International Journal for Housing Science and Its Applications
Publish August 6, 2025. Volume 46, Issue 3 Pages 8134-8146

https,//doi.org/10.70517/ijhsa463695

Research on the Quality Assessment Model of Ideological and Political Education in Colleges and Universities Based on Improved Cluster Analysis

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Abstract Quality assessment of ideological and political education in colleges and universities is an important link to ensure the effectiveness of education. This study constructs the quality assessment model of ideological and political education in colleges and universities based on the improved K-Means clustering algorithm, adopts hierarchical analysis to determine the weights of evaluation indexes, and designs the evaluation system that contains 6 first-level indexes and 23 second-level indexes. The initial clustering center selection method is optimized by density parameters, and weighted Euclidean distance calculation is introduced to reduce the influence of anomalies and improve the clustering effect. The empirical study collects 500 evaluation data of ideological and political education in a university and divides them into three grades of “good”, “medium” and “poor”, accounting for 50.6%, 37.6% and 11.8% respectively. The results show that the first-level index of Civic and Political Education has the highest score (18.34 points, 91.68%), and the score of team building is relatively low (10.57 points, 52.83%), and the overall evaluation is at a good level. Meanwhile, the distribution of students' performance was highly consistent with the distribution of clustered grades, which verified the validity of the assessment model. The conclusion of the study shows that the improved K-Means clustering algorithm has strong applicability in the assessment of the quality of ideological and political education in colleges and universities, and the results of the assessment can provide data support and improvement direction for ideological and political education in colleges and universities, and promote the accurate improvement of the quality of ideological and political education.

Index Terms Ideological and political education, Quality assessment, Hierarchical analysis method, Improved K-Means clustering algorithm, Evaluation index system, Data mining

I. Introduction

With the practice of ideological and political education and the deepening of theoretical research, it is more and more important to build a perfect ideological and political education evaluation system, to assess the actual effect of the practice of ideological and political education, and to study the basic theories of ideological and political education evaluation [1]-[3]. The evaluation of ideological and political education in colleges and universities has made a lot of achievements and accumulated a lot of experience in the long-term practice and development. These achievements and experiences are both the value embodiment made by the evaluation of ideological and political education in colleges and universities, and also the proper meaning of promoting the forward development of the basic theory of ideological and political education. At the same time, the evaluation method of education in the traditional path is also increasingly highlighting its inherent limitations, there are such stubborn problems as the evaluation dimension is relatively single, the evaluation method is not scientific enough, and so on, which has become an obstacle to the connotative development, high-quality development and modernization of college education in the new era [4]-[7]. To eliminate the chronic problems and promote the reform and development of ideological and political education evaluation in colleges and universities has become a realistic need to improve the ability and level of governance of ideological and political education in colleges and universities.

As big data, artificial intelligence and other cutting-edge technologies are gradually and widely used in education, the issue of evaluation of the effectiveness of education and teaching will also get better opportunities for innovation and development [8], [9]. Big data mining, artificial intelligence technology and other technologies can play a full role in the process of ideological and political education teaching. On the one hand, it can make dynamic correction and measurement of educators' educational and teaching behavior [10]. On the other hand, it can also track, judge and detect the general state of the educational object in real time, and by integrating the relevant factors, it can produce a result [11]. This includes not only the evaluation of the educational object's educational and teaching effects on the educator, but also the changes and reactions of the educational object's status of receiving education [12]. Therefore, the use of digital technology to deepen the reform of ideological and political education evaluation in colleges and universities in the new era is of great significance in promoting the modernization of the discipline.

Ideological and political education in colleges and universities is an important way to cultivate students' correct values and good moral qualities, which has a profound impact on the quality of talent cultivation in colleges and universities. At present, ideological and political education in colleges and universities is facing new opportunities and challenges, and the establishment of a scientific and objective assessment system is of great significance to improve the quality of ideological and political education. Quality assessment of ideological and political education is a key link to test the effect of education, and through systematic assessment, problems can be found, work can be improved, and resource allocation can be optimized. However, traditional assessment methods are mostly based on qualitative research, the evaluation standards and methods lack systematicity and consistency, and the assessment results are often influenced by subjective factors, making it difficult to accurately reflect the actual effects of education. At the same time, the existing assessment index system often focuses on process evaluation and ignores result evaluation, making it difficult to comprehensively measure the effectiveness of ideological and political education. In addition, the assessment results among different universities lack comparability, and the analysis methods of assessment data are relatively outdated, failing to give full play to the guiding role of assessment in the improvement of education quality. Along with the arrival of the big data era, it becomes possible to apply data mining technology to the field of education assessment. Cluster analysis, as an important method of data mining, can classify similar samples into the same category by mining the interrelationships between data samples, providing an objective basis for education quality assessment.

