Hindawi
Wireless Communications and Mobile Computing
Volume 2021, Article ID 3373535, 12 pages
https://doi.org/10.1155/2021/3373535

Research Article

Computer-Aided Teaching System Based on Data Mining

Yonghua Tang[1] **Qiang Fan**[2] **and Peng Liu**[1]

[1]*LuXun Academy of Fine Arts, Dalian 116600, China*
[2]*Criminal Investigation Police University of China, Shenyang 110035, China*

Correspondence should be addressed to Peng Liu; liupengpromise@lumei.edu.cn

Received 16 July 2021; Revised 9 September 2021; Accepted 21 September 2021; Published 11 October 2021

Academic Editor: Rajesh Kaluri

Copyright © 2021 Yonghua Tang et al. This is an open access article distributed under the Creative Commons Attribution License, which permits unrestricted use, distribution, and reproduction in any medium, provided the original work is properly cited.

The traditional teaching model cannot adapt to the teaching needs of the era of smart teaching. Based on this, this paper combines data mining technology to carry out teaching reforms, constructs a computer-aided system based on data mining, and constructs teaching system functions based on actual conditions. The constructed system can carry out multisubject teaching. Moreover, this paper uses a data mining system to mine teaching resources and uses spectral clustering methods to integrate multiple teaching resources to improve the practicability of data mining algorithms. In addition, this paper combines digital technology to deal with teaching resources. Finally, after building the system, this paper designs experiments to verify the performance of the system. From the research results, it can be seen that the system constructed in this paper has certain teaching and practical effects, and it can be applied to a larger teaching scope in subsequent research.

1. Introduction

With the continuous development and popularization of information technology, comprehensive informatization has become the inevitable development direction of this era. This is especially true in the field of education, and digital education makes teaching content more reliable and has a uniform standard [1]. From the recording and broadcasting online school in the late 1990s to the higher education resource sharing platform, "Love Course," which provides complete video resources, to the "China University MOOC" online open course class that integrates teaching, Q&A, testing, and homework teaching, to the "NetEase Cloud Classroom" that can realize real-time interactive online live teaching [2], modern education is closely related to the information age, and building a teaching platform based on information technology is the direction of reform of teaching informatization in major colleges and universities [3].

Teaching decisions are the process of analyzing, judging, exploring, and choosing teaching implementation plans in order to achieve teaching objectives. Teaching is a controlled dynamic complex system, to achieve effective control of system motion, requires timely confirmation of various elements and its interaction relationships in the system, and makes decisions according to the corresponding teaching principles. Data is an important basis for teaching decisions. The smart teaching platform provides data on the status of the learner but is currently only an evaluation method for students. In traditional teaching activities, students are often collected in the forms of students or exams due to the collection and analysis of students' data, and the teaching behavior of teachers has a great impact. With today's scientific and technical assistance, the extraction of teaching data is no longer a problem, but the use of teaching data is used in teaching evaluation, teaching management, statistical attendance, etc., and the teaching of teachers is not much. In summary, in the environment of education big data, how to help teachers give full play to the teaching process and how to use the data in the smart teaching platform to optimize the teaching decisions are the core issues of the research in education.

This paper applies data mining technology to computer-assisted teaching to build a data mining-based smart teaching system and improves the traditional teaching mode to improve the teaching effect.

2. Related Work

Regarding the characteristics and value of smart classrooms, literature [4] believed that mobile terminal-based interaction can help improve children's developmental learning and social skills. Literature [5] believed that with the help of wireless smart devices, learners' participation in classroom learning can be improved. Literature [6] believed that the teaching terminal based on the smart classroom can clarify the geographical location and learning progress of the students, determine the current teaching activities of students, recommend learning resources according to the needs of students, and support effective real-time collaboration and resource sharing between teachers and students, as well as students and students. Literature [7] believed that a smart classroom is a new type of classroom, and the fundamental goal is to cultivate students' wisdom. The smart classroom focuses not only on the knowledge level of the learner and the scores obtained in the exam but also on stimulating the potential of students and focusing on cultivating students' wisdom. Literature [8] believed that the cultivation of wisdom should exist throughout the entire classroom teaching process and use experience and accumulated thinking experience to enhance wisdom so as to achieve the ultimate goal of using wisdom to solve problems. Literature [9] reshaped and upgraded the flipped classroom and proposed a breakthrough from a flipped classroom to a smart classroom in terms of resource quality improvement and teaching method optimization.

As a probe into the teaching mode of the theoretical level in a wisdom classroom, Literature [10] believes that learners can personalize and autonomously learn from their own rhythm in wisdom class. Document [11] is a research on the autonomous constructive processing and treatment of learners in the smart classroom. Literature [12] believed that wisdom learning is in a contextual environment, providing students with a wide range of learning resources for students, and promotes new learning paradigms of education development. In order to achieve smart learning, literature [13] designed a smart learning system model including cloud computing, learning analysis technology, and mixed reality, reflecting the three major characteristics in the process of education, interactive, personalized custom, and independent control. Document [14] shows that on the basis of studying the intelligence learning connotation, the conceptual framework of wisdom learning is built, and four wisdom learning models are designed. Literature [15] believed that the technical characteristics of the wisdom class have designed a learning model based on the wisdom class, and the application research of the learning model is designed. Literature [16] gave a "three-section ten-step" structural model of the wisdom class through the comparison with traditional classroom teaching processes. As a research on wisdom classroom teaching practice, Literature [17] reshaped and upgraded the wisdom classroom learning environment from hardware and software, thereby solving the failure of teachers and students in LMS (Learning Management Services). Document [18] shows that based on the ITLA (Integrated Teaching and Learning Assistance) system, it studied important factors that determine the effective development of the wisdom class. Literature [19] is supported by the HiTeach Interactive System, compared to traditional classrooms and wisdom classroom teaching, exploring the positive significance of teaching in teaching. About wisdom classroom teaching evaluation, Literature [20] shows the response to the teaching strategy of the wisdom classroom teaching under the network learning space while presenting the teaching strategy of the teacher's teaching behavior and the student's learning behavior for teaching evaluation.

3. Spectral Clustering-Aided Teaching Algorithm

Spectral clustering is a very popular research field in cluster analysis. Its main idea is to obtain a graph cut through the feature decomposition of the graph (Laplacian matrix). It is a clustering method based on a graph cut. This research mainly introduces the spectral graph theory, the graph partition method, the spectral clustering algorithm of spectral clustering, and the problems existing in spectral clustering at present.

We first give a set $X = \{x_1, x_2, \cdots, x_n\}$, $x_i \in R^l$, which contains n data points. We assume that each data sample is regarded as a vertex V in the graph, and the edge E between the vertices is assigned a weight value W according to the similarity between the samples so that an undirected weighted graph $G = (V, E)$ based on the sample similarity is obtained. It can be defined with the following formula [21]:

$$w_{ij} = \exp\left(-\frac{d^2(x_i, x_j)}{2\delta^2}\right). \tag{1}$$

Among them, w_{ij} is the similarity value between points x_i and x_j, and $d(x_i, x_j)$ is the Euclidean distance between points x_i and x_j, and δ is the scale parameter, which controls the speed at which the similarity value w_{ij} decays with the Euclidean distance $d(x_i, x_j)$.

