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# A high-performance computing-supported model for monitoring the effect of ideological education in a big data environment

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ABSTRACT

This paper constructs a set of models for monitoring and evaluating the effect of Civics education through the research on the evaluation of Civics education based on educational big data environment. First, based on distributed gray cluster analysis, it analyzes and researches students' Civics learning behavior, and explores learners' learning characteristics by mining meaningful behavioral features for cluster analysis. The second is to design the Civics teaching quality evaluation model using principal component analysis, test the effects of population size and convolution kernel number on the performance of the Civics teaching quality evaluation model, and optimize the teaching quality evaluation model by using the dimensionality-reduced evaluation data. Distributed gray cluster analysis gets four clusters according to the characteristics of students' learning behaviors, which are divided into excellent, diligent, average, and negative students.PCA selection of evaluation indexes found that the cumulative contribution rate of the first 10 principal component indexes to the evaluation of the quality of Civic Teaching in colleges and universities has reached 95.63%, which indicates that these 10 indexes can adequately evaluate the quality of Civic Teaching in colleges and universities. When the number of population size is taken as 31 and the number of optimal convolution kernels is taken as 19 values, the RMSE of the evaluation model is 0.01973, and the test time consumed is 0.0783ms, which is the best performance. The constructed Civics education effect monitoring model can effectively assess students' learning behavior and efficiently and accurately evaluate the quality of Civics teaching.

*Keywords:* education effect monitoring, Civics education, distributed gray clustering, principal component analysis

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## 1. Introduction

In recent years, with the rapid development and popularization of information technology, big data technology gradually penetrates into various fields and plays a great role in the field of education. Ideological and political education in colleges and universities has always been the focus of educators' attention, and how to evaluate and research the effect of ideological and political education through big data technology has become a hot issue at present [1-4].

The evaluation of the effect of ideological and political education in colleges and universities based on big data technology can quantify and analyze the evaluation indexes by using big data analysis methods [5-6]. Through big data analysis, the ideological and political literacy of students can be measured and the efficiency of the utilization of educational resources can be assessed, so as to provide quantitative evaluation results for the ideological and political educators in colleges and universities, and to provide precise guidance and improvement direction for the ideological and political education in colleges and universities by scientifically and objectively evaluating the effectiveness and efficacy of ideological and political education [7-10]. And big data technology provides more timely educational support for colleges and universities by realizing dynamic monitoring and instant feedback of ideological and political education. However, although big data technology plays an important role in evaluating the effectiveness of ideological and political education in colleges and universities, it also faces some challenges [11-14]. How to protect students' privacy and information security, how to improve the scientificity and accuracy of data analysis methods, etc. In the future, big data technology will further deepen its application in the evaluation of the effectiveness of ideological and political education in colleges and universities, and continuously improve the scientificity and accuracy of evaluation [15-18].

Literature [19] based on questionnaires, in-depth interviews and other methods to find out the main problems of college students' network ideological education in the era of big data, through interviews revealed that college students use the Internet for a relatively long time, and their use of the campus website is more for focusing on academic performance. Literature [20] pointed out that through the creation of the "big data + thinking politics" teaching mode, the effectiveness and innovation of ideological education has been improved, effectively promoting the development of ideological education, and realizing the value of data and monitoring effect of ideological education. Literature [21] shows that with the wide application of big data in education, it is possible to accurately assess the effectiveness of Civic and political education, and reveals the great potential of big data in the field of education, which is an important driving force for the development of Civic and political education. Literature [22] proposed an intelligent teaching evaluation method based on big data technology, which utilizes a multi-class classification algorithm and is able to demonstrate effectiveness and feasibility in teaching evaluation classification. Literature [23] examined the big data technology in college counselors' civic and political education, and pointed out that big data helps to optimize the efficiency of counseling work, but exposes problems such as data privacy protection, and reasonably solving these problems helps to improve the quality of civic and political education with the help of big data technology. Literature [24] examined the methods of assessing the Civic and Political Education in colleges and universities, and proposed a model combining OBE with context, input, process and CIPP model, which showed better assessment accuracy and reliability compared with the traditional methods, and provided new ideas for the evaluation of Civic and Political Education. Literature [25] based on the advantages and disadvantages of the existing teaching evaluation system, constructed an effective evaluation index system for Civics and Political Science teaching, and used struts2, JSP and Hibernate technology to develop an online teaching evaluation system, which demonstrated to have good stability. Literature [26] constructed a multifunctional teaching evaluation model based on big data technology and integrating data collection, data analysis results visualization and so on, which provides reference for decision makers and helps to enrich the research strategy of intelligent teaching evaluation. Literature [27] analyzed the current IAP education evaluation system, emphasized its shortcomings, and examined the value of big data analysis in the evaluation of college students' IAP education, and proposed an evaluation method based on big data analysis with transparency and openness.