Based on the above background, this study constructs the ideological and political education quality evaluation index system containing 6 first-level indicators and 23 second-level indicators, and adopts hierarchical analysis to determine the weights of each indicator. Second, the initial clustering center is selected and the weights are introduced through density parameters, and the traditional K-Means clustering algorithm is improved to reduce the influence of anomalies and improve the clustering effect. Again, the improved K-Means clustering algorithm is applied to cluster and analyze the quality evaluation data of ideological and political education in colleges and universities, and the assessment model is constructed. Finally, the validity of the model is verified through empirical research, and the correlation between the assessment results and students' academic performance is analyzed to provide a decision-making basis for ideological and political education in colleges and universities. This study combines qualitative analysis with quantitative methods to overcome the limitations of strong subjectivity in traditional assessment and provide new ideas and methods for the assessment of the quality of ideological and political education in colleges and universities.

II. Research on Quality Assessment of Civic and Political Education

II. A. Design Requirements of Civic Education Quality Evaluation Indicator System

In the quality measurement of ideological and political education, the importance of evaluation indexes is self-evident. The optimization of evaluation indexes for the quality of ideological and political education in colleges and universities in the new era should focus on applicability, scientificity, advancement and systematicity.

II. A. 1) Applicability

The essence of applicability is consistency. The evaluation of the quality of ideological and political education should be consistent with ideological and political education in terms of its basic attributes, fundamental purpose and ultimate goal. This requires that the indicator system be set up for the evaluation of the quality of ideological and political education, reflecting the basic nature of ideological and political education, the system structure, the operation process, and the goal, and that the indicators themselves be consistent with the objective reality of ideological and political education, and that they be able to reflect the development of ideological and political education by taking care of the main body, the object, the mediator, the ring and other basic elements of ideological and political education as a whole.

II. A. 2) Scientific

To ensure the scientificity of the design of the index system for evaluating the quality of ideological and political education, it is necessary to follow the regularity of the quality evaluation of ideological and political education. It is necessary to absorb the beneficial results of the evaluation of the quality of education, explore the exclusive laws governing the quality evaluation of ideological and political education, organically unify the integrity of ideological and political education work with the specialization of the quality evaluation of ideological and political education, and realize that the quality evaluation of ideological and political education has rules to follow and laws to follow under the two-wheel impetus of theoretical research and practical exploration, so as to meet the needs of the regular development of ideological and political education.

II. A. 3) Advanced

The advanced design of the quality evaluation index system of ideological and political education requires that the evaluation indexes be forward-looking and reflect directionality. The quality evaluation of ideological and political education in colleges and universities should not only reflect the reality of ideological and political education in colleges and universities, make up for the shortcomings, strengthen the weaknesses, and raise the advantages through the evaluation, so as to achieve the purpose of evaluation for improvement and evaluation for construction, but also play the role of leading and driving the new concepts of ideological and political education, new ideas, new requirements, etc. into the practice of ideological and political education in colleges and universities through the evaluation of the quality of ideological and political education to effectively promote the continuous progress and development of the ideological and political education in colleges and universities. Through quality evaluation, new concepts, new ideas and new requirements of ideological and political education will be integrated into the practice of ideological and political education in colleges and universities, effectively promoting the continuous progress and development of ideological and political education in universities.

Table 1: Evaluation index system

Evaluation index system	First-level indicator	Symbol	Secondary indicators	Symbol
The quality of ideological and political education	Ideological and political education	A1	Education on ideals and beliefs	B1
			Education on situation and policy	B2
			Mental health education	B3
			Campus cultural activities	B4
	Party and League building	A2	Party and League organization construction	B5
			Thematic learning and education	B6
			Practice and Volunteer Service	B7
			Role models and support services	B8
	Construction of academic atmosphere	A3	Daily educational management	B9
			Academic norms and atmosphere	B10
			Course learning situation	B11
			Scientific research practice activities	B12
	Team building	A4	Organizational structure construction	B13
			Full-time and part-time team	B14
			Mentor team	B15
			The teaching staff	B16
			Student backbone team	B17
	Condition guarantee	A5	Reward policy	B18
			Employment and entrepreneurship guidance	B19
			Working and living conditions	B20
	Educational effect	A6	Student rewards and punishments	B21
			One-time employment rate	B22
			Scientific research and practical achievements	B23

II. A. 4) Systematic

The construction of the ideological and political education work system in colleges and universities is a systematic project, and its quality evaluation is also a systematic process involving multiple elements and many links. Therefore, the design of the indicator system for quality evaluation must uphold the system perspective, focus on the construction of the standard system, form an indicator system with comprehensive coverage, complete content, linkage and coordination of standards, and realize the optimization of the overall effectiveness of the quality evaluation indicator system by creating a standard complex. Based on a systematic perspective, the system must focus on the synergy of revising and changing the standard system, and ensure the consistency of the standard system, in order to ensure the smooth implementation of the evaluation work and the function of leading and safeguarding.

II. B. Construction of the evaluation index system

Under the design requirements of ideological and political education quality evaluation index system, the evaluation index system of ideological and political education quality in colleges and universities in the new era is constructed, which consists of 23 secondary indexes and 6 primary indexes, and the ideological and political education quality evaluation index system is shown in Table 1. This evaluation index system can provide help for the improvement of the quality of ideological and political education in order to improve the relevance and effectiveness of ideological and political education. The evaluation result of ideological and political education is not the final purpose, the evaluation is to improve and strengthen the existing ideological and political education, in order to promote the improvement of the quality of ideological and political education, and to guide and help the students to improve their quality, grow their talents, and develop in an all-round way.

