

# A Novel Grey Fuzzy Clustering Model and its Application on Students' Performance Evaluation

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**Abstract:** Aiming to address the issues of traditional student evaluation methods, which tend to be overly subjective and overlook the intrinsic data structure, this paper introduces a novel grey fuzzy clustering model named the grey entropy game-weighted fuzzy c-means (GEG-WFCM) model. Firstly, subjective weights are calculated using the subjective-objective relationship analysis method, while objective weights are determined through the entropy weight method. Then, a comprehensive approach is adopted, leveraging game theory to calculate the final weights. Based on these comprehensive weights, the relative grey correlation coefficient and fuzzy weighted c-mean algorithm are incorporated to yield the ultimate evaluation results. The proposed model was applied to evaluate student performance, and the experiments show that it can obtain scientific and reasonable results. The model not only acknowledges the expertise of experts but also respects the objectivity of the data, thus circumventing the limitations of purely subjective judgments, and surpassing traditional evaluation methods.

**Keywords:** Grey Correlation; Comprehensive Evaluation; Entropy Weight; Clustering; Fuzzy C-Means

## 1. Introduction

Evaluation of student performance is a comprehensive assessment of the learning process and certain stages of learning, which is designed to enable students to understand their mastery of knowledge and to identify their progress and shortcomings at this stage (Wu *et al.*, 2017). A scientific comprehensive student evaluation system can objectively reflect the problems in the teaching process and play a positive role in guiding teachers' teaching and students' development. Therefore, the establishment of a scientific and effective comprehensive evaluation system for students is a problem that needs to be solved urgently.

Numerous scholars have put forward various evaluation algorithms. For example, Liu *et al.* (2012) used AHP to identify the evaluation objectives and index weights, and fuzzy comprehensive evaluation to comprehensively evaluate the students' vocational ability. Wu *et al.* (2017) used a combination of factor analysis and cluster analysis to evaluate students' performance and finally classified students into several clusters through cluster analysis based on factor scores for objective and comprehensive evaluation. Rosadi *et al.* (2017) grouped data by fuzzy C-mean clustering

algorithm when assessing students' academic performance and validated their application. Wang (2022) improved the K-means algorithm based on student information to address the problem of large course differences in the evaluation of student performance and proved that the improved pan of this paper has obvious advantages through data. Ren *et al.* (2022) proposed a compartment energy consumption analysis model based on combined weighting (AHP and entropy weighting method) and grey-fuzzy comprehensive evaluation, which comprehensively evaluated the energy consumption of 22 compartments under the same special painting process, and selected the most reasonable cabin energy consumption scheme. Luo *et al.* (2022) propose a health condition rating system covering system level and device level, use the G1 group method and projection recourse method to get the optimal weights, propose an improved grey TOPSIS comprehensive evaluation model based on prospect theory, and verify the validity of the proposed model in this paper. Kou *et al.* (2022) determined the combination weights of the factors based on game theory, established a comprehensive evaluation model of the open pit mine truck scheduling system based on grey correlation analysis (GRA-TOPSIS), and verified the effectiveness of the model. Gu *et al.* (2023) proposed an employment quality evaluation model based on grey correlation and fuzzy C-mean (FCM) to address the defects of large errors in employment quality evaluation and compared the algorithm with other employment quality evaluation models to verify the superiority of the model. Zhao (2023) establishes a health state estimation method that combines grey clustering and fuzzy comprehensive evaluation methods to evaluate the health state of the power supply under multiple sets of data using grey clustering and demonstrates through examples that the method is effective in estimating the operating condition of the power supply that is normally degraded.

Most evaluation models are mainly constructed with fuzzy comprehensive evaluation, cluster analysis, grey cluster analysis, and other evaluation models combined with single-weight assignment methods. Nevertheless, the single-weight assignment way can't fully consider the characteristics of different indicators and the relationship between them, leading to unreasonable weight assignment. Fuzzy comprehensive evaluation relies on the subjective judgment of experts' experience, which may lead to insufficient accuracy of the evaluation results. A single clustering method may not be able to accurately reveal the intrinsic structure of data when dealing with complex and high-dimensional data.

