Quality Evaluation for Online Distance Education Based on Grey Relational Degree

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Abstract

Aiming to address the problems of low accuracy and long time consuming of existing education quality evaluation models, a new online distance education quality evaluation model based on grey correlation algorithm is proposed. Firstly, calculate the membership of education quality data, and complete the data collection through cluster mining. Secondly, construct the evaluation index system according to the set evaluation principles. Finally, the grey correlation degree algorithm is used to mine the correlation degree relationship of education quality index data and complete the construction of the evaluation model. The comparison test results show that the evaluation accuracy of the built model is 0.98, the response time is only 0.7s, the CPU proportion is only 27%, and the satisfaction rate is more than 0.97. Therefore, the model has higher application value.

Keywords: Grey correlation degree algorithm, Evaluation index system, Fuzzy c-means algorithm, Online distance education, Educational quality evaluation

1 Introduction

Online education mode is an effective supplement to traditional education methods [1-2]. Online distance education quality evaluation is an important part of online distance education activities. It is a process of measuring, analyzing, comparing, and giving value judgments to the process and results of online distance education activities by using effective evaluation techniques and means with the goal of improving teaching quality and effect [3-5]. Quality assessment is a key link in the quality assurance of online education model and a link between objective standards and actual processes [6]. However, the objective education quality evaluation method considers few influencing factors, resulting in the application of the evaluation method has great limitations and the problem of insufficient accuracy [7]. Therefore, relevant scholars have conducted in-depth research on this issue.

Reference [8] proposes the method of education quality evaluation based on decision tree. First, it analyzes the principle of quality evaluation, designs the quality evaluation function module, and carries out design research on the evaluation system from both hardware and software to obtain the final evaluation results. Reference [9] put forward an educational quality evaluation method based on discrete Poisson mixed model. In this method, each discrete Poisson component in the mixed model corresponded to a class of students with similar evaluation models, and the evaluation scores in the corresponding evaluation models were represented by the model parameters in the discrete Poisson distribution. Reference [10] proposes an education quality evaluation model based on representation learning. This method maps learners and resources one by one according to the representation learning principle. Based on the obtained mapping results, it constructs an education quality evaluation index system to judge whether learners' learning achievements reach the ideal level. However, this method needs to be tracked for a long time, resulting in high application limitations. Reference [11] proposes a quality evaluation model based on multi-objective evolution. This method first designs multiple module structures in the model structure, including database module, multi-function evaluation module, etc., and then sets a multi-level index system according to the evaluation criteria, and calculates the weight results of different indicators. Finally, the weight obtained is optimized by multi-objective evolutionary algorithm to obtain the final evaluation result. However, this method is time-consuming. Reference [12] proposes an education quality evaluation method based on feature offset compensation. This method uses a Glove pre-training model to obtain education quality data, calculate the impact factors of education quality data, and normalize the impact factors. Finally, the evaluation of education quality is completed through the cross loss function, but the evaluation method of teaching quality has the problem of low accuracy.

To solve the many unsolved needs of the existing methods mentioned above, a quality evaluation model of online distance education based on grey correlation algorithm is proposed. The detailed research technical route is as follows:

(1) The evaluation needs to be carried out on the basis of relevant data, set the clustering center of fuzzy C-means clustering, construct the objective function of online remote teaching data mining according to the membership matrix, and solve the objective function to complete the education data mining.

(2) Based on the data obtained from mining and the

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construction principles of multiple evaluation indicators, a detailed evaluation index system of education quality is constructed.

(3) After completing the construction of the indicator system, the grey correlation algorithm is introduced to build the education quality evaluation model. The output of the model is the final evaluation result.

(4) The experimental analysis takes online distance education data mining accuracy, education quality evaluation accuracy, evaluation response time, CPU percentage and satisfaction as indicators.

2 Data Mining in Online Distance Education

To obtain more accurate evaluation results, data was mined from the open online distance education platform. The fuzzy C-means clustering algorithm [13-15] used in this mining is the combination of fuzzy theory and C-means clustering algorithm, which gives it the advantages of both [16-18] to get more accurate mining results.

First, the online distance education data category B is set, so the fuzzy clustering process needs to set B clustering centers. The membership matrix is constructed according to the cluster center as shown in formula (1):

$$A = [Y_i^{''}]_{Bs}, \tag{1}$$

where A represents the membership matrix of online distance education quality data, and s represents the cluster center, $Y_i^{''}$ represents online distance education data sample.