Based on the research on the evaluation of IAP education based on educational big data, the article forms a set of systematic framework for testing the effect of learners' IAP learning, which mainly evaluates five aspects, namely, the course learning category, the teaching interaction category, the homework category, the test category, and the assessment category. And on the basis of the clustering algorithm, a distributed gray cluster analysis method is proposed, in which the data on each node of the cluster are firstly clustered locally, and then the nodes are aggregated to form the overall clustering results, so as to realize the evaluation and analysis of students' learning behavior. Then the principal component analysis method is used to weight the teaching quality assessment indexes, and the principal component dimensionality reduction idea is used to give each index a contribution degree, analyze the importance of each index, and understand whether the final evaluation results reach the qualified standard.

## 2. Evaluation and Monitoring of the Effectiveness of Civic and Political Education in Colleges and Universities

### *2.1. Research on the Evaluation of Civic Education Based on Educational Big Data*

The administrative departments in charge of education at all levels generally have a set of assessment programs to assess the quality of teaching and learning of ideology and politics in the region, and the content of the assessment has a leading role in the development of colleges and universities, as the saying goes, “what kind of evaluation baton, what kind of schooling guidance”. In addition, the results of the assessment should be fair and just, and a fair and just assessment program can stimulate healthy competition among colleges and universities and promote the healthy development of colleges and universities. Therefore, the assessment program should be in line with the current direction of the development of education, the organization and implementation of the assessment should also be fair and just.

In a certain region in order to measure the level of teaching quality of colleges and universities in the region, basically rely on the regional assessment program for the Civic and Political Education of colleges and universities to achieve. Civic education assessment program development is a more difficult problem, especially in the new curriculum reform and the new era of higher education institutions in the context of the reform of the way of educating people, Civic teaching education to implement the fundamental task of Lidu Shurenren, practicing the “five simultaneous education, comprehensive development” education concept. Many colleges and universities have developed characteristics in these aspects. Therefore, the assessment program of Civic and Political Education should take into account the characteristics of each college and university while implementing the relevant national education policies and solving the problem of the orientation of result evaluation. In the assessment of colleges and universities should also be fair and just, to solve the problem of objective and fair evaluation. Therefore, it is not easy to develop a reasonable assessment program. After researching and analyzing the original assessment program of quality management of Civics teaching in colleges and universities in the region, the evaluation program of Civics education results in colleges and universities in the region is optimized under the premise of combining the direction of the current education reform, combining the characteristics of the development of colleges and universities at different levels, and further collecting a number of data to increase the dimensions of the evaluation.

### 2.2. *Learning Effect Evaluation System*

Online teaching effect evaluation system is for the learner in the learning process to produce a variety of learning behavior records for analysis and reasoning, and finally form a set of test learners learning effect of the system framework, the learning effect evaluation system consists of a number of elements, mainly including the course learning class, teaching interaction, homework, testing, assessment of five aspects. The composition of the learner learning effect evaluation system is shown in Figure 1:

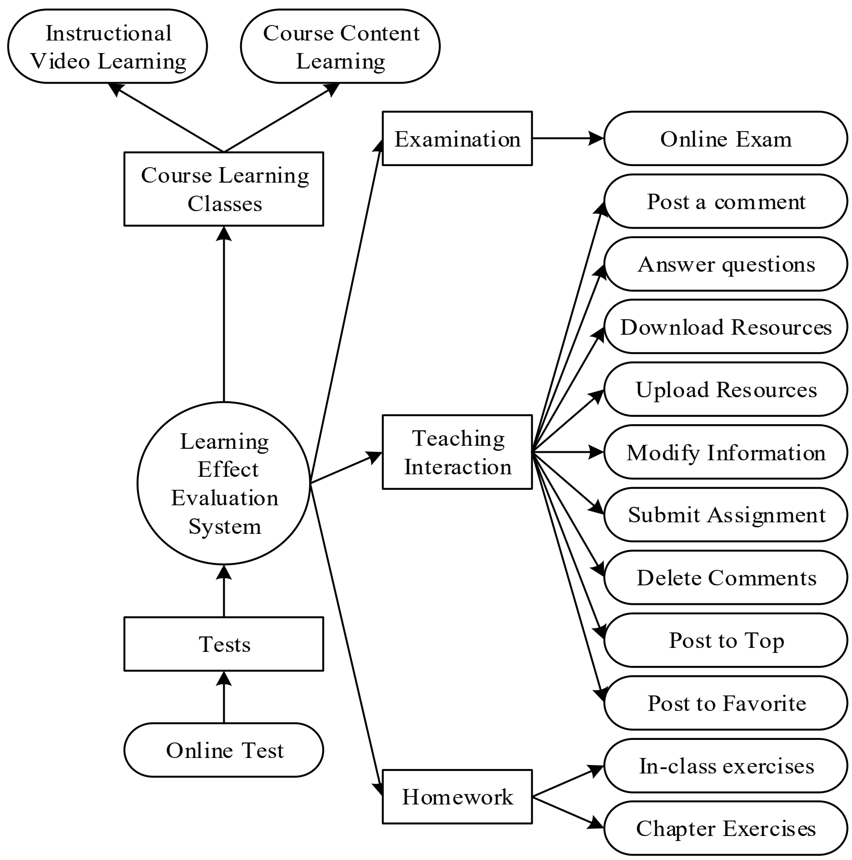


**Fig. 1.** Learning effect evaluation system components

The evaluation elements involved in the evaluation of online teaching effectiveness are listed in Figure 1.