The clustering problem can be expressed as a cut problem on the graph. The result of the cut is as far as possible to minimize the similarity between the two subgraphs and maximize the internal similarity. The quality of the clustering results is directly related to the quality of the cut criteria. As shown in Figure 1, through a cut strategy, H can be divided into one category, and all other points can be divided into another category. Alternatively, another classification strategy can be used to classify H, A, B, and C into one category and D, E, G, and F into another category. Obviously, the second cut strategy can divide undirected graphs into two more balanced categories. Common cut criteria include the minimum cut criterion, the normalized cut criterion, the ratio cut criterion, and the average cut criterion.

(1) Minimum cut set criterion

Now, we first consider the simplest case: two-way cut. The undirected weighted graph G is divided into two subsets A and B that do not want to intersect, where $A \cap B = \varnothing$, A

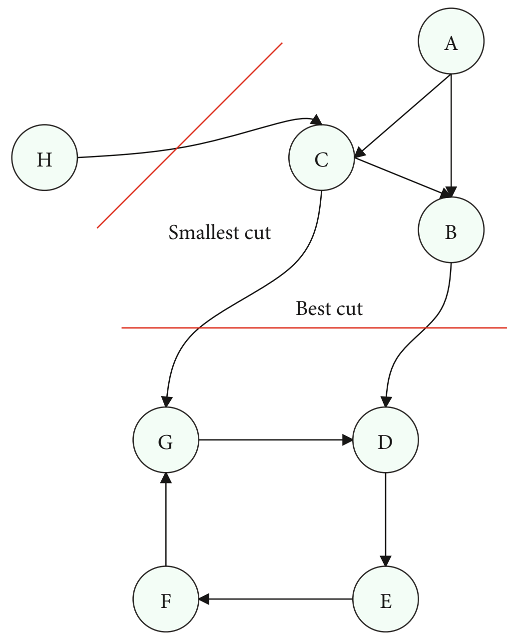

Figure 1: Undirected graph partition of spectral clustering.

$\cup B = V$. The easiest way is to take the method of minimizing the cut to produce two disjoint subsets. Cutting is defined as [22]

$$\mathrm{cut}(A, B) = \sum_{p\in A, q\in B} w(p, q). \tag{2}$$

$w(p, q)$ is the similarity between point p and point q. When the data point is in Euclidean space R^d, a reasonable default candidate similarity function is the Gaussian similarity function, which is defined as follows:

$$w_{ij} = \exp\left(\frac{-\left\|x_i - x_j\right\|}{2\delta^2}\right). \tag{3}$$

We used a clustering algorithm based on the graph theory to solve the segmentation problem, and we obtained very good segmentation results in the experiment. But at the same time, the minimum cut criterion is easy to produce unbalanced results: one type contains most data points, while the other type contains only a few data points or even only one data point. This is because the minimum cut does not consider the size of the cluster. In order to solve this problem, we proposed the normative cut set criterion. The experimental results show that this cutting method can obtain relatively balanced clustering results.

(2) Normative cut set criterion (Ncut)

The normative cut set criterion focuses on the data in the global scope, not only the local solution of the dataset. The Ncut algorithm has two-way partition and multiway partition. The two-way cut only uses the eigenvector corresponding to the second smallest eigenvalue of the Laplacian matrix for segmentation. However, the multipath cut uses k eigenvectors starting from the eigenvector corresponding to the second smallest eigenvalue to cluster together, where k is a predetermined constant. For the two-partition problem of cutting V into two regions, A and B, the objective function of the Ncut's optimized graph partition is shown in the following formula:

$$\mathrm{Ncut}(A, B) = -\frac{\mathrm{cut}(A, B)}{\mathrm{assoc}(A, V)} + \frac{\mathrm{cut}(A, B)}{\mathrm{assoc}(B, V)}. \tag{4}$$

Among them,

$$\mathrm{cut}(A, B) = \sum_{p\in A, q\in B} W(p, q), \tag{5}$$

is the minimum cut set shown above, and

$$\mathrm{assoc}(A, V) = \sum_{p\in A, q\in B} W(p, q), \tag{6}$$

is the total number of connections from all data points in A to all data points in graph G. From the criterion function, it can be seen that the normalized cut set criterion considers the separation state of the two subsets, so it can avoid unbalanced clustering results.

At the same time, Shi and Malik proposed another standard to measure the total normalized association criterion for a given divided area. Its formula is as follows:

$$\mathrm{Nassoc}(A, B) = \frac{\mathrm{assoc}(A, A)}{\mathrm{assoc}(A, V)} + \frac{\mathrm{assoc}(B, B)}{\mathrm{assoc}(B, V)}. \tag{7}$$

Among them, $\mathrm{assoc}(A, A)$ and $\mathrm{assoc}(B, B)$ are the total weights of the edges connecting the nodes in A and B, respectively. By inference, the relationship between these two division standards is $\mathrm{Ncut}(A, B) = 2 - \mathrm{Nassoc}(A, B)$. Obviously, in order to achieve a better clustering effect, it is necessary to minimize the noncorrelated function and maximize the correlation function at the same time.

The above criteria are all two-way division methods for undirected graphs. We proposed a method to divide the graph into k subgraphs. The objective function of the k-dimensional normalized cut set criterion can be written as follows:

$$\mathrm{MNcut}(A_1,\cdots,A_k) = \sum_{i=1}^{k} \frac{\mathrm{cut}\left(A_i, \overline{A_i}\right)}{\mathrm{vol}(A_i)}. \tag{8}$$

Among them, $\mathrm{vol}(A) = \sum_{i\in A} d_i$ is the number of data in dataset A. A_k is the complement of dataset A. When $k = 2$, multichannel division is equal to two-channel division.

(3) Average cut set criterion (Avcut)

The objective function of the average cut set criterion is as follows:

$$\mathrm{Avcut} = \frac{\mathrm{cut}(A, B)}{|A|} + \frac{\mathrm{cut}(A, B)}{|B|}. \tag{9}$$

It can be seen from the formulas of the normative cut set criterion and the average cut set criterion that these two formulas both express the relationship between the boundary loss and the correlation of the divided regions in the undirected weighted graph G in the form of the sum of ratios. This shows that the objective function of the minimum scale cut set criterion and the normalized cut set criterion can be cut more accurately. Their common disadvantage is that it is easy to segment very small subgraphs containing only a few points, and they are undersegmented. It can be seen from the experimental results in the literature that the cut result of the normative cut set criterion is better than that of the average cut set criterion.

(4) Ratio cut set criterion (Rcut)

The formula of the ratio cut set criterion function is as follows:

$$\mathrm{Rcut} = \frac{\mathrm{cut}(A, B)}{\min(|A|, |B|)}. \tag{10}$$

Among them, $|A|$ and $|B|$ represent the number of vertices of subgraphs A and B, respectively.

The advantage of this criterion is that when minimizing the criterion function, only the minimum similarity between classes needs to be considered, which reduces the possibility of oversegmentation, but the disadvantage is that the operating efficiency is too low.