In this study, we construct a fuzzy c-mean weighted clustering evaluation model, named GEG-WFCM, for comprehensive evaluation. The main contributions are:

1. By integrating the G1 method and entropy weight method through game theory, the model can comprehensively and flexibly consider both subjective and objective factors, leading to a more reasonable allocation of weights.
2. By introducing the relative grey correlation coefficient, the model objectively reflects the relative relationship between evaluation objects and evaluation indices, thus reducing the interference of subjective factors and improving the accuracy of the data.
3. By combining the relative gray correlation coefficient with the weighted fuzzy c-means clustering algorithm (WFCM), the model can better handle fuzzy and uncertain data, improving the accuracy and stability of clustering results.
4. The model is applied to the student comprehensive performance evaluation, and the results verify the effectiveness of the model.

## 2. GEG-WFCM Model

### 2.1 Preliminaries

**2.1.1 The group G1 method (G1).** The G1 method, also known as the ordinal relationship analysis method, is a subjective weighting method that is an improvement of the Analytic Hierarchy Process (AHP). This method uses the ordinal relationship established by decision-makers between different indicators as a standard for assigning weights to indicators (Ye *et al.*, 2023).

*2.1.2 The entropy weight method (EWM).* The EWM was developed from the information entropy theory proposed by Claude Shannon (Shannon, 1948), and it is an objective assignment method for determining weights, which is widely used in comprehensive evaluations of multiple indicators and decision analysis. The method is based on the concept of information entropy and determines the weight of each indicator by measuring its information.

*2.1.3 The game theory (GT).* The theoretical foundation of game theory can be traced back to the classic book published by John von Neumann and Oskar Morgenstern (von Neumann & Morgenstern, 1947). Game theory mainly studies the interaction between formalized incentive structures. It is a mathematical theory and method for studying phenomena with a struggle or competitive nature. Game theory considers the predicted and actual behaviors of individuals in a game and studies their optimal strategies.

*2.1.4 The Grey Relational Coefficient (GRC).* The GRC is used to measure the degree of correlation between two sequences and is suitable for decision analysis in the case of incomplete information. The grey correlation coefficient stresses the relative changes between the series and better reflects the actual correlation between the factors (Deng, 1989).

*2.1.5 The weighted fuzzy C-means (WFCM).* The FCM is a classical clustering algorithm that describes the degree to which each data point belongs to each cluster by dividing it into multiple clusters and assigning an affiliation to each data point (Peizhuang, 1983). Later, some scholars introduced weights to improve the FCM algorithm, i.e., weighted fuzzy C-mean (WFCM), which can reflect the importance of the indicators well enough and improve the accuracy of the clustering results. It can also adaptively adjust the weights of each feature to provide more flexible clustering results with better adaptability.

The current study firstly obtains subjective weights by the G1 method, objective weights by the entropy weight method, and finally comprehensive weights by game theory, thus overcoming the disadvantage of too much subjectivity of the AHP method. Then, the relative grey correlation coefficient of each index of each evaluation object is calculated, and the coefficient is brought into the WFCM clustering algorithm to get the final evaluation result. This evaluation method fully takes into account the non-linear relationship between the data, thus making the evaluation results more adaptable and objective.