II. C. Calculation of indicator weights

Hierarchical analysis is a typical system engineering method integrated from qualitative analysis to quantitative analysis, which mathematizes people's thinking process of the complex system, quantifies the qualitative analysis dominated by people's subjective judgments, numericizes the differences between various judgmental elements, helps people to maintain the consistency of the thinking process, and applies to the complex evaluation system of the quality of ideological and political education in colleges and universities, and it is a method that is currently being widely used method of determining weights [13]. When using hierarchical analysis to solve the weight of each evaluation index, only the evaluator needs to give a qualitative description of the relative importance of the two elements of each evaluation, and then through the hierarchical analysis method can be more accurate to find out the weight of each evaluation element, the hierarchical analysis method will be a good combination of qualitative descriptions and quantitative calculations, which are based on a rigorous mathematical theory, which greatly strengthens the scientific nature of the whole evaluation process. This greatly strengthens the scientificity and effectiveness of the whole evaluation process. To determine the weights of the evaluation elements by using the hierarchical analysis method, the following steps can usually be carried out:

II. C. 1) Establishment of judgment matrices

Hierarchical analysis is used to analyze the weights of the indicators, establish a clear hierarchical indicator system, and give the judgment matrix of the evaluation object. The judgment matrix indicates that for an element in the previous level, the status of the relative importance between the relevant elements in this level, assuming that the element a_k in the A level has a connection with the next level $B_1, B_2, \cdots, B_n$, and constructing the judgment matrix B to take the form of the following:

$$\begin{pmatrix} a_k & B_1 & B_2 & \dots & B_n \\ B_1 & b_{11} & b_{12} & \dots & b_{1n} \\ B_2 & b_{21} & b_{22} & \dots & b_{2n} \\ \dots & \dots & \dots & \dots & \dots \\ B_n & b_{n1} & b_{n2} & \dots & b_{nn} \end{pmatrix} \tag{1}$$

where $b_{ij}(i=1,2,3,...,n; j=1,2,3...,n)$ denotes the numerical expression of the relative importance of B_i to B_j for a_k, and usually b_{ij} can be taken to be expressed on a 1-9 scale.

Obviously, for judgment matrices there are:

$$b_{ii} = b_{jj}; b_{ij} = 1/b_{ji}(i,j=1,2,3,\cdots,n) \tag{2}$$

II. C. 2) Hierarchical ordering

Hierarchical single-ordering refers to the calculation of weights for the order of importance of the elements associated with this level with respect to an element of the previous level according to the judgment matrix. After calculating the single-ranking value of a level relative to the previous level of each indicator, with the weight of the previous level of the indicator itself weighted synthesis, you can calculate the relative importance of a level of indicators relative to the previous level of the entire level of the relative importance of the weight value, that is, the level of the total ordering weights. In this way, from top to bottom, you can calculate the lowest level of indicators relative to the highest level of the relative importance of the weight value or the relative order of merit of the ranking value. Hierarchical single sorting can be reduced to the problem of calculating the eigenroot and eigenvector of the judgment matrix, i.e., by calculating the maximum eigenvalue of the judgment matrix and its corresponding eigenvector (this model is calculated using the square root method), the relative importance weight value of a certain level of indicators relative to the relevant indicators of the previous level is calculated.

For judgment matrix B, the calculation steps are:

The feature vector W is obtained from $BW = \lambda_{\max} W$ and normalized to get the feature vector:

$W = \left[w_1, w_2, \cdots w_n\right]^T$ as the ranking weights of the elements $B_1, B_2, \cdots, B_n$ at this level with respect to the target element a_k. The square root method is adopted here to compute the eigenvectors and principal eigenvalues. The elements in the judgment matrix B are multiplied row-wise:

$$\prod_{j=1}^{n} a_{ij} (i = 1, 2, 3, \cdots, n) \tag{3}$$

Then calculate:

$$\overline{w}_i = \sqrt[n]{\prod_{j=1}^{n} a_{ij}} \tag{4}$$

obtained by normalizing $\overline{w}_i$ again:

$$w_i = \frac{\overline{w}_i}{\sum_{j=1}^{n} \overline{w}_j} \tag{5}$$

Finally, the required feature vector can be obtained: $W = \left[w_1, w_2, \cdots w_n\right]^T$.

From this, the degree of influence of each indicator on the evaluated is determined and quantified to form the weight set A. For the primary (level 1) indicator, the weight set $A = \{a_1, a_2, \cdots, a_n\}$, and the individual weight sets of the sub (level 2) indicators affecting level 1 indicators are $A_1, A_2, \ldots, A_n$, this method of mathematizing the thinking process simplifies the system analysis and calculation, in order to make the weights of each performance indicator better reflect the degree of influence of each indicator on the overall performance, and then construct the judgment matrix and test its consistency based on the statistical results of the leadership decision-making and expert consultation.