(5) Minimum-maximum cut set criterion (Mcut)

The min-max cut criterion maximizes $\mathrm{assoc}(A, A)$ and $\mathrm{assoc}(B, B)$ while minimizing $\mathrm{cut}(A, B)$. The objective function of this criterion is as follows:

$$\mathrm{Mcut} = \frac{\mathrm{cut}(A, B)}{\mathrm{assoc}(A, A)} + \frac{\mathrm{cut}(A, B)}{\mathrm{assoc}(B, B)}. \tag{11}$$

Among them, $\mathrm{assoc}(A, A)$ and $\mathrm{assoc}(B, B)$ are the total weights of the edges connecting the nodes in A and B, respectively. By minimizing the criterion function, undersegmentation or only segmentation of smaller subgraphs containing a few vertices can be avoided. Therefore, by minimizing the minimum-maximum cut set criterion function, a more balanced cut set can be obtained, but the realization speed is relatively slow. Both the minimum-maximum cut set criterion and the normative cut set criterion can satisfy the clustering principle that the similarity within a class is small, but the similarity between classes is large. The difference is that when the overlap between classes is too large, the cut effect of the normative cut set criterion is not as good as the minimum-maximum cut set criterion.

The adjacency matrix (denoted as W or A) is also called the similarity matrix, and the Laplacian matrix (denoted as L) is a common representation of graphs. The similarity matrix of the weighted graph uses real numbers to reflect the different relationships between the vertices. The elements in this matrix can be expressed by the following formula:

$$w_{ij} = \exp\left(-\frac{d^2(x_i, x_j)}{2\delta^2}\right), \quad i \neq j. \tag{12}$$

Among them, x_i is the i-th sample point in the dataset, and $d(x_i, x_j)$ is the distance between the sample point x_i and the sample point x_j. The distance can use any form of distance function, and the more commonly used is the Euclidean distance $\|x_i - x_j\|$. In the formula, δ is the nuclear radius, which is a parameter that needs to be given in advance. In the clustering algorithm, the attenuation rate w_{ij} is constrained by the parameter δ, so a proper value of δ must be given to improve the clustering accuracy of the algorithm. The row vectors in w_{ij} represent the distribution of the dataset, and they are usually distributed on the hypersphere of the k-dimensional space. Researchers usually use degrees to represent the distribution of the dataset around the point, and the diagonal matrix composed of all the degree values as diagonal elements is the degree matrix, which is usually represented by D:

$$D_{ij} = \sum_{i=1}^{n} w_{ij}. \tag{13}$$

Among them, n is the number of sample points.

The Laplacian matrix is $L = D - W$, where D is the degree matrix and W is the similarity matrix. Most spectral clustering algorithms cut graphs based on the spectrum of the Laplacian matrix. Laplacian matrices can be divided into two types: nonnormalized Laplacian matrix L and normalized Laplacian matrix. The normalized Laplacian matrix includes a symmetric form (denoted as L_s) and a random walk form (denoted as L_r).

There are many spectral clustering algorithms. The difference lies in how to choose the object function and how to construct the affinity matrix of the graph, but the basic framework is the same.

Step 1. According to the given dataset, the algorithm constructs a graph matrix, and there are different methods for different situations.

Step 2. The algorithm solves the first k eigenvectors of the matrix and constructs the eigenspace R^k.

Typical spectral clustering algorithms such as the Shi and Marik algorithm; Kan R, Vempala S, and Vetta A algorithm; Ng, Jordan, and Weiss algorithm; link algorithm; and Markov random walk algorithm have achieved the expected application effect.

(1) SM algorithm

The normative cut set criterion is a very popular technique in spectral clustering, and it has achieved good results

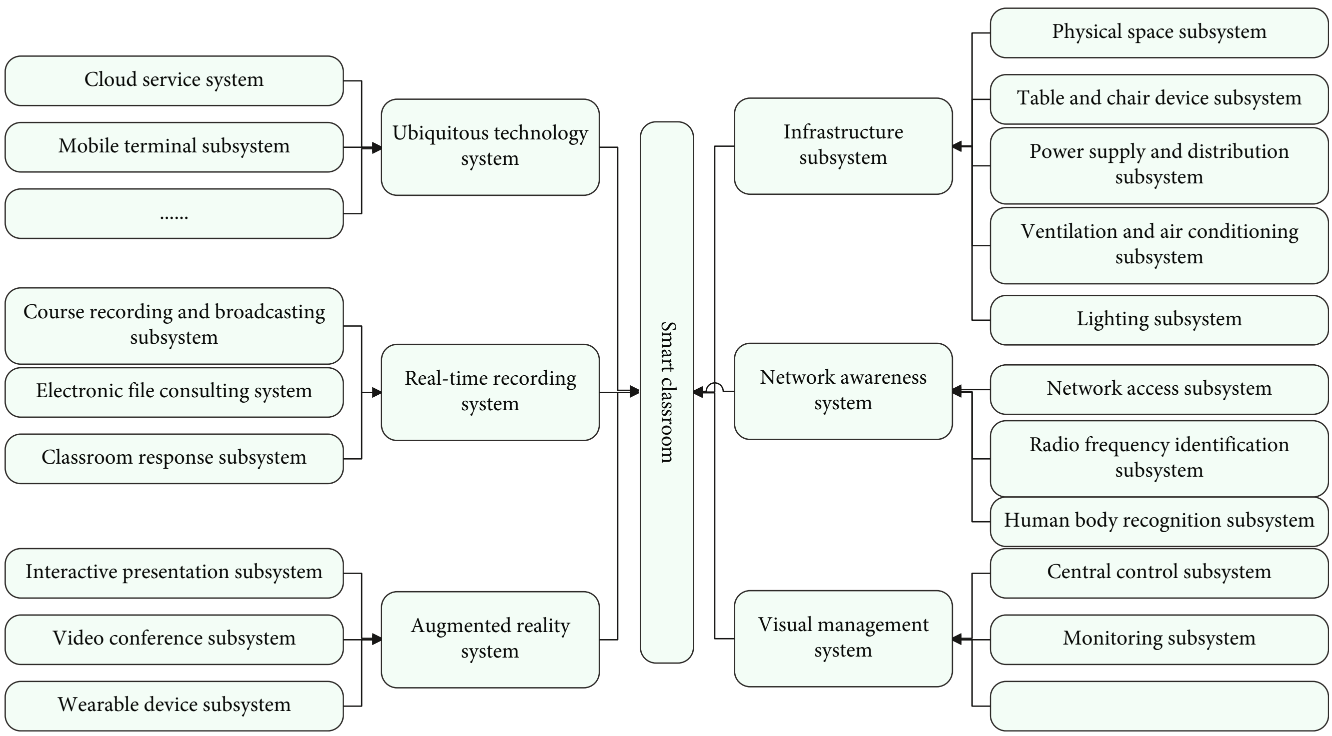

Figure 2: Smart classroom “I-SMART” model.