Course learning category, including: teaching video learning, course PPT learning, etc;

Teaching interaction category, including: posting comments, answering questions, downloading resources, uploading resources, modifying information, submitting assignments, deleting comments, posting on top, posting on top, and so on;

Homework, including: chapter exercises, in-class exercises, etc;

Tests, including: online tests, etc;

Assessment, including: online test, etc.

### 2.3. *Student learning behavior assessment method based on distributed gray cluster analysis*

Evaluation and analysis of students' learning behavior facilitates the evaluation of teaching quality from students' learning process, which helps teachers or schools to improve teaching quality from students' learning process. As each student will form an evaluation result when evaluating, so when the analysis scope is larger, the amount of data will be more and more, this paper proposes a distributed gray clustering analysis method based on clustering algorithms, firstly, local clustering of data on each node of the cluster, and then the nodes are aggregated to form the overall clustering results, which can effectively realize the analysis of the evaluation of students' learning behaviors. The overall distributed gray clustering algorithm design and local clustering process are as follows.

2.3.1. Algorithm design based on distributed gray clustering. A large number of student learning behavior evaluation datasets obtained from the monitoring system are evenly distributed to each node under the Hadoop cluster, and then each node executes its own clustering algorithm to obtain local clustering results, which are then merged to form the clustering results of the whole dataset. The algorithm is designed as follows:

1) Distribute the entire student learning behavior dataset evenly to each sub-node under the Hadoop cluster, try to form a sub-dataset node for a school, and construct a Map function for each node;

2) For each sub-node, calculate the gray class affiliation value of each indicator and the clustering coefficient of each gray class using the whitening weight function;

3) According to the parameter values obtained in (2), local clustering is carried out for each node using Combiner, and local clustering results are obtained;

4) Integrate the clustering results of each sub-node with Reduce function, and combine all the clustering results according to the merging rule to get the final gray clustering results.

2.3.2. Steps of gray clustering evaluation method:

1) Classification criteria. In this study, the evaluation scale is divided into four levels: "generally good, good, very good, and excellent". "Excellent" scores 8-10, "Very Good" scores 5-8, "Good" scores 2-5, and "Moderately Good" scores 0-2.

2) Establishment of gray sample matrix. Invite $p$ expert to score the indicators based on the actual situation of the project, and establish the gray sample matrix $D_i = \left[ d_{ijq} \right]$, $d_{ijq}$ for the expert $q$ to the sub-indicator $j$ under the indicator $i$ assignment.

3) Construct the clustering weight matrix. $Y_{ij}$ subordinate $e$ to the gray class of the clustering coefficient is $X_{ije} = \sum_{q=1}^{p} f\left(d_{ijq}\right)$, the total coefficient of clustering $X_{ij} = \sum_{e=1}^{4} f\left(X_{ije}\right)$, to get the clustering weight vector $r_{ije} = \frac{X_{ije}}{X_{ij}}$, then the gray clustering weight matrix is:

$$R_i = \begin{bmatrix} r_{i11} & r_{i12} & \cdots & r_{i14} \\ r_{i21} & r_{i22} & \cdots & r_{i24} \\ \vdots & \vdots & \ddots & \vdots \\ r_{ij1} & r_{ij1} & \cdots & r_{ij4} \end{bmatrix}$$

4) Synthesize the evaluation matrix for clustering. Operate the weight vector with the gray clustering weight matrix to obtain the clustering assessment:

$$B = W \times R \tag{1}$$

5) Calculate the final evaluation score. From $F = [1, 3.5, 6.5, 9]$, the final score of the judged object is:

$$K = B \times F \tag{2}$$

### *2.4. Teaching quality assessment methods based on principal component analysis*

According to the regulations of the Ministry of Education, each indicator of teaching quality has a qualified standard value, and each assessment result is rated by the evaluator according to the actual situation, and at the same time, when there are multiple indicators to jointly evaluate something, there is bound to be which indicator is relatively the most important and which is relatively unimportant, and in this section of the study, the main method of principal component analysis is used to find the value of the indicator's weights and utilize the principal component dimensionality reduction ideas, to give each indicator a contribution, so that both the importance of each indicator can be analyzed, but also to understand whether the final evaluation results meet the qualification standards.

