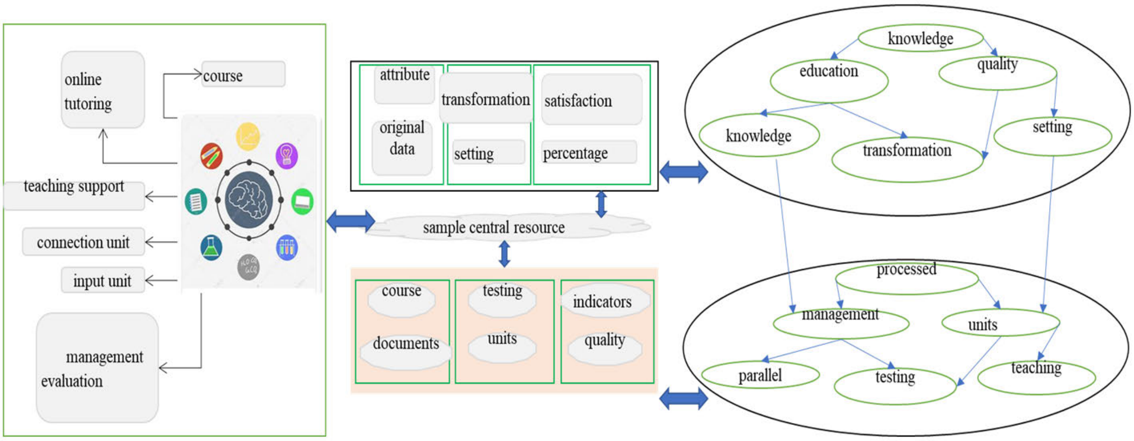

FIGURE 7. Information topology of educational management evaluation.

and information exchange. The basis of storage management learning evaluation is mainly reflected in the ability to centrally store the collected information in a central database or file system, and perform storage management according to the subsystems and their categories. The online learning evaluation basis collection system has the characteristics of unified user rights management. After users log in to the system, they can obtain corresponding information or services according to their accessible rights.

C. EXAMPLE APPLICATION AND ANALYSIS

In order to collect more evaluation basis, it is necessary to improve the collection method of evaluation basis. This paper realizes the extraction of network learning evaluation basis by constructing a staged intelligent evaluation module. The system has the function of automatically generating test papers, so it can easily realize staged testing. The input-output indicators of online course education are divided into two categories: positive indicators and negative indicators. In this paper, if we only look at the target of efficiency value, the output index is a positive index, that is, the larger the index value, the greater the comprehensive benefit of online course education reflected. The input index is a reverse index, that is, under the condition of a certain output, the smaller the index value, the higher the comprehensive benefit of the online course education. However, from the perspective of the goal of promoting the overall development of online course education, the more investment, the better, which is a positive indicator, otherwise it will not conform to the logic of realistic development. Therefore, Figure 8 adopts the latter, and investment is also a positive indicator.

According to the division of indicators in the evaluation system of college teachers' ability, the academic index is composed of two secondary indicators, the h index of published papers with a weight of 0.5, and the author's contribution degree with a weight of 0.5. After reading and researching relevant literature, the frequency of citations of papers published by university teachers is generally used to quantify the academic ability of university teachers or the influence of papers. Although this evaluation method has certain rationality, it can more objectively reflect the academic ability of a college teacher. All evaluation units have an efficiency value, which is between 0-100%. Every evaluation unit with a score of 100% is relatively efficient, and every evaluation unit with a score below 100% is relatively inefficient. A decision unit with an efficiency score of 60% is equivalent to 60% of the true efficiency of a decision unit with an efficiency score of 100%. Therefore, the efficiency score of each evaluation unit will change with the input-output data of other evaluation units. Evaluation scale: 5 points are very satisfied, 4 points are relatively satisfied, 3 points are generally satisfied, 2 points are dissatisfied, and 1 point is very dissatisfied as the evaluation scale.