II. C. 3) Consistency test

The ideal judgment matrix should satisfy the consistency condition, however, due to the influence of experts' knowledge level and personal preference, it is often difficult to satisfy the consistency condition of the realistic judgment matrix, especially when n is larger. Therefore, for this kind of non-consistent judgment matrix, in order to ensure the credibility and accuracy of its ranking results, it is also necessary to test the consistency of its judgment quality.

From matrix theory and AHP method, we know that when the maximum eigenvalue $\lambda_{\max}$ of the n-order judgment matrix A is closer to n, the consistency of A is better. When the n-order judgment matrix does not have consistency, the corresponding eigenvalue of the judgment matrix will change. Therefore, the degree of consistency of the judgment matrix can be checked by using the eigenvalue changes of the judgment matrix. The quantitative measure of the degree of consistency is called the consistency index CI, which Saaty defines as:

$$CI = \frac{\lambda_{\max} - n}{n - 1} \tag{6}$$

In order to measure the consistency indicator CI, the method of revising the CI with the average random consistency indicator RI is proposed. Average random consistency indicator RI.

The consistency test procedure is as follows:

To find the approximation of $\lambda_{\max}$, let the nth-order judgment matrix A has been found, and the normalized eigenvector of A is: $W = [w_1, w_2, \cdots w_n]^T$, then the maximum eigenvalue of the nth-order judgment matrix A $\lambda_{\max}$ can be approximated by the following equation:

$$\lambda_{\max} = \frac{1}{n}\sum_{i=1}^{n}\frac{(AW)_i}{w_i} \tag{7}$$

The CR was calculated and the results were compared with the corresponding RI. to calculate the random consistency ratio:

$$C.R. = \frac{CI}{RI} \tag{8}$$

The consistency of the n-order judgment matrix A is acceptable if $CR < 0.1$. Otherwise, the individual judgment matrices at this level need to be adjusted so that the total hierarchical ordering has a satisfactory consistency.

II. D.Cluster analysis

Cluster analysis divides data samples into a number of clusters by mining the interrelationships between them so that there is a high degree of similarity between the data samples in the divided clusters and a large degree of dissimilarity between the data samples in the non-identical clusters, and the resulting set of clusters is called a cluster.

II. D. 1) Principles of cluster analysis

Cluster analysis adopts unsupervised learning method, and its analysis process is mainly divided into two parts: firstly, according to the sample attributes, mathematically determine the similarity of the samples and divide the similar data samples into the same cluster. Secondly, the criterion function is applied to verify the results of cluster analysis. Generally speaking, there is a high degree of similarity between the samples classified as the same cluster, while there is no similarity or low similarity between the samples of different clusters.

II. D. 2) Cluster analysis algorithms

This type of algorithm uses distance as a measure, and its steps mainly include the following steps: first step, apply the principle of minimization of criterion function to divide the dataset of n data into k clusters and satisfy k<n. Second step, iteratively loop the dataset, whose principle is that the distance between the data in the same cluster is sufficiently close, and the distance between the different clusters is sufficiently far. In the third step, the second step is repeated until the termination condition is satisfied and at least one data in each cluster and each data belongs to and only belongs to one cluster, typical algorithms based on the division are: K-Means, K-Medoids, and so on.

II. D. 3) K-Means algorithm

The idea of K-Means algorithm is: first determine k points as the initial center of the cluster, and divide the data into the cluster class with the closest distance to the center point, and then by calculating the average value of the data to the center of the new cluster distance to the center point of the new cluster center point, and again the newest cluster center point, and so on repeat until the results of the division remain unchanged [14]. According to the above description, the main points to realize the K-Means algorithm:

(1) Selection of the number of clusters k.

(2) The average value of the distance from each sample point to the “cluster center”.

(3) Update the “cluster center” according to the newly divided clusters.

The process of K-Means algorithm is as follows:

(1) Select k objects as the initialization centers of the clusters.

(2) Calculate the distance from the data to each center, and classify the data into the cluster with the closest distance.

(3) Recalculate the average value of each cluster and update it as the new cluster center.

(4) Repeat 2 and 3 continuously until the criterion function converges.

Advantages and disadvantages of K-Means algorithm:

(1) Advantages: the principle of the algorithm is simple, interpretable, quick to implement, data analysis, convergence speed, the algorithm only needs to call the number of clusters k a parameter.

(2) Disadvantages: the value of the number of clusters k is difficult to determine, it is sensitive to noise and abnormal data, the use of iterative method, the clustering results are generally locally optimal.

II. D. 4) Improved k-means clustering algorithm

Improvement of the initial clustering center selection can avoid the selection of isolated points, so this paper uses the density parameter to select the initial clustering center, and at the same time introduces the weights, and the weighted Euclidean distance reduces the distance between the normal data and the clustering center, which reduces the influence of the anomalous points and optimizes the clustering effect.