2.4.1. Fundamentals of Principal Component Analysis (PCA). Pearson first proposed the concept of principal components for non-random variables. Principal Component Analysis (PCA) is a common method of dimensionality reduction of data, which can simplify the problem processing by extracting the main characteristics of things. The main idea is to convert high-dimensional data into low-dimensional data through linear transformation, and to downgrade the original data to form a set of new indicators that are not related to each other to replace the original indicators, in order to process and analyze the data, and the principle of principal component analysis is shown in Figure 2. After the linear transformation, the larger the variance contribution rate of the new indicator is, the more information the indicator contains, which is called the first principal component. If the first principal component cannot fully reflect the original data, the second principal component will be selected, and so on. Using the method of principal component analysis to streamline the processing of the original variables can effectively reduce the interference of human subjective factors, thus obtaining more reliable results in the subsequent analysis of the data and making the obtained results more objective and scientific.

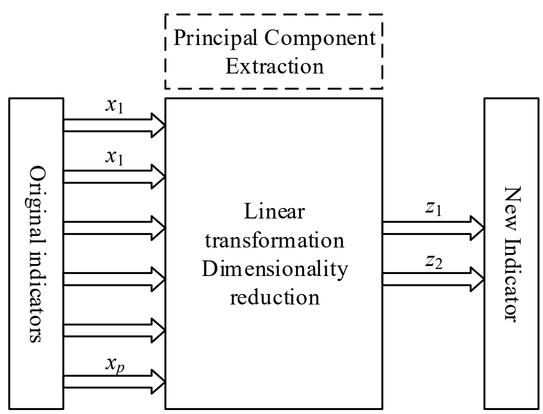


**Fig. 2.** Principle diagram of PCA

The main differences between the principal components obtained by using the principal component analysis (PCA) method and the original analyzed data are (1) each principal component consists of a linear transformation of the original variables. (2) Each principal component is independent of each other and has no correlation. (3) The number of principal components formed after linear combination is much less than the number of original variables. (4) Most of the information of the original variables can be maintained by the newly obtained principal components.

2.4.2. Specific computational steps for principal component analysis. According to the introduction of the principal component analysis method (PCA) mentioned above, the indicators in the learning effect evaluation system of Civic Education mentioned above are analyzed by principal component analysis. The specific calculation steps of principal component analysis are as follows:

1) Raw data preprocessing. The comprehensive idea of principal component analysis is to characterize the original $m$ indicators $x_j$ through fewer indicators $Z_i$. Due to the existence of different positive and negative impact indicators in the original data (the evaluation indicators in this paper are all ratios, without considering the impact of the unit of measurement), in order to compare the significance of the variables, it is necessary to preprocess the original data first. This involves using the values of the inverse variables to normalize the negative indicators and converting all the data to the same dimensions. The normalized data can then be used to construct a normalization matrix.

$$z=\begin{pmatrix} z_1 \\ z_2 \\ \cdots \\ z_n \end{pmatrix}=\begin{pmatrix} z_{11} & z_{12} & z_{13} & \cdots & z_{1p} \\ z_{21} & z_{22} & z_{23} & \cdots & z_{2p} \\ \cdots & & & \cdots & \\ z_{n1} & z_{n2} & z_{n3} & \cdots & z_{np} \end{pmatrix} \tag{3}$$

2) Solve the correlation coefficient matrix for the normalized matrix.

$$R=\left[r_{ij}\right]_p xp=\frac{Z^T Z}{n-1} \tag{4}$$

$$r_{ij}=\frac{\sum Z_{kj}\cdot Z_{kj}}{n-1},(i,j=1,2,\ldots,p) \tag{5}$$

3) Determine the principal components. Solve for the eigenroots of the correlation coefficient matrix, solve the eigenequation $|\lambda E-R|=0$, and find the eigenvalues $\lambda_1(i=1,2,\cdots p)$. $R$ is a positive definite matrix, so its eigenvalues $\lambda_1$ are all positive. Calculate its variance contribution ratio.

$$b_i=\frac{\lambda_i}{\sum_{i=1}^{p}\lambda_i} \tag{6}$$

In accordance with the principle of selecting the number of principal components, select the cumulative contribution rate of $\geq 80\%$ to determine the principal components.

4) Calculation of indicator weights. The degree of correlation between each indicator and the principal components can be characterized by the initial factor loading matrix coefficients, explaining the variation of each principal component variable. Firstly, the, loading coefficient calculation is carried out. Second, multiply the coefficients of each linear combination by the variance explained ratio, sum the results, and then divide by the cumulative variance explained ratio to calculate the composite score coefficients. The combined score coefficients were summed and normalized to obtain the weights of the indicators.

$$k_i=\frac{L(Z_i,x_j)}{\sqrt{\lambda_i}}(i=1,2,\ldots,p;j=1,2,\ldots,11) \tag{7}$$

$$T=\frac{\sum\limits_{kibi}^{i=1}}{\sum\limits_{bi}^{i=1}} \tag{8}$$

$$T_1=\frac{T}{\sum_{i=1}^{n}T_i} \tag{9}$$

5) Calculate the scores for each principal component and establish an equation for the relationship between the principal components and the study items.