Through the analysis of education management evaluation in Figure 9, it is found that online education is of great help to graduates in their careers. Through the study of online education, 97.64% of graduates have enhanced self-confidence, and 95.17% of graduates have acquired business knowledge. In order to improve, 92.36% of the graduates obtained a diploma, and 90.31% of the graduates' job skills were improved. In terms of positions and salaries, 68.85% of the graduates got a promotion in the position, and 84.25% of the graduates got an increase in the salary. Using the results of single ordering of all levels in the same level, the weights of the importance of all elements in this level can be calculated for the previous level, which is the total ordering of levels. Hierarchical total sorting needs to be performed in a layer-by-layer order from top to bottom. For the highest level, the single-level ordering is the total ordering.

D. DISCUSSION

This paper proposes a perceived behavioral model of intelligent education management evaluation method for assessing

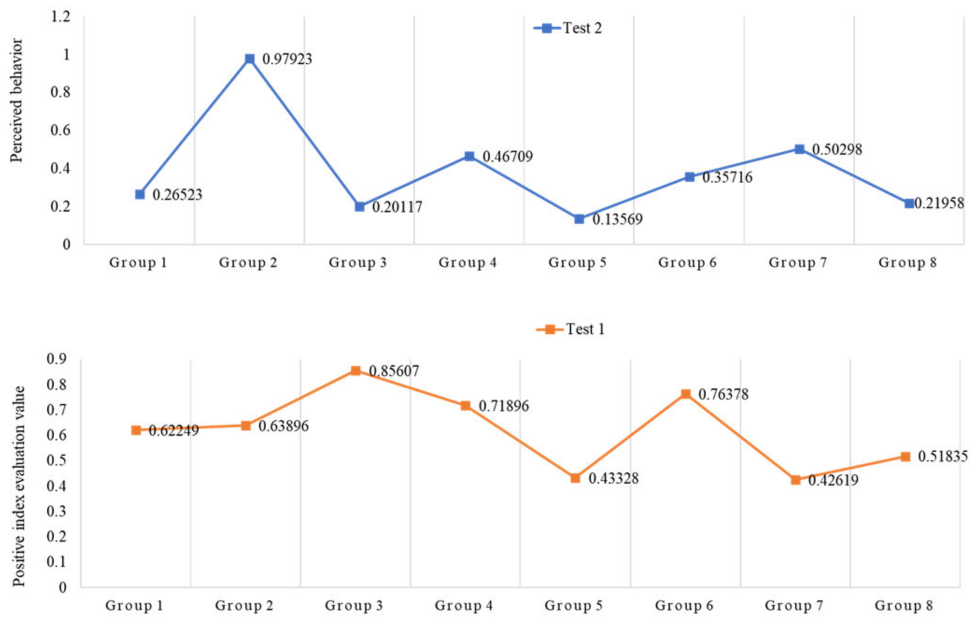

FIGURE 8. Evaluation of positive indicators of perceived behavior.