Assume that the dataset to be clustered has n samples, i.e., $s=\{x_1,x_2,\cdots,x_n\}$, and that each sample point is m -dimensional, denoted by $x_i=\{x_{i1},x_{i2},x_{i3},\cdots,x_{im}\}, i=1,2,3,\cdots,n$, and the k initial clustering centers are $c_1,c_2,\cdots,c_k$.

The density of the sample points reflects the closeness of the points, and the initial clustering center selects the points with the highest density to prevent random selection to isolated points. Weighted Euclidean distance is used to increase the degree of differentiation between data attributes and reduce the influence of anomalous points. First, the density of the sample points is calculated according to the density parameter formula, the initial clustering center selects the point with the highest density, and the weighted average Euclidean distance is used as the radius, and the set S_1 is composed of all the points in this region. Then, the sample points with the highest density in $S-S_1$ continue to be selected with the weighted average Euclidean distance of the remaining data points as the radius, the set S_2 consists of all the points in this region, and so on, until k sets are found. Finally, each set $S_1,S_2,...,S_k$ as the new clustering center of that set, and the clustering error sum of squares is calculated by the error squared formula.

When calculating the distance, the weights of the data of different dimensions of the sample points are calculated by the formula:

$$w_{id}=x_{id}\left(\frac{1}{n}\sum_{i=1}^{n}x_{id}\right)^{-1} \tag{9}$$

The weighted Euclidean distance between two samples is given by:

$$d_w(x_i,x_j)=\sqrt{\sum_{d=1}^{m}w_{id}(x_{id}-x_{jd})^2} \tag{10}$$

The weighted average Euclidean distance of the sample data points is calculated as:

$$d_{wm}=\frac{1}{n^2}\sum_{i=1}^{n}\sum_{j=1}^{n}d_w(x_i,x_j) \tag{11}$$

Density parameter of the sample data points. The number of points in a region centered on any point x_i in the dataset, with an average distance d_{wm} as the radius. It is called the density parameter of the point x_i based on the distance d_{wm}, denoted as $\rho(x_0,d_{wm})$, which is computed as:

$$\rho(x_i,d_{wm})=\sum_{j=1}^{n}u(d_{wm}-d_w(x_i,x_j)) \tag{12}$$

Eq. $u(x)=\begin{cases}1, & x\geq 0,\\ 0, & \text{other}\end{cases}$. The clustering error sum of squares is given by:

$$E=\sum_{j=1}^{k}\sum_{x_i\in c_j}|x_i-c_j|^2 \tag{13}$$

where, $x_l\in c_j$ means that x_l is a point in the region centered at c_j with d_{wm} as radius. The accuracy is calculated as:

$$c=\frac{n}{N}\times 100\% \tag{14}$$

where, n is the number of data correctly assigned to the specified class. N is the total number of data.

II. E. Assessment models

For the collected teaching evaluation forms, data mining, analyze and derive certain data to study the application of cluster analysis technology in the quality evaluation system of ideological and political education, in this paper, the improved K-Means algorithm will be applied to construct the quality evaluation model of ideological and political education in colleges and universities.

II. E. 1) Data preparation

In data mining, data preparation includes all the activities involved in constructing the final dataset from the raw data. These data will be the input values for the model.

In this paper, the data in the ideological and political education quality evaluation form of the first semester of the 2022-2023 academic year in a key university in a province are screened to find out 500 evaluation data on ideological and political education and students' performance tables, and the cluster analysis K-Means algorithm is applied to these data to study the association rules between the evaluation results of teachers' teaching and students' performance.

II. E. 2) Data pre-processing

Data stored in computer system databases are not suitable for direct data analysis and mining due to problems such as noise, missing and redundancy. Therefore, further preprocessing of raw data is required. The data preprocessing stage requires data cleaning, integration, generalization, transformation and other steps, and the final preprocessed data should be characterized by accuracy, completeness and consistency. The data in the evaluation table of ideological and political education is based on the specific performance of the lecturers, and is scored sequentially (each item is worth 5 points) with reference to the 23 secondary indicators under the 6 primary indicators in the ideological and political education quality evaluation index system. However, the data collected need to be cleaned up of gaps, noise and isolated data, and 500 complete teaching evaluation data will be retained in the end.

II. E. 3) Data conversion

Ideological and political education evaluation index system has 6 first-level indicators, 23 second-level indicators, for these 23 second-level indicators data clustering is unnecessary, so through the calculation we derived 6 first-level indicators rating table in the original data samples. 6 first-level indicators of the value is equivalent to the sum of the value of the individual second-level indicator scores. After conversion, we convert the 23 second-level indicator scores into the relevant data for the 6 first-level indicators, and organize the 500 collected data as raw data samples for cluster analysis of the 6 first-level indicator mathematics.

II. E. 4) Data mining

After data collection, preprocessing and transformation, the data samples used in data mining can be obtained, in the cluster analysis of data mining, we use the K-Means algorithm, this algorithm usually starts by selecting K data out of n data as the initial clustering center. Then the rest of the objects are assigned to the corresponding clusters based on their similarity to the selected initial clustering centers. Finally, the corresponding mean value of each cluster center is obtained by calculation, and this process is repeated to obtain the final convergence of the standard measure function to complete the task. In the actual operation process, we divide the 500 sample data into three clusters, and randomly select three data as the center points of the initial cluster analysis, so that the number of the three clusters represents the clustering results of "excellent", "qualified" and "unqualified" in the evaluation of ideological and political education in colleges and universities.