$$z_i = T_1 X_1 + T_2 X_2 + \cdots + T_i X_j (i = 1, 2, \ldots, m) \tag{10}$$

6) Calculate the composite score.

$$z = T_1 Z_1 + T_2 z_2 + \cdots T_i z_i \tag{11}$$

# 3. Assessment of students' learning behavior and teaching quality in Civic Education

## 3.1. *Assessment of Civic Education Students' Learning Behavior Based on Gray Cluster Analysis*

3.1.1. Data sets and pre-processing. In this study, the Civics and Political Education course for the class of 2023 students majoring in Business Administration in a university in Guangdong Province is selected as the research object, and the behavioral data of 286 students of the major in the spring semester of 2024, when studying the Ideological and Political Education course on the Learning Pass platform, totaling more than one million records of online learning behaviors, are collected, and the personal information of the students is encrypted.

The data collected in this study involved interactive behaviors such as discussions, submitting assignments, and logging into the system. Among them, there were 20 homework tasks, 18 quiz tasks, 34 sign-in tasks, 248 total task points, 41 courseware resources, and 189 video resources for this ideology and politics course.

Data cleaning is based on the principle of processing irrelevant data, duplicate values, missing values, and dirty data in the original dataset. First of all, due to the limited number of subjects in this study, we did not screen individual cases, and only replaced the values of abnormal behavior indicators with missing values. For example, if a learner does not submit an assignment, replace this outlier with a missing value. Second, remove metrics with more than 80% missing values. Among them, the missing values of "uploading resources", "deleting comments" and "modifying information" were 87.36%, 82.61% and 96.78%, respectively, indicating that students generally did not have the two learning behaviors of uploading resources, deleting comments and modifying information, so these three indicators can be deleted. In addition, the missing values of "post to top" and "post to refine" are also large, so they can be combined into the learning behavior of "posting". The proportion of missing values in other indicators is less than 80% and is retained.

3.1.2. Describing the statistical results. According to the analysis of the evaluation system of the learning effect in 2.2, through the data cleaning of the learning behavior data, after the statistics, the descriptive statistical results of the learning behavior data about the Civics course are shown in Table 1.

**Table 1.** Learning behavioral data statistics results

| Index | Maximum | Minimum | Mean value | Standard deviation |
|---|---|---|---|---|
| Teaching video viewing completion degree | 100% | 0 | 54.87% | 0.374 |
| Degree of completion of course content | 100% | 0 | 67.29% | 0.452 |
| Number of comments posted | 287 | 0 | 14.45 | 23.372 |
| Number of questions answered | 108 | 0 | 6.36 | 17.255 |
| Number of downloaded resources | 41 | 0 | 11.21 | 8.278 |
| Number of work submission | 20 | 2 | 14.23 | 3.172 |
| Number of posting | 93 | 0 | 1.04 | 11.238 |

| | | | | |
|---|---|---|---|---|
| In-class practice completion rate | 100.00% | 0 | 42.29% | 0.283 |
| Chapter practice completion rate | 100.00% | 0 | 53.71% | 0.206 |
| Normal test score | 100 | 25.43 | 56.72 | 23.407 |
| Online final exam score | 100 | 38.39 | 76.54 | 12.382 |

As can be seen from Table 1, the maximum number of comments posted by some students is 287, indicating that they actively address issues in the Civics course through interaction with their peers and teachers. The difference between the maximum and minimum values of all learning behaviors is large, as well as the standard deviation of the behavioral statistics, in which the standard deviation of the number of comments posted and the number of questions answered are 23.372 and 17.255, respectively, which indicates that there are large differences in the learning behaviors among students. The average score of students' online examination in the Civics course was 76.54, indicating that students in this school achieved relatively good learning results in the Civics course.

3.1.3. Cluster Analysis of Learning Behavioral Characteristics. In order to continue to mine students' learning behavioral characteristics of the Civics course, this study adopts the gray clustering algorithm to conduct cluster analysis of the 11 behavioral characteristics after the selection of the above features.

In order to increase the efficiency of independent learning and improve the learning effect, on the basis of the above model, this paper carries out cluster analysis for learning groups. In order to determine the optimal K-value, the clustering results for different K-values were evaluated in this study using the Davidson Boulding Index (DBI index). The main idea of DBI index is to calculate the ratio of the sum of intra-cluster distances to the sum of extra-cluster distances to optimize the choice of k-value, avoiding the local optimum in the algorithm due to the calculation of the objective function only.The smaller the DBI index, the smaller the intra-cluster clustering is implied and the larger the distance between clusters is, i.e., the more reasonable the clustering result tends to be. The range of K value is set from 2 to 8, and the contour coefficient values corresponding to different K values are shown in Fig. 3.