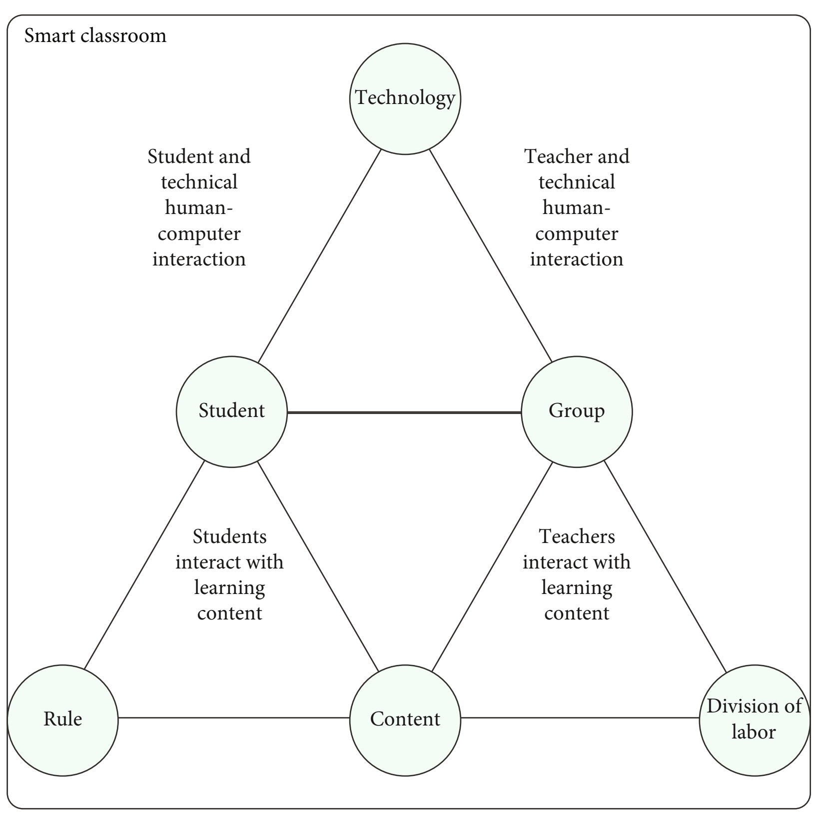

Figure 3: Interactive teaching model in a smart classroom environment.

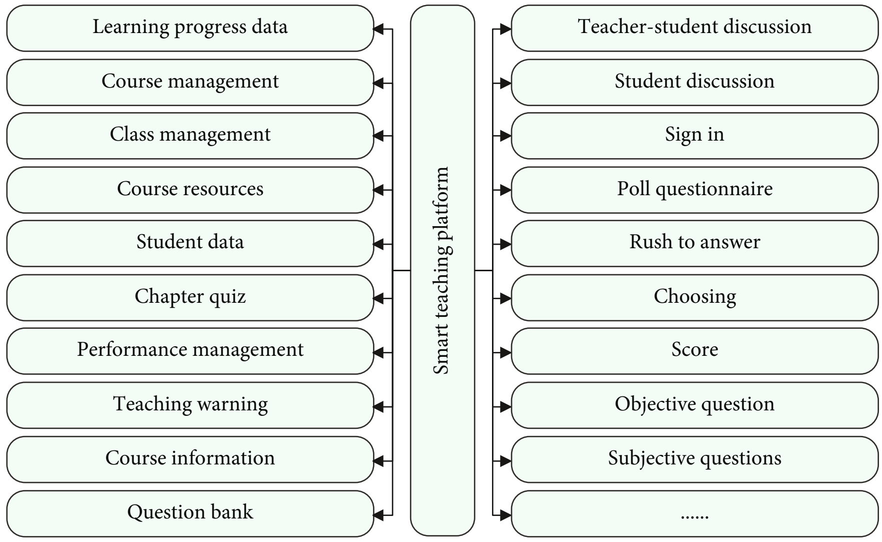

Figure 4: Data in the smart teaching platform.

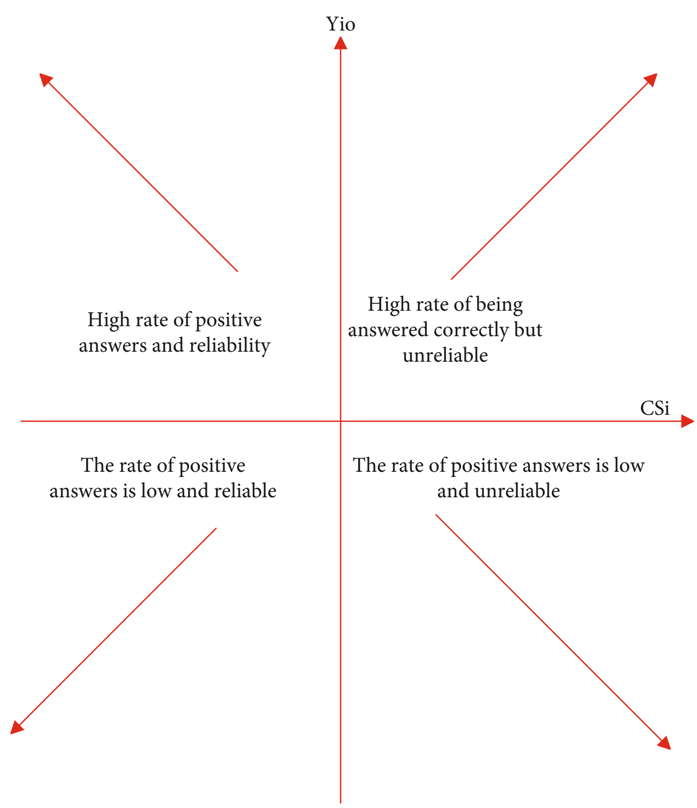

Figure 5: Yio-CSi model.

in the application of image segmentation. The normative cut set criterion can be described as follows:

$$\begin{cases} \min \quad \mathrm{Ncut}(A, B) = \min \dfrac{x^T(D-W)x}{x^T Dx} \\ \text{s.t.} \quad x^T \mathrm{We} = x^T De = 0. \end{cases} \tag{14}$$

This is an NP-hard problem. Fortunately, the problem can be solved by relaxing the discrete constraint of x. We assume that x is a real value, the objective function can be solved by the Rayleigh quotient, and this problem can be transformed into the second smallest eigenvalue of the solving formula $(D-W)x = \lambda Dx$. The SM algorithm can be described as follows.