## 2.2 Combined subjective and objective weighting solution

*2.2.1 Initialize the original matrix.* Assuming  $n$  students and  $P$  indicators, let  $A = \{A_1, A_2, A_3, \dots, A_n\}$  be the set of students and  $C = \{C_1, C_2, C_3, \dots, C_p\}$  be the set of indicators to obtain a raw data matrix  $D$  of  $N * P$ :

$$D = \begin{matrix} & X_1 & X_2 & \cdots & X_p \\ \begin{matrix} A_1 \\ A_2 \\ \vdots \\ A_n \end{matrix} & \begin{bmatrix} E_{11} & E_{12} & \cdots & E_{1p} \\ E_{21} & E_{22} & \cdots & E_{2p} \\ \vdots & \vdots & \ddots & \vdots \\ E_{n1} & E_{n2} & \cdots & E_{np} \end{bmatrix} \end{matrix} \quad (1)$$

*2.2.2 Calculate the indicator subjective weight.* The G1 method is in essence a subjective weighting method improved and optimised based on hierarchical analysis. When the AHP has a large amount of data, too many evaluation indicators, and is too cumbersome to solve, the G1 method overcomes these shortcomings by introducing the idea of group decision-making and considering the weight of each expert.

Each expert's weight is  $d_q$  and  $0 < d_q < 1$ .

$$W_j = \sum_{i=1}^m d_q \omega_j^q \tag{2}$$

where  $W_j$  denotes the composite weight of the indicator at  $j$ ,  $\omega_j^q$  is the weight of the indicator at  $q$  for the expert and  $m$  is the total number of experts. Thus, the subjective weights are obtained.

2.2.3 Determine the objective weight of each indicator using the entropy weighting method. The data in  $D$  was first normalized according to the following formula:

$$e_{ij} = \frac{E_{ij} - \min(E_{1j}, E_{nj})}{\max(E_{1j}, E_{nj}) - \min(E_{1j}, E_{nj})} \quad (1 \leq i \leq n, 1 \leq j \leq p) \tag{3}$$

Firstly, based on the standardized decision matrix, the weight of each evaluation object under each indicator is obtained, i.e. the weight of the  $i^{\text{th}}$  evaluation object concerning the value of the  $j^{\text{th}}$  indicator.

$$P_{ij} = \frac{e_{ij}}{\sum_i^n e_{ij}}, 0 \leq P_{ij} \leq 1 \tag{4}$$

It is then possible to create the weighting matrix for the new data as follows:

$$P = \begin{matrix} & X_1 & X_2 & \cdots & X_p \\ \begin{matrix} A_1 \\ A_2 \\ \vdots \\ A_n \end{matrix} & \begin{bmatrix} p_{11} & p_{12} & \cdots & p_{1p} \\ p_{21} & p_{22} & \cdots & p_{2p} \\ \vdots & \vdots & \ddots & \vdots \\ p_{n1} & p_{n2} & \cdots & p_{np} \end{bmatrix} \end{matrix} \tag{5}$$

Then find the entropy value of each indicator, according to equation (6):

$$e_j = -\frac{1}{\ln(n)} \sum_{i=1}^n p_{ij} \ln p_{ij}, j = 1, 2, \dots, e_j \geq 0 \tag{6}$$

The entropy method assigns weights based on the degree of difference in the sign values of each indicator, which results in the corresponding weights of each indicator:

$$d_j = 1 - e_j \tag{7}$$

If  $p$  denotes the number of indicators then the weight of each indicator is defined as

$$W_j = \frac{d_j}{\sum_{i=1}^p d_i} \tag{8}$$

Finally, the objective weights of indicators are obtained.

2.2.4 Solve for composite weights using the game theory methodology approach. According to game theory,  $N$  weight calculation methods are chosen to form a set of weights  $W = \{w_1, w_2, w_3, \dots, w_n\}$ , for any linear combination of these  $N$  vectors,  $w = \sum_{k=1}^N a_k w_k^T$  that can be obtained, and dispersion minimization is performed for  $w$  and  $w_k$  according to the optimal strategy.

$$\text{Min} \left\| \sum_{k=1}^N a_k w_k^T - w_j^T \right\|^2, j = (1, 2, \dots, N). \tag{9}$$

Based on the differential properties of matrices, the optimal first-order derivative condition satisfies the following equation:

$$\begin{bmatrix} w_1 w_1^T & \cdots & w_1 w_N^T \\ \vdots & & \vdots \\ w_N w_1^T & \cdots & w_N w_N^T \end{bmatrix} \begin{pmatrix} a_1 \\ \vdots \\ a_N \end{pmatrix} = \begin{pmatrix} w_1 w_1^T \\ \vdots \\ w_N w_N^T \end{pmatrix} \tag{10}$$