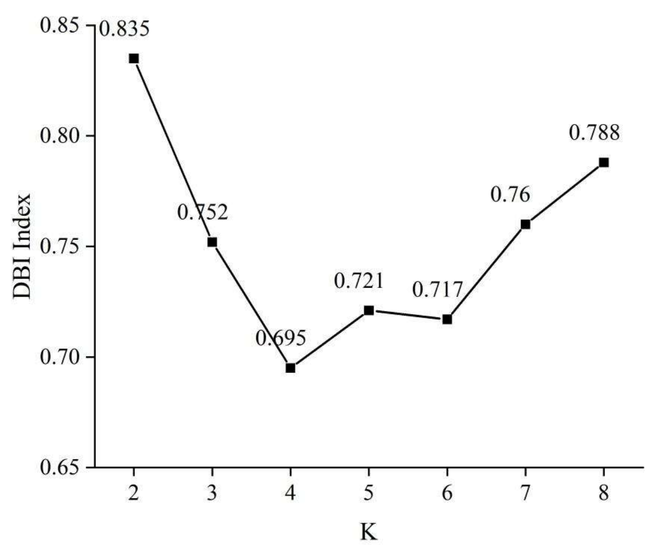


**Fig. 3.** The number of different clusters and their corresponding DBI index

From Fig. 3, when K=4, the DBI index is 0.695 and the clustering results are most reasonable. Therefore, the value of K is selected to be determined as 4.

The 11 behavioral features after screening were subjected to cluster analysis, and four clusters were obtained, and the clustering results are shown in Table 2.

**Table 2.** Clustering results describe statistics

| Trait | Cluster 1 (38 people) | Cluster 2 (142 people) | Cluster 3 (93 people) | Cluster 4 (13 people) |
|---|---|---|---|---|
| Teaching video viewing completion degree | 92.37% | 80.28% | 61.76% | 38.39% |
| Degree of completion of course content | 94.26% | 83.97% | 64.04% | 40.92% |
| Number of comments posted | 31.73 | 17.34 | 10.28 | 3.82 |
| Number of questions answered | 25.39 | 12.48 | 6.11 | 2.03 |
| Number of downloaded resources | 36.48 | 20.37 | 8.45 | 1.18 |
| Number of work submission | 19.73 | 17.28 | 13.39 | 4.30 |
| Number of posting | 11.36 | 5.47 | 2.32 | 0.74 |
| In-class practice completion rate | 91.29% | 80.10% | 61.38% | 37.81% |
| Chapter practice completion rate | 92.54% | 82.96% | 65.30% | 40.72% |
| Normal test score | 90.38 | 78.79 | 64.18 | 48.71 |
| Online final exam score | 94.07 | 85.35 | 72.36 | 53.94 |

In order to better analyze the learning effects of students from different clusters, this paper presents the learning effects through Figure 4.

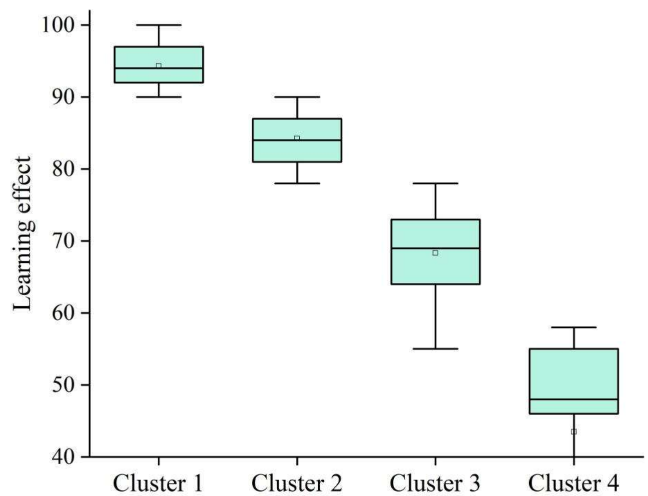


**Fig. 4.** Analysis of learning effect of each cluster

According to Figure 4, the upper limit, average value and lower limit of the learning effect of each cluster are decreasing in the order of Cluster 1, Cluster 2, Cluster 3 and Cluster 4. Therefore, the online learning groups in this paper are categorized into the following four types: exceptional students (Cluster 1), diligent students (Cluster 2), average students (Cluster 3), and negative students (Cluster 4).

As can be seen from Table 2, there are 38 students of Cluster 1 excellence type, accounting for 13.24% of the total number of students, whose completion rates of the learning content of the Civics course are all over 90%, with frequent teaching and learning interactive behaviors, excellent performance in assignments and tests, and an average of 94.07 online grades in the assessment category. For the excellence-type students, the online learning resources should be enriched, the depth of learning should be broadened, and the students should be guided to develop to a broader and deeper level.

There are 142 students in Cluster Category 2 Diligent type students, accounting for 49.48% of the total number of students, and the learning effect is only lower than that of the Excellence type students. Behavioral characteristics such as course-type learning and assignment-type completion were also superior for diligent students. For the diligent type students, they should increase the amount of knowledge reserve and actively participate in teacher-student interactions to accumulate learning experience so as to improve their academic performance.