II. E. 5) Operational Strategies

In this paper, the number of clusters delineated by the K-Means algorithm is K=3. And the specific way of classification is to determine the center of the clusters first, in this paper, according to the distribution of the data, randomly select three data as the initial center point of the three clusters, and then measure the Euclidean distance, i.e., the distance between the other elements and the center of the clusters and the element with the closest Euclidean distance from the center point is added to the center of the clusters. This cycle, by calculating the average value of the data in each class to get the new clustering center, and continue to repeat the calculation, the final results of the cluster analysis.

III. Analysis of the Quality Assessment of Ideological and Political Education in Colleges and Universities

III. A. Indicator weighting analysis

III. A. 1) Relative weight calculation and consistency test

The hierarchical analysis method relies to a large extent on the experience of experts, and the influence of subjective factors is very great; at most, it can only exclude serious non-consistency in the thinking process, but it cannot exclude the possible arbitrariness and one-sidedness of individual experts, and the adoption of the judgment results of only one expert may result in random errors. In order to avoid the above problems, after screening out 2 experts who failed the consistency test, using yaahp software to construct the evaluation index model of this study, and then inputting the judgment matrix data of 10 experts who passed the consistency test into the group decision-making panel one by one to summarize the data, and then using the expert data assembly method to weight geometric mean of each expert sorting vector to finally get the relative weight value. The results of relative weight calculation and consistency test are shown in Tables 2 to 8, which indicate the six primary indicators and the subordinate secondary indicators, respectively. The results show that the judgment matrix CR (0.041, 0.027, 0.066, 0.073, 0.082, 0.093, 0.069) of each indicator satisfies the requirement of consistency test ($CR<0.1$), which indicates that the calculated relative weights of each indicator meets the requirements of the study, and can be further carried out in the follow-up study.

Table 2: Calculation of the relative weight of first-level indicators

Index	A1	A2	A3	A4	A5	A6	Weight	CR
A1	1	0.33	0.125	0.5	0.25	0.2	0.1797	0.041
A2	0.2	1	0.2	0.2	0.125	0.125	0.1264	
A3	0.33	0.33	1	0.33	0.5	0.125	0.2046	
A4	0.33	0.125	0.33	1	0.125	0.33	0.1624	
A5	0.2	0.2	0.125	0.2	1	0.2	0.1368	
A6	0.2	0.33	0.33	0.2	0.33	1	0.1901	

Table 3: The absolute weight of the secondary indicators under A1

Index	B1	B2	B3	B4	Weight	CR
B1	1	0.33	0.33	0.1	0.2151	0.027
B2	0.5	1	0.25	0.5	0.3329	
B3	0.25	0.2	1	0.5	0.2648	
B4	0.5	0.125	0.1	1	0.1872	

Table 4: The absolute weight of the secondary indicators under A2

Index	B5	B6	B7	B8	Weight	CR
B5	1	0.5	0.125	0.1	0.2027	0.066
B6	0.25	1	0.33	0.33	0.2928	
B7	0.1	0.5	1	0.5	0.2867	
B8	0.333	0.125	0.2	1	0.2178	

Table 5: The absolute weight of the secondary indicators under A3

Index	B9	B10	B11	B12	Weight	CR
B9	1	0.5	0.125	0.1	0.2306	0.073
B10	0.25	1	0.33	0.33	0.2983	
B11	0.1	0.5	1	0.5	0.2559	
B12	0.33	0.125	0.2	1	0.2152	

Table 6: The absolute weight of the secondary indicators under A4

Index	B13	B14	B15	B16	B17	Weight	CR
B13	1	0.5	0.125	0.1	0.33	0.1630	0.082
B14	0.25	1	0.33	0.2	0.5	0.2150	
B15	0.33	0.25	1	0.5	0.33	0.2377	
B16	0.33	0.2	0.25	1	0.5	0.2150	
B17	0.2	0.2	0.125	0.5	1	0.1693	

Table 7: The absolute weight of the secondary indicators under A5

Index	B18	B19	B20	Weight	CR
B18	1	0.25	0.33	0.3358	0.093
B19	0.25	1	0.25	0.3061	
B20	0.2	0.5	1	0.3581	

Table 8: The absolute weight of the secondary indicators under A6

Index	B21	B22	B23	Weight	CR
B21	1	0.5	0.5	0.4346	0.069
B22	0.2	1	0.2	0.2359	
B23	0.33	0.33	1	0.3295	

III. A. 2) Absolute weight calculation and consistency test

Absolute weight is the weight value of a layer of elements to the entire target layer, which intuitively reflects the weight value of the same layer of elements in a certain evaluation system, not only limited to the relative weight of a relevant indicator. According to the theory of hierarchical analysis (AHP), it can also be called the total hierarchical ordering, which is calculated as the sum of the product of the weight of the single ordering of the layer (relative weight) and the total ordering of the factors belonging to the previous layer (absolute weight), and the calculation of the absolute weight and consistency test are shown in Table 9. Taking B1 as an example, the absolute weight = A1 absolute weight × B1 relative weight = 0.1797 × 0.2151 = 0.0387, and it satisfies the consistency test, and the same is true for the remaining 22 secondary indicators. In addition, the first-level indicator is the highest level, so the relative weight of the first-level indicator = the absolute weight of the first-level indicator.