The coefficients  $(a_1, a_2, a_3, \dots, a_n)$  were normalized to obtain the optimal weighting coefficients and the final weights were determined as follows:

$$w^* = \sum_{k=1}^N a_k^* w_k^T \tag{11}$$

### 2.3 Evaluation result solving

2.3.1 Data standardisation. In order to carry out the data into the FCM algorithm for cluster analysis, the raw data is first normalized with the following formula:

$$h_{ij} = \frac{E_{ij}}{\max(E_{1j}, E_{nj})} (1 \leq i \leq n, 1 \leq j \leq p) \tag{12}$$

The normalization matrix obtained is:

$$H = \begin{matrix} & X_1 & X_2 & \cdots & X_p \\ \begin{matrix} A_1 \\ A_2 \\ \vdots \\ A_n \end{matrix} & \begin{bmatrix} h_{11} & h_{12} & \cdots & h_{1p} \\ h_{21} & h_{22} & \cdots & h_{2p} \\ \vdots & \vdots & \ddots & \vdots \\ h_{n1} & h_{n2} & \cdots & h_{np} \end{bmatrix} \end{matrix} \tag{13}$$

2.3.2 Calculate the grey correlation coefficient. The optimal sequence  $A^+$  and the worst sequence  $A^-$  were obtained from the normalized evaluation matrix, and the grey correlation coefficients between each index and the positive ideal solution for each evaluation object were calculated according to Equation (14):

$$\gamma_{ij}^+ = \gamma(A_j^+, A_{ij}) = \frac{\min_i \min_j S(A_j^+, A_{ij}) + \rho \max_i \max_j S(A_j^+, A_{ij})}{S(A_j^+, A_{ij}) + \rho \max_i \max_j S(A_j^+, A_{ij})} (1 \leq i \leq n, 1 \leq j \leq p) \tag{14}$$

where  $\rho \in [0, 1]$ , in general, and  $\rho = 0.5$  are substituted to find the result.

The grey correlation coefficient of each indicator with the negative ideal solution was calculated according to equation (15):

$$\gamma_{ij}^- = \gamma(A_j^-, A_{ij}) = \frac{\min_i \min_j S(A_j^-, A_{ij}) + \rho \max_i \max_j S(A_j^-, A_{ij})}{S(A_j^-, A_{ij}) + \rho \max_i \max_j S(A_j^-, A_{ij})} (1 \leq i \leq n, 1 \leq j \leq p) \tag{15}$$

2.3.3 Calculate the relative grey correlation coefficient. According to the grey correlation coefficient of each index of the evaluation object with the positive and negative ideal solutions can be obtained as the relative grey correlation coefficient, the formula is as follows:

$$\varepsilon_{ij} = \frac{\gamma_{ij}^+}{\gamma_{ij}^+ + \gamma_{ij}^-} (1 \leq i \leq n, 1 \leq j \leq p) \tag{16}$$

This results in a new decision matrix as follows:

$$R = \begin{matrix} & X_1 & X_2 & \cdots & X_p \\ \begin{matrix} A_1 \\ A_2 \\ \vdots \\ A_n \end{matrix} & \begin{bmatrix} \varepsilon_{11} & \varepsilon_{12} & \cdots & \varepsilon_{1p} \\ \varepsilon_{21} & \varepsilon_{22} & \cdots & \varepsilon_{2p} \\ \vdots & \vdots & \ddots & \vdots \\ \varepsilon_{n1} & \varepsilon_{n2} & \cdots & \varepsilon_{np} \end{bmatrix} \end{matrix} \tag{17}$$