There were 93 students in Cluster 3 General Type, and the level of each teaching interaction behavior of this cluster was below the average, indicating that the General Type students had poor learning initiative and were not strongly motivated to learn. Their online final grade average was 72.36. Average students account for 32.40% of the total number of students, which is a large proportion. For general type students, they should improve their independent learning by actively participating in group collaborative learning, teacher supervision, homework assistance, etc. to enhance their interest in learning, improve their learning ability, and then improve their learning effect.

There are 13 students in Cluster 4 Negative-type students, which have poor performance in all learning behaviors, less active online learning in the Civics course, lower quiz score scores, almost no participation in discussions, and a much lower course content completion rate than that of other students. For negative students, they can improve their learning motivation through self-motivation, make personalized learning plans, and strengthen communication with teachers and students to improve their learning initiative, complete their learning tasks by heart, and gradually improve their learning performance.

### *3.2. Teaching quality assessment methods based on principal component analysis*

3.2.1. Data sources. In order to test the effectiveness and superiority of the evaluation method proposed in this paper, the collected data on the evaluation of the teaching quality of college Civics courses from 2020 to 2024 are utilized. In accordance with the evaluation index system of the quality of teaching Civics in colleges and universities constructed in this paper, 250 sets of data of Civics quality evaluation indexes in 5 years were collected, of which 50 sets of data were available in each year, 45 sets of data in a year were used as the training data, and 5 sets of data were used as the test data.

3.2.2. Quality Evaluation System for Civics Teaching. The evaluation index system is an important index to measure the learning effect of Civics in colleges and universities, and it is a prerequisite to ensure the quality of teaching. This paper combines the teaching feedback based on students' learning and practicing ability to construct a set of English teaching quality evaluation system based on the quality of Civics teachers, teaching attitude, teaching content, teaching method, teaching effect and teaching feedback, as shown in Table 3. The system is divided into six large indicator layers, and each large indicator layer is divided into several elements. This indicator system can not only reflect the teaching quality from the perspective of teachers' teaching, but also analyze the teachers' teaching quality from the students' feedback, which makes the evaluation more diversified.

**Table 3.** Ideological and political teaching quality evaluation index system

| | Index level | Evaluation index |
|---|---|---|
| Ideological and political teaching quality evaluation index system | Teacher Quality A | Clear educational objectives A1 |
| | | Solid professional knowledge A2 |
| | | Teaching and presentation level A3 |
| | Teaching attitude B | Coaching patient positive B1 |
| | | Teach carefully B2 |
| | | Strict attitude B3 |
| | Teaching Content C | Conceptual theory accurate C1 |
| | | Full content C2 |
| | | Contact actual C3 |
| | | Depth of expertise C4 |

| | | |
|---|---|---|
| | Teaching Method D | Good at inspiring D1 |
| | | Various modes D2 |
| | | Focus on personality D3 |
| | | Inspire innovation consciousness D4 |
| | Teaching effect E | Interest in learning improves E1 |
| | | Knowledge understanding master E2 |
| | | Problem solving skills E3 |
| | | Comprehensive quality E4 |
| | Teaching feedback F | Student test scores F1 |
| | | Student learning process performance F2 |
| | | Student feedback survey score F3 |

3.2.3. Principal Component Analysis (PCA) to select evaluation indicators. Using PCA method, analyzing 250 groups of teaching index data of Civics teaching evaluation, selecting the indexes with higher contribution to the evaluation of Civics teaching quality in colleges and universities through dimensionality reduction, the results of the principal component analysis of Civics teaching quality evaluation indexes are shown in Figure 5. As can be seen from Figure 5, the cumulative contribution rate of the first 10 principal component indicators to the evaluation of the quality of college Civics teaching has reached 95.63%. The results show that the first 10 indicators can represent all the indicators to evaluate the quality of Civics teaching, and these indicators cover the quality of Civics teachers, teaching attitude, teaching content, teaching methods, teaching effects and teaching feedback, which further indicates that the teaching quality evaluation index system proposed in this paper is reasonable.