Next, the objective function of mining in online distance education is constructed as:

$$F(A, B') = \sum_i^B Y_i^{''} \| Y_k^{'} - s_i \|, \tag{2}$$

Where $F(A, B')$ represents the objective function, $Y_k^{'}$ is the initial cluster center, and s_i is the i cluster center.

Meanwhile, the formula for calculating the membership degree of online distance education sample data is:

$$A_i^{''} = \frac{\sum_i^B \| Y_k^{'} - s_i \|^t}{\| Y_k^{'} - s_i \|^t}, \tag{3}$$

where $A_i^{''}$ represents the membership of online distance education quality sample data, and t represents the number of iterations.

After calculating membership, the cluster centers of online distance education sample data are updated. The update formula of the cluster center is shown in formula (4):

$$s_k = \frac{\sum_i^B Y_k^{'} A_i^{''}}{\sum_i^B Y_k^{'}}, \tag{4}$$

where s_k represents the cluster center of the updated online distance education sample data.

The iteration stop threshold ω of online education sample data mining is set, and the final education sample data is obtained by combining the threshold ω with the education sample data clustering mining center. The constraint conditions of iteration stop threshold are shown in formula (5):

$$\| s_{k+1} - s_k \| < \omega. \tag{5}$$

When the constraint condition shown in formula (5) is met, the mining of online distance education sample data is stopped.

Based on the online distance education quality data obtained from the above mining, carry out the follow-up online distance education quality evaluation.

3 Multi-level Index System in Education Quality Evaluation

Based on the sample data of online distance education mined above and supported by the construction principles of the evaluation index system, the index system of education quality evaluation is constructed.

When determining the quality evaluation indicators of online distance education, we should follow the 3R principle, relevance principle, systematic principle, universality principle, difference principle and data availability principle, of which the 3R principle is lightweight, reuse and recycling [19]. Therefore, according to the above principles and combined with the actual teaching situation, the quality evaluation index system of online distance education is constructed. The evaluation index system is shown in Table 1.

In Table 1, the evaluation indicators include the orientation of the teaching center, the idea of running a school, the teachers, the orientation and planning of the school, the accessibility of courseware and resources, the utilization rate of courseware and resources, the resource transmission performance, rapidity, stability, the privacy of teaching information, teaching methods, teaching flexibility, etc. The indicators in the above construction system can effectively reflect the current situation of online distance education, thus improving the evaluation reliability of the model.

Table 1. Online distance education quality evaluation index system

Target layer	Criteria layer	Index layer
Evaluate the quality of online distance education	Online distance education school positioning	Orientation of teaching center
		Thinking about educational thoughts
		Thoughts on running a school
		Drop-out rate
		Employment rate
		Teachers
		School orientation planning
	Online distance education courseware and resources	Courseware compilation
		And easy availability of courseware
		And real-time of courseware and resource
		Content enrichment of courseware
		Courseware content integrity
		The utilization rate of courseware and resources
	Online distance education courseware and resources	Resource transmission performance
		Fastness and stability
		Timeliness of network maintenance
		Network update frequency
		Privacy of teaching information
	Online distance education service	Timeliness of reply
		Educational assistance
		Cost of education
		Teaching feedback
	Online distance education method	Teaching method
		Teaching situation
		Teaching flexibility
		Teaching pertinence
		Teaching practice
		Teaching supervision

4 Quality Evaluation Model Based on Grey Relational Degree

After the construction of the above indicator system, the grey correlation algorithm is used to build the education quality evaluation model to obtain accurate evaluation results.

Grey Relational Analysis (GRA) is a method of grey system analysis, which uses "Grey Relational Analysis" as the basis to measure the correlation between different indicators. In this algorithm, correlation degree is an index between two systems. If the change trend of the two indicators is consistent, it can be said that the degree of correlation between the two indicators is high, and vice versa, the degree of correlation is low [20-22].

The set of evaluation indicators is shown in formula (6):

$$U_0 = \{u_0(1), u_0(2), \cdots, u_0(n)\}, \tag{6}$$

where U_0 represents the set of educational quality evaluation indicators, $u_0(n)$ represents the n educational quality evaluation indicator, and the total number of online distance education quality evaluation indicators is n [23-24].

Acquisition of online distance education quality evaluation index data samples, the evaluation index data sample is shown in formula (7):

$$U_0^{'} = (U_0, U_1, \cdots, U_m), \tag{7}$$

where $U_0^{'}$ is the evaluation index data sample, and U_m is the m-th evaluation index set.