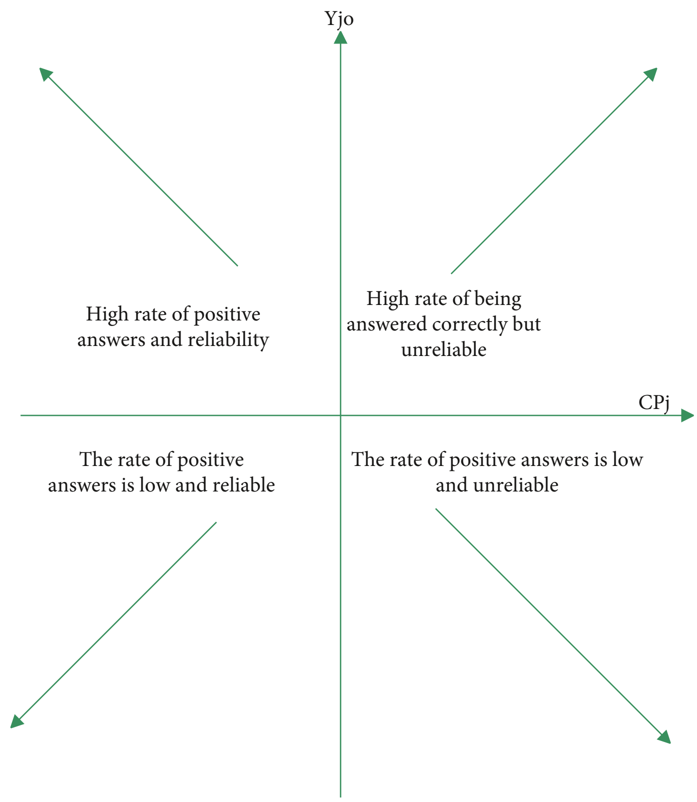

FIGURE 6: Yjo-CPj model.

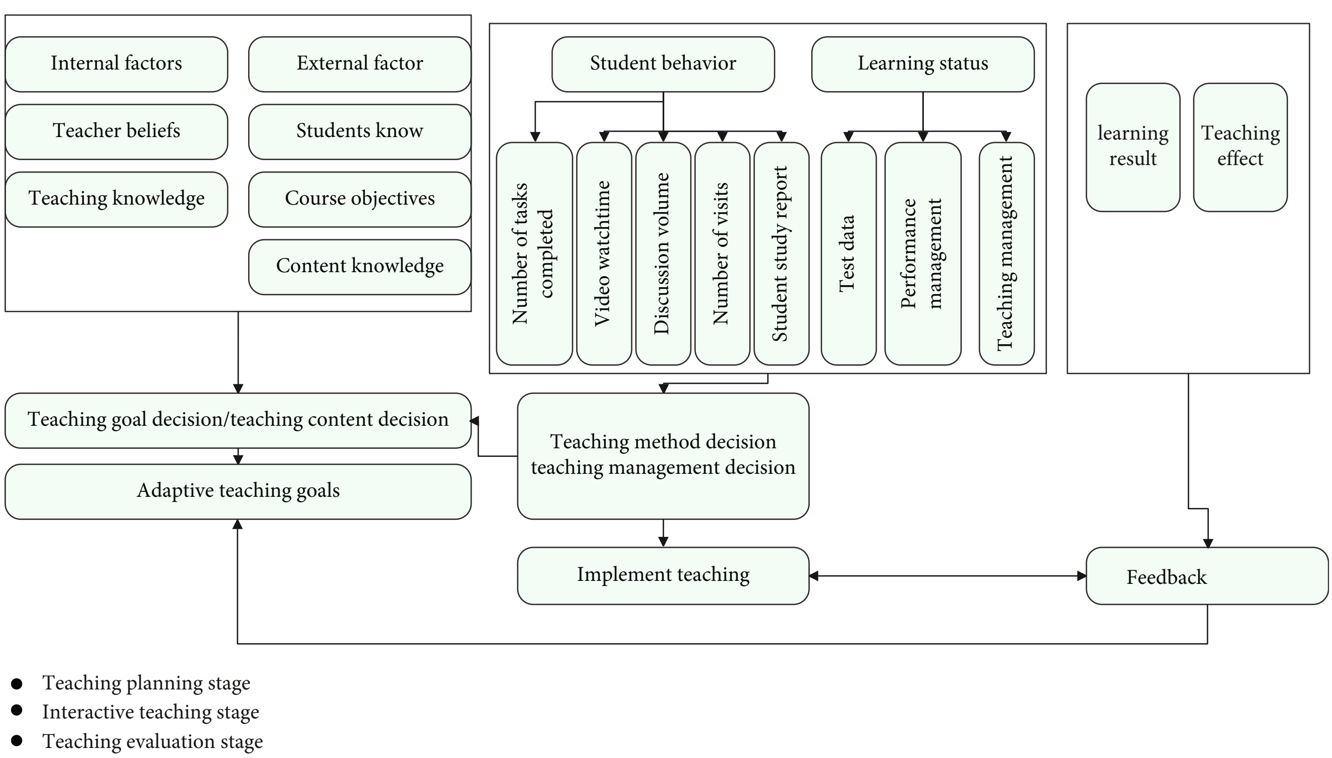

FIGURE 7: Teaching decision model based on teaching data.

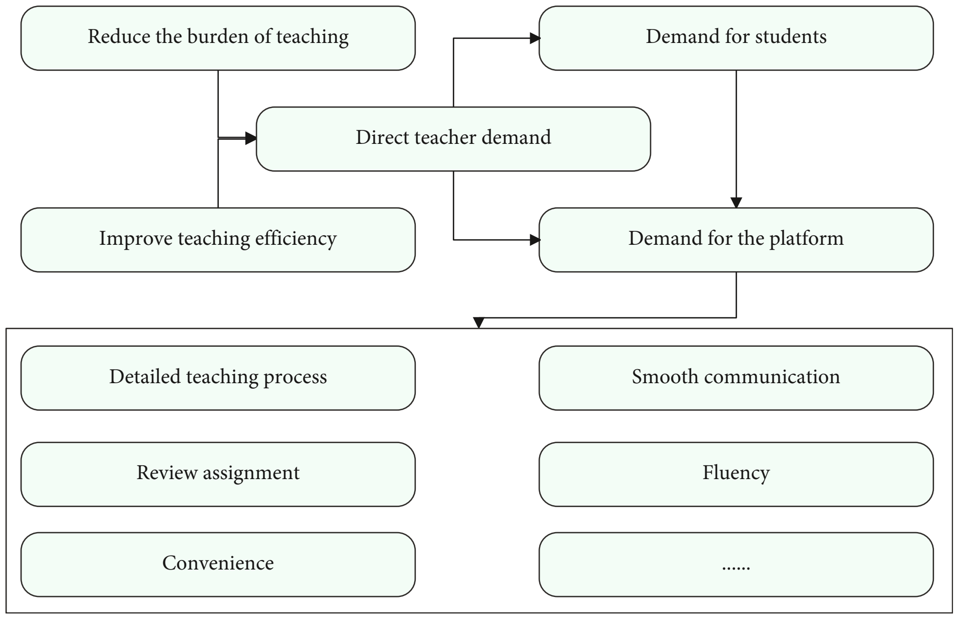

Figure 8: Teacher-platform-student needs analysis.