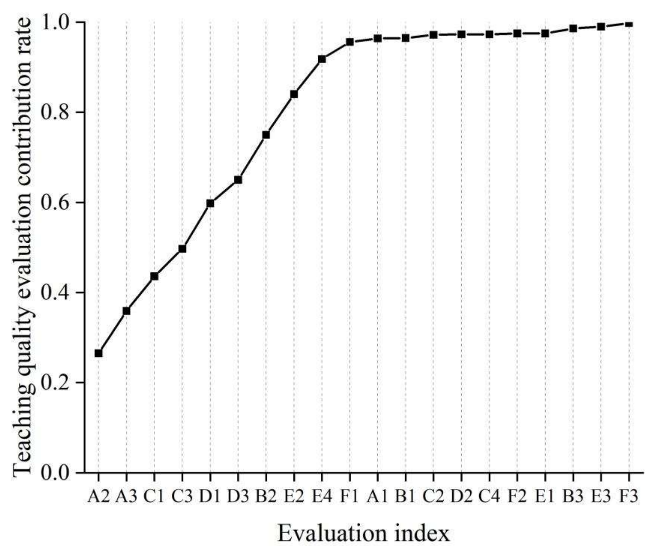


**Fig. 5.** Results of principal component analysis of teaching quality evaluation index

3.2.4. Evaluation of performance impact analysis. In order to investigate the influence of the population size and convolution kernel number of PCA algorithm on the performance of the Civics Teaching Quality Evaluation Model, the teaching quality evaluation model is tested by using the evaluation data after dimensionality reduction, and the results of the evaluation error RMSE and evaluation time under different combination parameters are counted. The results of the influence of different population sizes and number of convolution kernels on the RMSE and evaluation time of the evaluation model are given in Fig. 6 and Fig. 7, respectively.

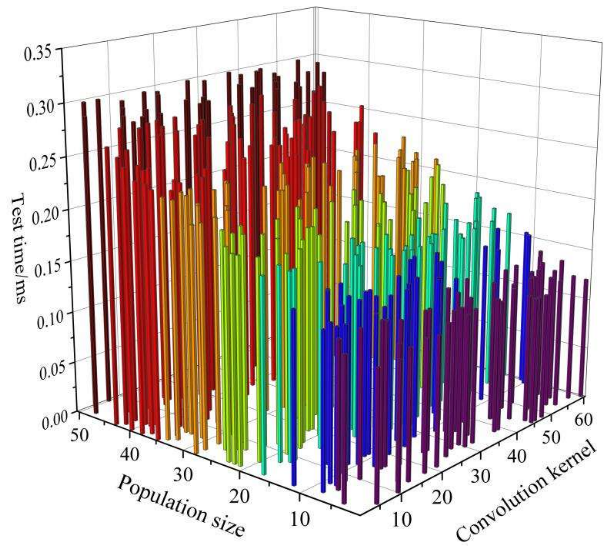


**Fig. 6.** The effect of evaluation error results

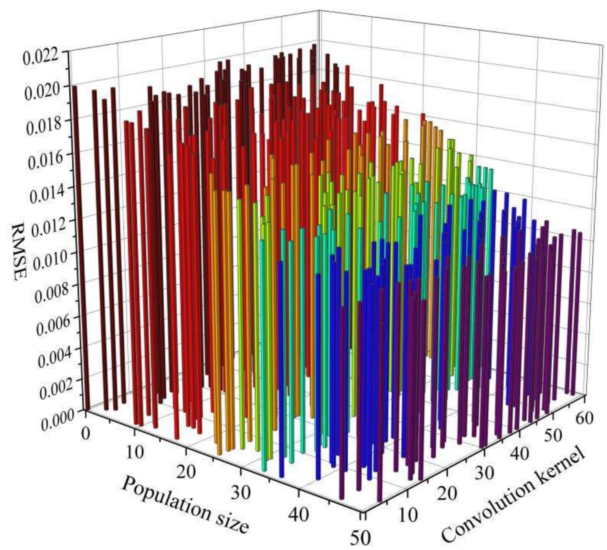


**Fig. 7.** Impact of test time results

As can be seen in Figure 6, the RMSE tends to decrease slightly as the hummingbird population size increases and decreases as the number of convolution kernels increases. From Fig. 7, it can be seen that the evaluation time of the test sample set after dimensionality reduction has a slight tendency to increase as the population size increases, and as the number of convolution kernels increases, the evaluation time of the test samples increases. In summary, the optimal number of population size for this experiment is taken as 31 and the optimal number of convolution kernels is taken as 19.

## 4. Conclusion

The article constructs a model for monitoring the effect of Civics education in the big data environment through the gray clustering analysis of the assessment of students' learning behavior in Civics education and the selection of Civics teaching quality evaluation indexes by PCA with principal component analysis.

Cluster analysis of students' Civics learning behavior characteristics found that when K=4, the DBI index is 0.695, and the clustering result is the most reasonable, so the students are divided into four cluster classes: excellence-type, diligent-type, general-type and negative-type students. There are 38 students of excellence type, accounting for 13.24%, and the learning effect of this type of students is 94.17 on average; there are 142 students of diligent type, accounting for 49.48%, and the learning effect is 86.33 on average; there are 93 students of general type, and the learning effect is 72.36 on average; and there are 13 students of negative type, who have poor performance in each learning behavior and little motivation in learning, and need to be guided by teachers.

The cumulative contribution rate of the first 10 principal component indicators of the Civics teaching quality evaluation system constructed in the article to the evaluation of the quality of Civics teaching in colleges and universities has reached 95.63%, and the evaluation effect of the 21 indicators has reached 99.98%. It proves the efficiency and rationality of the constructed evaluation system. With the increase of hummingbird population size and number of convolution kernels, the evaluation error result RMSE decreases, and the evaluation time of test samples increases. The number of population size is selected to be 31 and the number of convolution kernel is 19 for the best evaluation performance.

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