2.3.4 Put the new grey correlation coefficient decision matrix into the weighted FCM cluster analysis. Regarding the evaluation sample set  $A = \{A_1, A_2, A_3, \dots, A_n\}$ ,  $n$  represents the number of samples;  $k$  evaluation samples are:  $A = \{A_1, A_2, A_3, \dots, A_{kp}\}$ ,  $p$  represents the number of indicators. The quality of the evaluation is mainly divided into  $C$  levels, i.e. there are  $C$  clustering centers, which can be represented as  $V = \{V^1, V^2, \dots, V^C\}$ , then the membership matrix can be represented as  $U = \{u_{ik}\}_{C \times V}$ , which meets the following conditions

$$\sum_{i=1}^c u_{ik} = 1, 1 \leq k \leq n \tag{18}$$

where  $u_{ik} \in [0,1], 1 \leq i \leq C, 1 \leq k \leq n$ , denotes the degree of affiliation belonging to the  $k$  evaluation sample at the  $i$  level.

$$d_{ik}^{(w)} = \sum_{j=1}^p w_j \| A_{kj} - v_{ij} \| \tag{19}$$

$d_{ik}^{(w)}$  is the weighted Euclidean distance with indicator weights,  $w_j$  is the weight of the  $j^{\text{th}}$  indicator, and the objective function is defined as:

$$J(U, V) = \sum_{i=1}^c \sum_{k=1}^n (u_{ik})^m (d_{ik}^{(w)}) \tag{20}$$

where  $m$  is the fuzzy weighted index.

2.3.5 Update the sample cluster centers to get the final clustering results. The grade of the evaluation quality result is  $C$ , the initialized clustering center for quality assessment is  $V_0$ , the number of iterations is  $t = 0$  and the iteration stopping threshold is set to  $\varepsilon$ . The membership of the evaluation sample is calculated according to the formula.

$$u_{ik} = \sum_{j=1}^c (d_{ik}^{(w)} / d_{jk}^{(w)})^{\frac{2}{m-1}} \tag{21}$$

Update the cluster center as follows:

$$v_i = \sum_{j=1}^n u_{ik}^m x_j / \sum_{j=1}^n u_{ik}^m \tag{22}$$

If  $|V_{(k+1)} - V_k| < \varepsilon$ , the clustering center is obtained, and the evaluation model is built according to the clustering center, otherwise,  $k = k + 1$  returns to the calculation iteration, i.e.,

Equation (22), and the final iteration stops, the clustering center of each evaluation object is obtained, and according to the principle of the maximum degree of affiliation, the clustering result of the evaluation object is obtained.

### 3. Students' performance evaluation with the GEG-FCM model

In this section, we take the comprehensive evaluation of student's performance in the course of "Programming Language" at a university as an example, select two classes with a total of 94 students' course performance as the experimental data samples, and obtain the clustering results and analyses and discusses them by bringing the sample data into the algorithmic procedure. All data are analyzed and calculated with Python software.

#### 3.1 Students' performance evaluation

*3.1.1 Establishment of evaluation indicators.* Based on the evaluation of technical courses in higher education and the characteristics of student evaluation, combined with the principles of developmental and diagnostic evaluation, specific student course evaluations are designed with the following indicators:

- (1) Classroom performance: students' performance in participating in the classroom learning process, including attendance, class discussion, hands-on work, group inquiry, answering questions, etc.
- (2) Assignment grades: including online and offline assignments and experimental designs
- (3) Curriculum Design: Comprehensive Major Assignment Design and Report Presentation
- (4) Mid-term test: a stage test of students' learning and application of course knowledge in the first half of the semester.
- (5) Final Examination: A summative examination of the student's learning and application of course knowledge during the semester.

The specific system for constructing indicators is shown in Table 1.

*3.1.2 Determination of subjective weights of indicators.* According to the calculation steps of the G1 method, let the experts rank and score the importance of each indicator, and finally get the subjective weight of each indicator obtained by the G1 method  $W_1 = [0.0955, 0.1337, 0.1873, 0.24305, 0.3402]$ , the scoring results are displayed in Table 2.