In order to eliminate the impact caused by the dimension of the indicator, the dimensionless processing of the education quality evaluation indicator data sample is introduced. First, the extreme value method is introduced to eliminate the dimension of the indicator sample data. The calculation formula is shown in formula (8):

$$U_i^{'}(l) = \frac{U_i(l) - U_{\min}}{U_{\max} - U_{\min}}, \tag{8}$$

where $U_i^{'}(l)$ represents the index sample data after the extremum method, $U_{\min}$ is the minimum indicator data, and $U_{\max}$ is the maximum indicator data.

Update formula (7) according to the above formula to obtain new evaluation index data samples. The updated formula is:

$$U_0^{''} = (U_0^{'}, U_1^{'}, \cdots, U_m^{'}), \tag{9}$$

where $U_0^{''}$ represents the new online distance education quality evaluation index data sample.

Calculate the grey correlation coefficient in the education quality evaluation model of the grey correlation algorithm to prepare for the calculation of the grey correlation degree. The formula is:

$$\varphi_i(l) = \frac{\min |U_0^{'}(l) - U_0^{''}| + a \max |U_0^{'}(l) - U_0^{''}|}{|U_0^{'}(l) - U_0^{''}| + a \max |U_0^{'}(l) - U_0^{''}|}, \tag{10}$$

where $\varphi_i(l)$ represents grey correlation coefficient, a represents the grey correlation parameter.

According to the grey correlation coefficient calculated by formula (10), the education quality evaluation model is constructed. The expression is shown in formula (11):

$$V_i = \frac{\sum_{i=1}^{n} \varphi_i(l)}{n}. \tag{11}$$

The output result of formula (11) is the final education quality evaluation result, and the construction of the education quality evaluation model has been completed.

5 Experimental Analysis

5.1 Experimental Scheme

After the evaluation model is built, the actual application performance of the model needs to be evaluated. Therefore, on this basis, comparative analysis experiments are designed. The experimental scheme is as follows:

Step 1: Experimental data. Before the experiment, it is necessary to clarify the research object and give specific experimental data.

Step 2: Experimental performance index. In order to analyze the performance of this method, the accuracy of education quality evaluation, the response time of evaluation, and students' achievement are selected as the performance indicators, and the specific calculation formula of the performance indicators is given.

Step 3: Performance analysis. Through the above performance indicators, the performance of the evaluation method is specifically analyzed, and the experiment is carried out in the form of comparative analysis. The comparative methods are the proposed method in this paper, the method in reference [8] and the method in reference [9].

5.2 Experimental Data

The online distance education platform of a university is selected as the research object. The data selected from the platform is from the civil engineering major. The number of teachers participating in the experiment is 10, and the total number of students is 160. The student is a sophomore student, with a total of 4 classes. Detailed experimental data are shown in Table 2.

The proportion of online distance education hours in professional courses, and the civil engineering professional courses selected for the experiment are engineering mechanics, fluid mechanics, geotechnical mechanics, engineering geology and computer application. The online distance education duration of five courses is shown in Figure 1.

Table 2. Experimental data

Serial number	Data name	Numerical value
1	Professional	Civil engineering
2	Teachers' number	10
3	Students' number	160
4	Courses	Engineering mechanics/ fluid mechanics/ geotechnical mechanics/ etc/
5	Score evaluation	E-test papers

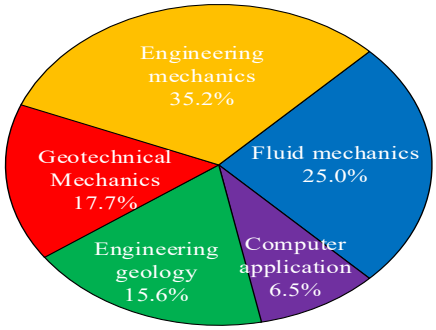

Figure 1. Proportion of online distance education duration of different courses

5.3 Experimental Performance Indicators

The evaluation precision of education quality, evaluation response time, student achievement, CPU proportion, and satisfaction degree are taken as the performance indicators. The evaluation precision of education quality is the score of method evaluation result compared with the actual evaluation result, with the highest score being 1. The calculation formula of the quality evaluation accuracy of online distance education is:

$$Y = \frac{Y_1}{Y_2}, \tag{12}$$

where Y indicates the accuracy of education quality evaluation, Y_1 indicates the evaluation result score of evaluation method, and Y_2 indicates the actual evaluation result score.