Table 9: Absolute weight calculation and consistency check

Target layer	First-level indicator	Absolute weight	Secondary indicators	Relative weight	Absolute weight	CR
The quality of ideological and political education	A1	0.1797	B1	0.2151	0.0387	0.088
			B2	0.3329	0.0598	
			B3	0.2648	0.0476	
			B4	0.1872	0.0336	
	A2	0.1264	B5	0.2027	0.0256	
			B6	0.2928	0.0370	
			B7	0.2867	0.0362	
			B8	0.2178	0.0275	
	A3	0.2046	B9	0.2306	0.0472	
			B10	0.2983	0.0610	
			B11	0.2559	0.0524	
			B12	0.2152	0.0440	
	A4	0.1624	B13	0.163	0.0265	
			B14	0.215	0.0349	
			B15	0.2377	0.0386	
			B16	0.215	0.0349	
			B17	0.1693	0.0275	
	A5	0.1368	B18	0.3358	0.0459	
			B19	0.3061	0.0419	
			B20	0.3581	0.0490	
	A6	0.1901	B21	0.4346	0.0826	
			B22	0.2359	0.0448	
			B23	0.3295	0.0626	

III. B. Analysis of assessment modeling examples

III. B. 1) Determining the population to be studied

In this example, 500 tables about ideological and political education in colleges and universities were organized for the feedback data obtained from the evaluation tables of ideological and political education in colleges and universities in the first semester of the academic year 2022-2023, and an improved K-means clustering method was adopted based on these data to study the correlation that exists between the evaluation data of ideological and political education and students' grades.

III. B. 2) Data pre-processing

We obtained evaluation data from the school's Registrar's Office on the participation of the college's faculty in college ideological and political education during the first academic year of the 2022-2023 school year. The evaluation data of ideological and political education in higher education is defined about the teachers' performance in the classroom, referring to a total of 23 secondary indicators under the 6 primary indicators in the teaching evaluation form, which are obtained by going to the scoring in order (where each item is scored out of 5). We needed to clean up the missing values for processing, and finally retained 500 complete evaluation data. After data conversion, we get the following six aspects: "ideological and political education (A1)", "party and caucus construction (A2)", "study style construction (A3)", "team building (A4)", "condition guarantee (A5)", and "education effect (A6)". In the experiment, these six aspects were used as the main indicators, and the six attributes of the 500 data samples that had been collected and processed were used to realize the clustering of data.

III. B. 3) Cluster analysis process

According to the above operation, we can get the data samples as shown in Table 10 below, this paper in the real calculation process of the 500 samples of data divided into three clusters, these three clusters are “better”, “medium” and “Poor”. The data samples in Table 10 are entered in a certain form, and the sample data waiting to be entered are stored in the data.dat file.

Num1ist (number of data samples) = 500.

Numopt (number of attributes) = 6.

NC1uster (number of clusters) = 3.

Table 10: Data sample for the quality evaluation of ideological and political education

Index	A1	A2	A3	A4	A5	A6
B1	98	97	104	117	84	98
B2	116	114	111	101	58	116
B3	115	106	96	95	88	115
B4	104	91	103	118	84	104
B5	97	98	99	106	100	97
B6	116	103	95	116	70	116
B7	95	103	101	109	92	95
B8	96	109	114	111	70	96
B9	102	95	93	111	99	102
B10	114	98	113	99	76	114
B11	97	113	93	111	86	97
B12	93	107	116	110	74	93
B13	109	93	112	106	80	109
B14	95	108	96	95	106	95
B15	106	116	92	116	70	106
B16	105	99	106	109	81	105
B17	111	115	104	107	63	111
B18	93	113	113	95	86	93
B19	115	103	112	102	68	115
B20	102	116	104	93	85	102
B21	102	118	91	91	98	102
B22	91	105	90	118	96	91
B23	109	103	108	95	85	109

III. B. 4) Analysis of results

In the experiment, we collected 500 samples, and used the improved K-Means clustering algorithm to conduct experimental studies on the data of each of these samples including 6 attributes (referring to "ideological and political education A1", "party group construction A2", "study style construction A3", "team building A4", "condition guarantee A5", and "educational effect A6"), the number of clustering processes k=3, and the results after cluster analysis are shown in Table 11.

Table 11: The result of clustering

Index	A1	A2	A3	A4	A5	A6	Number of samples
B1	24.41	27.25	26.74	4.38	7.76	28.35	253
B2	21.17	24.18	23.64	4.03	6.14	24.14	188
B3	15.17	19.06	19.07	3.11	4.59	19.79	59

Out of 100 samples:

Cluster I (better), there are 253 samples, and the percentage 253/500 = 50.6%.