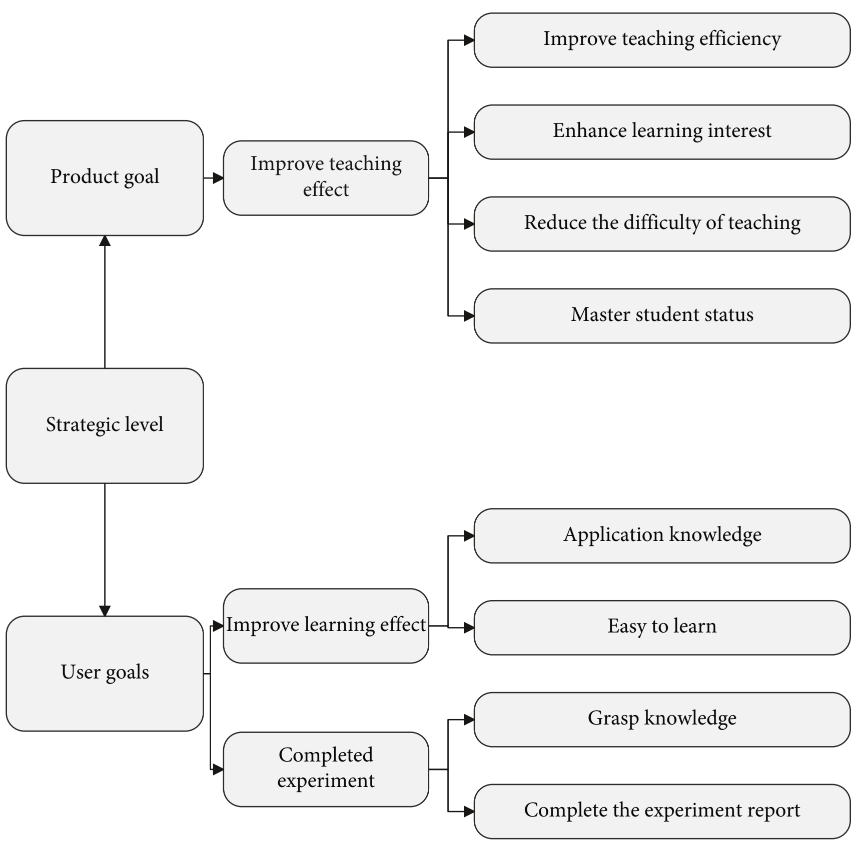

Figure 9: The strategic layer of the smart teaching platform.

Step 1. The algorithm first constructs the similarity matrix $W \in R^{N\times N}$ and calculates the Laplacian matrix according to the formula $L = D - W$.

Step 2. The algorithm calculates the first k-generated eigenvalues $\lambda_1, \lambda_2, \cdots, \lambda_k$ and obtains the corresponding eigenvector $v_1, v_2, \cdots, v_k$ according to the formula $(D - W)x = \lambda Dx$.

Step 3. The algorithm uses the eigenvectors calculated in the second step to construct a matrix $Q \in R^{N\times K}$.

Table 1: Statistical table of the evaluation of the mining effect of teaching resources.

No.	Resource mining	No.	Resource mining	No.	Resource mining
1	92.9	21	91.4	41	84.1
2	77.4	22	90.6	42	77.7
3	82.6	23	81.0	43	91.2
4	89.6	24	84.1	44	79.3
5	83.8	25	78.4	45	92.1
6	91.6	26	90.1	46	91.4
7	82.1	27	81.3	47	87.8
8	83.7	28	83.3	48	79.0
9	90.5	29	92.6	49	78.3
10	92.6	30	83.8	50	92.0
11	90.2	31	84.0	51	84.1
12	88.3	32	92.8	52	90.5
13	91.5	33	81.1	53	92.4
14	89.5	34	90.2	54	78.5
15	86.7	35	92.1	55	77.1
16	92.7	36	80.0	56	81.3
17	80.1	37	85.8	57	88.1
18	92.6	38	82.1	58	88.9
19	90.0	39	85.2	59	81.6
20	87.2	40	82.9	60	91.6

Step 4. The algorithm uses the second smallest eigenvalue and the corresponding Fiedler vector to find the cutting point to cut the graph through the Fiedler vector so that Ncut is the smallest. In the Fiedler vector, the larger than this point is divided into one category, and the smaller than this point is divided into another category. The normalized adjacency matrix defined by the algorithm is as follows:

$$N = D^{-1/2} W D^{-1/2} : N(i, j) = \frac{W(i, j)}{\sqrt{D(i, i) D(j, j)}}. \quad (15)$$

Step 5. The algorithm uses the k-means algorithm to cluster the matrix O into k categories $C_1, C_2, \cdots, C_k$.

The computational complexity of solving the eigenvalue problem of all eigenvectors is $O(n^3)$, where n is the number of input sample sets.

(2) NJW algorithm

The above SM algorithm only uses Fiedler vectors, but the NJW algorithm uses k feature vectors at the same time. Because when calculating the k-way partition, using more feature vectors will achieve better results. The NJW algorithm can be described as follows:

Input: N data points $\{x_i\}_{x=1}^{N}$

Output: cluster $A_1, A_2, \cdots, A_k$, where $A_i = \{j \mid r_j \in c_i\}$

Step 1. The algorithm constructs the similarity matrix $W \in R^{N\times N}$, the diagonal matrix D, and the Laplacian matrix $L = D^{-1/2} W D^{-1/2}$ through the formula $w_{ij} = \exp\left(-d^2(x_i, x_j)/2\delta^2\right)$, $i \neq j$.

Step 2. The algorithm calculates the first k eigenvectors of the Laplacian matrix $v_1, v_2, \cdots, v_k$.

Step 3. The algorithm uses the eigenvector $v_1, v_2, \cdots, v_k$ calculated in the second step to construct a matrix $Q \in R^{N\times K}$.

Step 4. The algorithm forms a normalized matrix M by normalizing the rows to norm 1, where $m_{ij} = x_{ij}/\sqrt{\sum_k x_{ik}{}^2}$.

Step 5. The algorithm makes $r_i \in R^K$ a vector corresponding to the i-th row of the normalized matrix M.

Step 6. The algorithm uses typical clustering algorithms such as the k-means algorithm to cluster the abovementioned matrix into k classes. By repeatedly executing the NJW algorithm, the scale parameter δ, which measures the similarity between sample points, can be obtained, but this increases the time used by the algorithm.

(3) Markov random walk algorithm

Another point of view in spectral clustering is the Markov random walk algorithm. It uses a probability model to obtain the spectrum method, and the random walk on the spectrum is considered to be a random jump from one node to another node. Spectral clustering can be understood as looking for such a graph partitioning; that is, the random walk stays in the same class for a long time and rarely stays in another class. From this point of view, random walk and graph partitioning have the same idea.

The random transition matrix $P = D^{-1} W$ can be obtained from the normalized similarity matrix W, so the sum of each row of the matrix is 1. Among them, P_{ij} is the probability from point v_i to point v_j. The Markov random walk algorithm is basically the same as the NJW algorithm. The Markov random walk algorithm has achieved good results and can automatically determine the clustering value.

In addition to the above SC algorithm, there are many other SC algorithms. Perona and Freeman proposed the PF algorithm. Scott et al. proposed the SLH algorithm, and WISS combined the SLH algorithm and the SM algorithm to propose a new algorithm. Ding et al. proposed a new division criterion Mcut. In addition, Meila et al. proposed a new spectral clustering algorithm called the MS algorithm under the framework of the Markov random walk.