The evaluation response time refers to the time from

the input data to the output results. The shorter the response time, the higher the working effect of the education quality evaluation model. The evaluation response time performance index does not need to be calculated and obtained through the formula. The value is directly calculated through the software provided by the computer to obtain the data.

The student achievement index is counted by the electronic test paper of the online distance education network platform. A high score for the student achievement index indicates that the evaluation model has achieved good application effect in the evaluation of education quality, indicating that the evaluation model can bring a positive role in promoting online distance education, thus improving student achievement.

The CPU proportion is automatically counted by the computer own software. Lower index value brings better actual operation effect of the evaluation method.

Satisfaction can effectively reflect whether the teaching quality evaluation method has been recognized by users in its practical application. Higher value will cause higher recognition degree.

5.4 Evaluation Performance Analysis

5.4.1 Data Mining Accuracy of Education Quality

Taking the accuracy of online distance education quality data mining as an indicator, compare this method with the methods of reference [8] and reference [9], and compare the accuracy of education quality data mining of the three methods in the five courses of engineering mechanics, fluid mechanics, geotechnical mechanics, engineering geology and computer application. For the convenience of experiment, the course number is 1, 2, 3, 4 and 5. The precision results of online distance education quality data mining are shown in Figure 2.

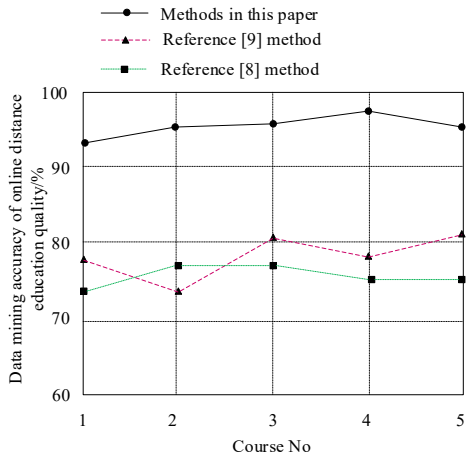

Figure 2. Precision results of education data quality mining by different methods

From the comparison results of online distance education quality data mining accuracy shown in Figure 2, the mining accuracy of the method in this paper has always maintained above 90%, with a maximum of 97%; The maximum mining accuracy of reference [8] method is only 77%, and that of reference [9] method is 81%. From the above data, the precision of data mining of online distance education quality in reference [8] and reference [9] is lower than that in this paper, so this paper can provide strong data support for online distance education quality evaluation.

5.4.2 Accuracy of Education Quality Evaluation

Make statistics on the accuracy of education quality evaluation to analyze the three types of education quality evaluation accuracy. The comparison results of the accuracy of education quality evaluation of the three methods are shown in Table 3.

Table 3. Precision results of educational quality evaluation by different methods

Courses	Accuracy of quality evaluation		
	The proposed method	Reference [8]	Reference [9]
Engineering mechanics	0.98	0.95	0.90
Fluid mechanics	0.99	0.94	0.91
Geotechnical mechanics	0.99	0.92	0.88
Engineering geology	0.98	0.95	0.86
Computer application	1.00	0.93	0.92

According to the accuracy results of education quality evaluation in Table 3, the accuracy of the methods in this paper are all above 0.98, and the highest accuracy reaches 1.00. The maximum accuracy of the reference [8] method is 0.95, while the minimum value of the reference [9] method is 0.86. Therefore, the evaluation model of online distance education quality evaluation is the most accurate and has the basic feasibility.

5.4.3 Evaluate the Response Time

Analyze the evaluation response time of the methods in this paper, reference [8] and reference [9], by taking the average value for different courses, and verify the evaluation efficiency of different methods through this performance index. The response time results are shown in Figure 3.

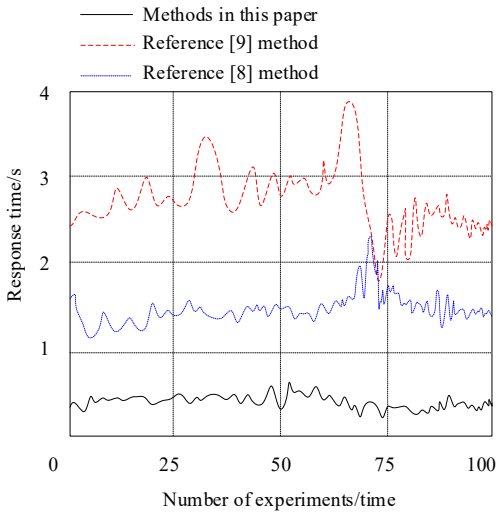

Figure 3. Evaluation response time results of different evaluation methods

In Figure 3, the evaluation response time of the method in this paper is the shortest and the most stable, and its response time curve is generally below 0.7s, while the response time curve of the method in Reference [8] is generally above 1s, and the response time curve of the method in Reference [9] is generally higher, with its minimum value reaching more than 1.7s, and the maximum response time reaching 3.8s.