Cluster 2 (moderate), there are 188 samples, and the percentage 188/500 = 37.6%.

Cluster 3 (poor), with a total of 59 samples and a percentage of 59/100 = 11.8%.

In addition, 500 student grades were collected for the first semester of the 2022-2023 academic year for the college's political and ideological education courses (a total of five courses), and 500 grade data samples were compiled ranging from a score of 0 to a score of 100. To facilitate comparisons and documentation, the data samples were analyzed for general grades by dividing the grade data samples into three grades of 85 or above, 85 to 65 (both 85 and 65), and below 65. And three bands with scores below 65. Comparing and analyzing the three number bands, the percentage of each score band is shown in Table 12.

Table 12: The distribution of students' academic performance

Score range	Number of samples	Number of samples
86 points or above (including 86 points)	353	0.706
85 to 65 points	117	0.234
Less than 65 points (excluding 65 points)	30	0.06

Through the above analysis, we can see that the percentage of the samples in the above 3 score bands in the total sample is almost the same as the percentage of the 3 grades in the clustering process (50.6%, 37.6%, 11.8%), which indicates that the clustering model based on the evaluation table of the quality of ideological and political education in colleges and universities is relatively successful.

We then look at the total scores of each item, and since the number of samples is not the same, we need to add weights. The overall scores of the 6 individual items are as follows:

Civic and political education A1=18.72*70.6%+17.99*23.4%+15.16*6%=18.34, 17.44/20≈91.68%.

Party building A2=16.99*70.6%+17.18*23.4%+17.55*6%=17.07, 16.03/20≈85.34%.

Academic style building A3=17.23*70.6%+16.84*23.4%+17.55*6%=17.16, 16.12/20≈85.79%.

Team building A4=11.16*70.6%+8.12*23.4%+13.12*6%=10.57, 9.79/20≈52.83%.

Condition guarantee A5=8.79*70.6%+7.38*23.4%+9.34*6%=8.49, 7.94/10≈84.93%.

Effectiveness of parenting A6=9.83*70.6%+7.38*23.4%+9.34*6%=9.23, 8.67/10≈92.37%.

The final scores from high to low are as follows: Ideological and political education A1 (18.34), study style construction A3 (17.16), Party and League building A2 (17.07), team building A4 (9.79), educational effect A6 (9.23), and condition guarantee A5 (8.49). Originally, in the evaluation of the quality of ideological and political education, the 100-point score was divided into 20 points for "ideological and Political Education", 20 points for "Party and League Building", 20 points for "Study style Building", 20 points for "team Building", 10 points for "Conditions and Guarantees", and 10 points for "educational effectiveness". We can see that all the scores are above the relatively good level (the relatively good level is half of the total score for each item). It indicates that the overall situation of ideological and political education is above average and the result is good. Therefore, in future ideological and political education, teachers should pay more attention to inspiring students. In terms of the latest knowledge in the subject, they should combine theory with practice to better cultivate students' ability to solve problems.

IV. Conclusion

The quality assessment model of ideological and political education in colleges and universities determines the weights of the indicators through hierarchical analysis, and uses the improved K-Means clustering algorithm to realize data mining and analysis, which greatly improves the scientificity and objectivity of the assessment. The empirical study shows that the assessment results based on improved clustering analysis are highly consistent with the actual distribution of students' grades in 500 assessment data of ideological and political education in colleges and universities. The assessment data showed that the first-level index of ideological and political education scored the highest, reaching 18.34 points (91.68%), followed by 17.16 points (85.79%) for the construction of academic style and 17.07 points (85.34%) for the construction of party and group, while the index of team building was relatively low, with 10.57 points (52.83%). Cluster analysis divided the samples into three levels, of which "good" level accounted for 50.6%, "medium" level accounted for 37.6%, and "poor" level accounted for 11.8%, and this distribution had a significant correlation with the distribution of students' scores (more than 85 scores accounted for 70.6%, 65-85 scores accounted for 23.4%, and less than 65 scores accounted for 6%). The results of the data analysis support the effective application of the improved K-Means clustering algorithm in education quality assessment, which provides a quantitative basis for decision-making in ideological and political education in colleges and universities. In the future, the assessment index system should be further improved, the data sample coverage should be expanded, and the dynamic adjustment mechanism of index weights should be strengthened, so that the assessment results can more accurately reflect the status quo of education quality, and provide directional guidance for the continuous improvement of the quality of ideological and political education in colleges and universities.

Funding

Project Name: Research and Practice Project on Vocational Education and Teaching Reform in Henan Province in 2022. Research and Practice of Curriculum Aesthetic Education Construction in Vocational Colleges (No.2022682);

General Project of Humanities and Social Science Research in Universities of Henan Province"; Project Name: "Research on Moral Education of China Excellent Traditional Culture Empowering Universities, Primary and Secondary Schools" (Project Number: 2025-ZDJH-549); Project Host: Song Lili.

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