(1) The Choice of the Laplacian Matrix. In the spectral clustering algorithm, it is very important to construct the similarity graph matrix. After the number of data samples is given, the most commonly used formula for constructing similarity graphs and selecting the Laplacian matrix is as

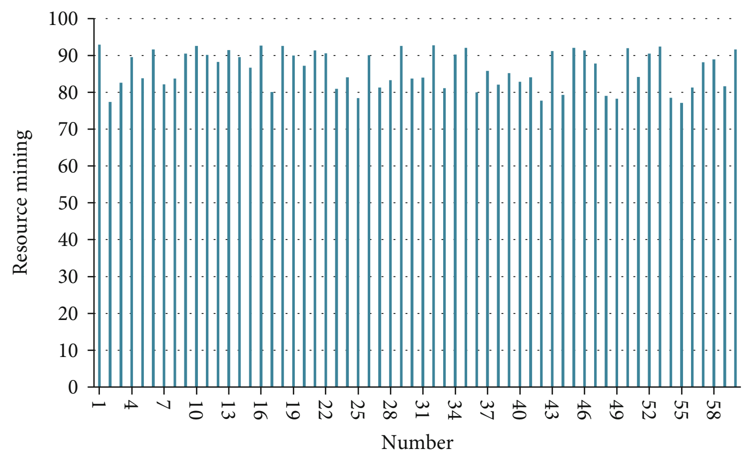

Figure 10: Statistical diagram of the evaluation of the mining effect of teaching resources.

follows:

$$w_{ij} = \exp\left(\frac{-\left\|x_i - x_j\right\|}{2\delta^2}\right). \quad (16)$$

In this paper, some commonly used Laplacian construct methods have been collected, but how to select the Laplacian matrix is uncertain.

(2) Selection of Parameters. The spectrum clustering is uncertain when constructing similar matrices, and the determination of 8 is often necessary to obtain the uncertainty of clustering results according to the experience of the researcher and multiple attempts. So the choice of parameters is an important research direction.

(3) Determination of the Number of Clusters. The choice of clustering directly affects the cluster results. Now, the current spectrum clustering research does not give a strategy for the number of choices of clusters, which is also a more important research direction in cluster research.

(4) Differential Problems with Uneven Distribution of Density Distribution. The existing spectrum clustering method is still unable to obtain a good clustering effect for the density distribution.

4. Computer-Aided Teaching System Based on Data Mining

After the SMART conceptual model was put forward, this paper designs the “I-SMART” model from the aspect of hardware and software configuration, which provides framework support for the construction of smart classrooms (Figure 2).

Under the guidance of the activity theory, based on the above analysis of teaching elements and types of teaching interaction, an interactive teaching model in a smart classroom environment is proposed (Figure 3).

Table 2: Statistical table of the evaluation of the teaching effect.

No.	Teaching effect	No.	Teaching effect	No.	Teaching effect
1	80.4	21	92.4	41	76.3
2	80.6	22	72.9	42	90.9
3	87.3	23	94.8	43	82.2
4	76.3	24	89.1	44	91.6
5	87.7	25	76.9	45	77.3
6	74.8	26	90.8	46	75.2
7	83.3	27	79.2	47	85.0
8	73.5	28	78.6	48	86.5
9	84.3	29	91.7	49	87.4
10	90.2	30	81.2	50	93.7
11	87.9	31	85.0	51	83.8
12	78.2	32	93.1	52	80.0
13	88.5	33	74.8	53	89.9
14	72.5	34	89.3	54	93.7
15	79.6	35	90.8	55	90.1
16	86.8	36	88.1	56	90.3
17	73.9	37	82.8	57	93.4
18	93.1	38	83.4	58	94.6
19	80.6	39	95.0	59	86.5
20	85.2	40	80.0	60	80.9

There are nine modules in the teaching platform: homepage, statistics, classroom activities, homework, examination, discussion, information, notification, and management. Users can directly access teaching data. The various types of data that can be read by the teacher after being automatically collected by the platform and analyzed by the model are summarized in Figure 4.

Through the correlation analysis of multiple factors in the S-P table, it can provide a clear direction for teaching decision-making. S-line tomography is used to analyze the types of students. Using the Yio-CSi (Student Positive Answer Rate-Student Attention Coefficient) model (Figure 5), we can find the students with the best and stable grades, the students with the worst and stable grades, and the students with unstable

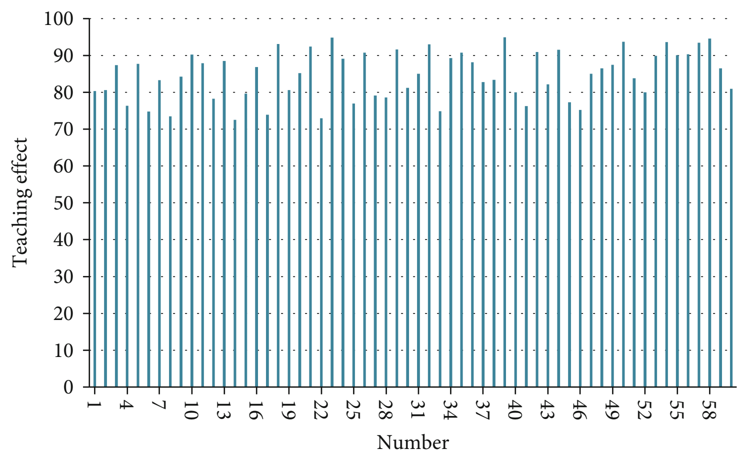

Figure 11: Statistical diagram of the evaluation of the teaching effect.

grades that cannot be found in the general statistical description. Using the Yjo-CPj (Question Positive Answer Rate-Question Attention Coefficient) model (Figure 6), it is possible to find knowledge points that students understand and are reliable, knowledge points that students seem to understand but are unreliable, knowledge points that are not understood by students, and knowledge points that are not understood but have accidental factors. Based on this, we make scientific decisions on the selection and application of teaching media.

This research is based on the smart teaching platform environment and attaches importance to the value of the data captured by the platform in the process of monitoring student behavior and status. Therefore, it is considered to incorporate the data that can be used for decision-making into the decision model to form a teaching decision model based on the data of the smart teaching platform, as shown in Figure 7.

The users of the education platform are not only students but also teachers, so we have to think deeply about teachers' needs for online education platforms. We can further analyze the teacher's demand for the ergonomic experimental teaching platform in two aspects. Among them, one is the demand between the platform and the teacher, and the other is the demand between the teacher and the student, as shown in Figure 8.

The strategic layer of the platform is shown in Figure 9. User goals refer to what kind of needs the users hope to meet through the product. The main users of the platform are students. For students, the most important goal of this platform is to help students improve their learning effects. On the one hand, it shows that students can learn and apply knowledge faster through this platform, and on the other hand, it shows that students can quickly learn how to use this platform, that is, the ease of learning of the platform.

5. Performance Test of the Computer-Aided Teaching System Based on Data Mining

The above constructs a computer-aided teaching system based on data mining. After constructing the system, the performance of the system is verified, and the system operation performance and system teaching effect are mainly studied. The research on its operating performance is mainly the effect of teaching resource mining. This paper obtains effective resources from the massive network teaching resources through the simulation system, tests multiple sets of statistical data, and evaluates the collected data through expert evaluation methods. The results are shown in Table 1 and Figure 10.