5.4.4 CPU Ratio

CPU share can increase with poor or unstable operations or complex algorithms which can affect the performance of the computer, possibly leading to a computer crash. *Therefore, when applying different evaluation methods, the CPU share and application performance are taken into consideration. The total test time is 48h, and the CPU ratio is shown in Figure 4.

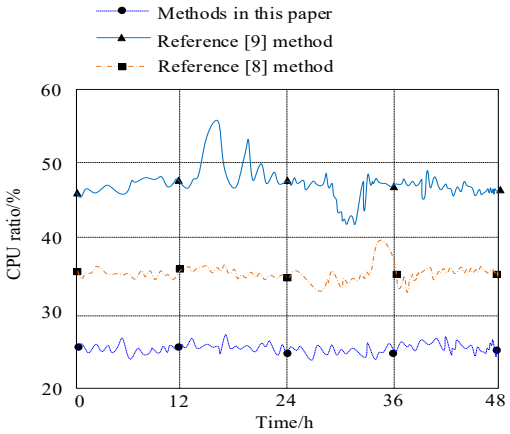

Figure 4. CPU ratio results

In Figure 4, the CPU ratio curve of the method in this paper is the most stable, and there is no large fluctuation within 48h, but the two literature methods have one and two large fluctuations within 48h, which indicates that the two literature methods are not stable in the operation process. The CPU ratio value shows that the highest CPU ratio of the method in this paper is 27%, and the lowest CPU ratio of the two methods in the literature is 33% and 42% respectively.

5.4.5 Degree of Satisfaction

The quality of a method is also reflected in whether the method can be recognized by users. Therefore, in order to verify the satisfaction of different teaching quality evaluation methods, the satisfaction reflects whether the evaluation method is recognized or not. The highest satisfaction value is 1.A satisfaction value above 0.8 indicates that a user was recognized, and a value greater than 0.9 indicates that a user is very recognized. The closer the index value is to 1, the higher the degree of recognition. The satisfaction test results are shown in Table 4.

In Table 4, the user satisfaction of the three methods reached more than 0.80, indicating that the three methods have been recognized and reached the qualification standard. The highest satisfaction value was the method in this paper at 0.99, indicating that the method in this paper can meet the use requirements to the maximum extent under the condition of meeting the use standard, and has been recognized by university users.

Table 4. Analysis of satisfaction results of different methods

Number of participants/ people	Degree of satisfaction		
	This paper	Reference [8]	Reference [9]
15	0.98	0.90	0.88
30	0.97	0.92	0.89
45	0.99	0.91	0.91
60	0.97	0.90	0.91
75	0.97	0.91	0.88
90	0.98	0.93	0.87
105	0.99	0.93	0.89
120	0.99	0.91	0.92
135	0.97	0.90	0.91
150	0.98	0.92	0.91

6 Conclusion

This paper proposes a new quality evaluation model of online distance education based on grey correlation algorithm. The model collects the data of online distance education, builds the evaluation index system of online distance education quality, introduces the gray correlation algorithm, and builds an efficient and accurate online distance education quality evaluation model. The test results show that the evaluation accuracy of the method in this paper is up to 0.98, the evaluation response time is always below 0.7s, and the CPU proportion is only 27%. It has been recognized in practical application, and its satisfaction has reached more than 0.97, which verifies the effectiveness, feasibility, and higher practical application value of the evaluation method in this paper. The education quality evaluation model studied can effectively evaluate the online distance education situation of different schools, help schools adjust online teaching strategies in a timely manner, and has a broad application prospect. In this study, due to the limitation of time and space, only five courses were evaluated. In future research work, the quality of online distance education will be evaluated for more courses.

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Biographies

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Weina Fu got her BSc from Jilin University, China in 2003, MSc from Jilin University, China in 2006, and PhD from Inner Mongolia University in 2012. She now acts as an Associate Professor in Hunan Normal University, has published more than 20 papers in high-quality journals, with highest citation nearly 500. Her main research domain is intelligent education.