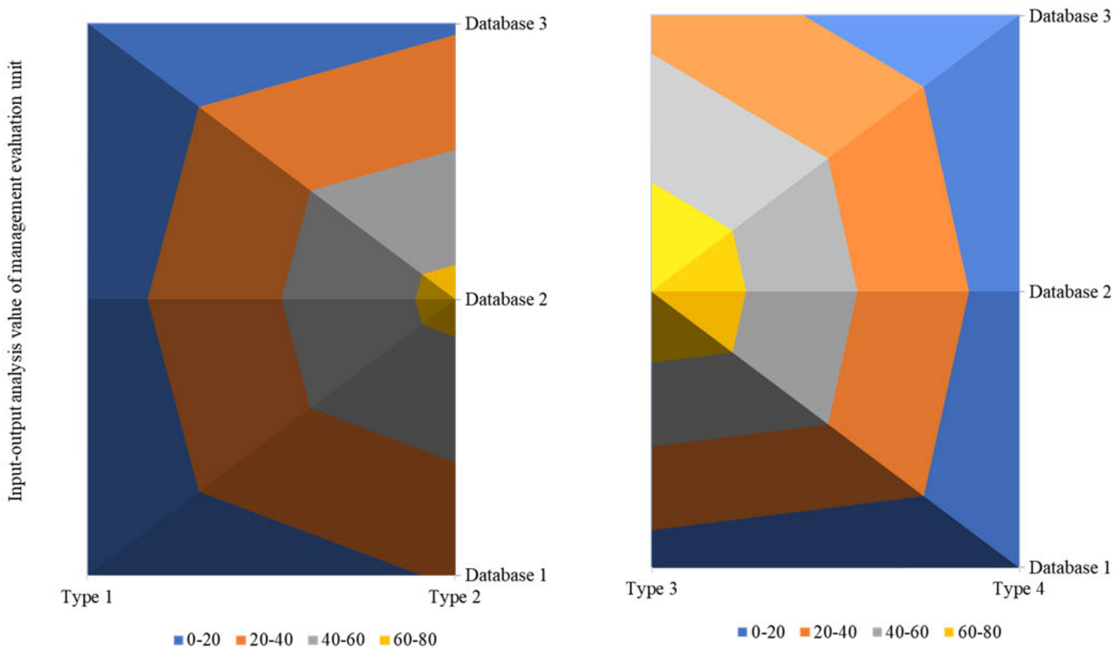

FIGURE 9. Analysis of education management evaluation results.

the quality of interaction between users and learning management systems in a blended learning environment. The paper presents a qualitative analysis of data collected from a case study at the Guizhou Institute of Finance and Economics, focusing on how users' perceptions of quality interact with different aspects of the learning system. Again, although this paper does not have a dedicated discussion section, the authors do provide some explanation of their findings throughout the article.

V. CONCLUSION

This paper constructs a smart education management evaluation model based on the perception behavior model. The paper has developed an evaluation system to assess the ability of college teachers in various dimensions. To evaluate the teachers, students are given questionnaires constructed according to the system, and the results are tallied. Then, the usefulness and reliability of the evaluation system are tested by the methods of curve fitting and distance based on the ranking of teachers obtained by the two methods. In terms of scoring model research, this study combines the characteristics of review texts, extracts high-frequency words in postgraduate reviews, and summarizes six evaluation dimensions.

At the same time, natural language processing methods and deep learning technology are introduced, and the word2vec model is integrated to perform semantic analysis and sentiment classification training on unstructured comment texts, and obtain the scores of the tutors in each dimension. Finally, on the basis of proving the usability of the evaluation system, the teacher's ability is predicted by creating a model trained by the perceptual behavior pattern network. The experimental results show that the relative error of the model is small and the determination coefficient of the model is as high as 0.9 or more, and the prediction effect is good. Future research will collect a larger amount and more dimensions of data, introduce more factors, and further explore the research.

This method of intelligent educational management evaluation can promote practical applications, efficiency and effectiveness of educational management in the field of education. The significance of this method is that it can improve the objectivity and scientific nature of the evaluation process and enable managers to better understand students' perceived behavioral habits and behavior patterns so that they can better develop educational strategies and management programs. In addition, the method can provide data support for theoretical research in the field of education, thus promoting the development and progress of the educational field.

The limitations of this study include the following: Limitations of data sources. This study targets a particular school or institution, and the sample size and diversity are more limited and cannot fully reflect the overall situation in the field of education. Moreover, there may be limitations and uncertainties in the acquisition of data. Limitations of measurement tools. The measurement tools used in this study are mainly questionnaires and observations, which may be subjective and biased, and may not fully reflect the perceived behavior patterns of students. Limitations of the research method. This study mainly used quantitative research methods, which failed to gain insight into the influence of students' specific backgrounds, family environments, and other factors on their perceived behavior patterns, while qualitative research methods may have more depth and breadth. Limitations of the conclusions. The findings of this study are only applicable to a specific school or institution and cannot be generalized to other educational fields. Meanwhile, further research and experiments are needed to verify and improve the validity and practicality of the evaluation method.

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