From the above research, we can see that the system constructed in this paper can effectively tap the required teaching resources. After that, this paper evaluates the teaching effect of this system through a small-scale teaching test, and the statistical results are shown in Table 2 and Figure 11.

It can be seen from the above experiments that the system constructed in this paper has certain teaching and practical effects, so it can expand the scope of teaching in follow-up research and conduct practical research from the perspective of multiple subjects and multiple audiences.

6. Conclusion

The smart education system based on data mining services is a typical current smart education. It realizes the intelligence, visualization, and high efficiency of classroom teaching, and its application conforms to the concept of building a strong education nation and is more in line with the specific requirements of educational modernization. With the continuous progress of cloud computing, artificial intelligence, big data, and other technical means, the service quality of the smart education system has also been upgraded, which provides favorable conditions for the safe and effective operation of the system. This paper combines data mining technology to build a computer-aided teaching system and builds the function of the teaching system based on the actual situation. The constructed system can carry out multi-subject teaching. Moreover, this paper uses a data mining system to mine teaching resources and combines digital technology to process teaching resources. After constructing the system, this paper designs experiments to verify the performance of the system. From the research results, it can be seen that the system constructed in this paper has certain teaching and practical effects.

Data Availability

The labeled datasets used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare no competing interests.

Acknowledgments

This study is sponsored by the following: (1) Research and Practice of Mixed Teaching Mode of Criminal Technology Courses Based on OBE Concept—take Speech Recognition and Appraisal Course as an example (No. 5-3 1017501)—and (2) application research of IPv6-based video transmission and control technology in teaching platform—Scientific research project (No. NGII20180124).

References

[1] R. Nunes Linhares, C. Mário Guimarães Alcântara, E. Ávila Gonçalves, F. Ramos, and M. José Loureiro, "Teaching evaluation by teachers from Brazil and Portugal: a comparative analysis," *American Journal of Educational Research*, vol. 5, no. 5, pp. 546–551, 2017.

[2] N. Huang, "Analysis and design of university teaching evaluation system based on JSP platform," *International Journal of Education & Management Engineering*, vol. 7, no. 3, pp. 43–50, 2017.

[3] J. A. Moreno-Murcia, Y. Silveira Torregrosa, and N. Belando Pedreño, "Questionnaire evaluating teaching competencies in the university environment. Evaluation of teaching competencies in the university," *Naer Journal of New Approaches in Educational Research*, vol. 4, no. 1, pp. 54–61, 2015.

[4] S. Liu and P. Chen, "Research on fuzzy comprehensive evaluation in practice teaching assessment of computer majors," *International Journal of Modern Education & Computer Science*, vol. 7, no. 11, pp. 12–19, 2015.

[5] L. Zhou, H. Li, and K. Sun, "Teaching performance evaluation by means of a hierarchical multifactorial evaluation model based on type-2 fuzzy sets," *Applied Intelligence*, vol. 46, no. 1, pp. 34–44, 2017.

[6] J. Porozovs, L. Liepniece, and D. Voita, "Evaluation of the teaching methods used in secondary school biology lessons," *Journal of Pedagogy and Psychology "Signum Temporis"*, vol. 7, no. 1, pp. 60–66, 2015.

[7] M. A. Oliveros, A. García, and B. Valdez, "Evaluation of a teaching sequence regarding science, technology and society values in higher education," *Creative Education*, vol. 6, no. 16, pp. 1768–1775, 2015.

[8] M. S. Cerón and F. M. del Sagrario Corte Cruz, "The evaluation of teaching: some consequences for Latin America," *Revista Mexicana De Investigacion Educativa*, vol. 20, no. 67, pp. 1233–1253, 2015.

[9] L. Liu, J. Feng, Q. Pei et al., "Blockchain-enabled secure data sharing scheme in mobile-edge computing: an asynchronous advantage actor–critic learning approach," *IEEE Internet of Things Journal*, vol. 8, no. 4, pp. 2342–2353, 2021.

[10] K. Angell, E. Tewell, and Long Island University, Brooklyn, "Teaching and un-teaching source evaluation: questioning authority in information literacy instruction," *Communications in Information Literacy*, vol. 11, no. 1, pp. 95–121, 2017.

[11] M. Brkovic and P. Chiles, "'Spector - the sustainability inspector': participatory teaching, learning and evaluation game for architects, architecture students and pupils," *Facta Universitatis*, vol. 14, no. 1, pp. 1–20, 2016.

[12] T. H. Reisenwitz, "Student evaluation of teaching: an investigation of nonresponse bias in an online context," *Journal of Marketing Education*, vol. 38, no. 4, pp. 139–144, 2015.

[13] Y. Jiang and Y. Wang, "Evaluation of teaching quality of public physical education in colleges based on the fuzzy evaluation theory," *Journal of Computational and Theoretical Nanoence*, vol. 13, no. 12, pp. 9848–9851, 2016.

[14] W. Shang, J. Chen, H. Bi, Y. C. Sui, Y. Chen, and H. Yu, "Impacts of COVID-19 pandemic on user behaviors and environmental benefits of bike sharing: a big-data analysis," *Applied Energy*, vol. 285, article 116429, 2021.

[15] F. Garofalo, P. Mota-Moya, A. Munday, and S. Romy, "Total extraperitoneal hernia repair: residency teaching program and outcome evaluation," *World Journal of Surgery*, vol. 41, no. 1, pp. 100–105, 2017.

[16] G. Gong and S. Liu, "Consideration of evaluation of teaching at colleges," *Open Journal of Social Sciences*, vol. 4, no. 7, pp. 82–84, 2016.

[17] H. Zhao, "College physics teaching model design and evaluation research of students' seriousness," *Open Cybernetics & Systemics Journal*, vol. 9, no. 1, pp. 2017–2020, 2015.

[18] N. D. Tran, "Reconceptualisation of approaches to teaching evaluation in higher education, issues in educational research," *Issues in Educational Research*, vol. 25, no. 1, pp. 50–61, 2015.

[19] P. Wu, S. P. Low, J. Y. Liu, J. Pienaar, and B. Xia, "Critical success factors in distance learning construction programs at Central Queensland University: students' perspective," *Journal of Professional Issues in Engineering Education and Practice*, vol. 141, no. 1, article 05014003, 2015.

[20] E. A. Willis, A. N. Szabo-Reed, L. T. Ptomey et al., "Distance learning strategies for weight management utilizing social media: a comparison of phone conference call versus social media platform. Rationale and design for a randomized study," *Contemporary Clinical Trials*, vol. 47, no. 6, pp. 282–288, 2016.

[21] H. J. Ye, D. C. Zhan, and Y. Jiang, "Fast generalization rates for distance metric learning," *Machine Learning*, vol. 108, no. 2, pp. 267–295, 2019.

[22] Y. Luo, Y. Wen, T. Liu, and D. Tao, "Transferring knowledge fragments for learning distance metric from a heterogeneous domain," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 41, no. 4, pp. 1013–1026, 2019.