*3.1.3 Determination of objective weights for indicators.* The original data matrix is normalized and the objective weights of each indicator are finally obtained through the calculation steps of each formula of the entropy weighting method:  $W_2 = [0.0895, 0.06673, 0.5313, 0.18482, 0.1274]$ .

*3.1.4 Determination of composite weights for indicators.* According to the calculation method of game theory and the relevant formula, the two methods are combined with the optimal strategy to obtain the weight coefficients of 0.248 and 0.752, respectively. Then the final coupling weights are synthesised as  $W = [0.091, 0.083, 0.446, 0.199, 0.18]$ .

*3.1.5 Data standardisation.* The standardization of the students' scores on the various indicators resulted in the raw data matrix, as shown in Table 2.

**Table 1.** Indicator system for comprehensive evaluation of student achievement

<i>Level 1 indicators</i>	Secondary indicators
<i>Ordinary grades</i>	Classroom performance
	Assignment grades
	Curriculum design
<i>Examination results</i>	Mid-Term test
	Final examination

**Table 2.** Raw data on student performance

Student number	Classroom performance	Assignment grades	Curriculum design	Mid-term test	Final examination
1	0.99	0.99	0.9789	0.5111	0.4081
2	0.98	1	0.9889	0.9111	0.7040
3	0.97	1	0.9684	0.9	0.5612
4	0.95	0.94	0.9789	0.9222	0.5408
5	0.94	1	0.9684	0.8555	0.8979
6	0.88	1	0.9789	0.8777	0.5816
...	...	...	...	...	...
94	1	1	0.9684	0.7111	0.4081

3.1.6 *Determining positive and negative ideal solutions.* Based on the scoring matrix, the maximum value of each indicator is selected as the ideal solution, and the minimum value of each indicator is selected as the negative ideal solution:

$$A^+ = [1.0, 1.0, 1.0, 1.0, 1.0]$$

$$A^- = [0.85, 0.70, 0.94736842, 0.477777, 0.0408163]$$

3.1.7 *Calculation of the relative grey correlation coefficients.* Finally, the relative grey correlation coefficients for each indicator for each student were obtained according to the formula, and the coefficients are listed in Table 3.

3.1.8 *FCM weighted cluster analysis.* The above grey correlation coefficient matrix, brought to the design of the FCM weighted clustering algorithm program, sets the number of clusters for 4, the student performance is divided into four categories, respectively, the results are unsatisfactory, the results are average, good results, good results of the four major categories, respectively, with 1 ~ 4 to correspond to the various levels. After many iterations, the final weighted clustering results are obtained, as shown in Figure 1.

The normalized data is brought into the weighted FCM algorithm for calculation and the results are compared and analyzed with the grey FCM algorithm as shown in Figure 2.

It can be seen from Figure 2 that the two curves converge, indicating that the two algorithms are roughly the same in terms of clustering results, and the agreement rate is about 95.7%, which can be concluded that the grey FCM clustering algorithm is more scientific and reasonable. The results of the final student evaluation are shown in Table 4.

### 3.2 Results

According to the data in Figure 1, it can be found that most of the student's grades are at the average level and above, and only a small number of students' grades are at the unsatisfactory level, which indicates that most of the students in the course meet the overall objectives of the course and have a good learning effect. Among the students whose course grades are at an unsatisfactory

**Table 3.** Relative grey correlation coefficients for each indicator for each student

Student number	Classroom performance	Assignment grades	Curriculum design	Mid-term test	Final examination
1	0.5586	0.6111	0.5052	0.3346	0.4414
2	0.5495	0.6191	0.5052	0.6162	0.5957
3	0.5405	0.6191	0.4947	0.6087	0.5212
4	0.5225	0.5714	0.5052	0.6237	0.5106
5	0.5135	0.6191	0.4947	0.5787	0.6968
6	0.4594	0.6191	0.5052	0.5937	0.5319
...	...	...	...	...	...
94	0.5676	0.6191	0.4947	0.4812	0.4414



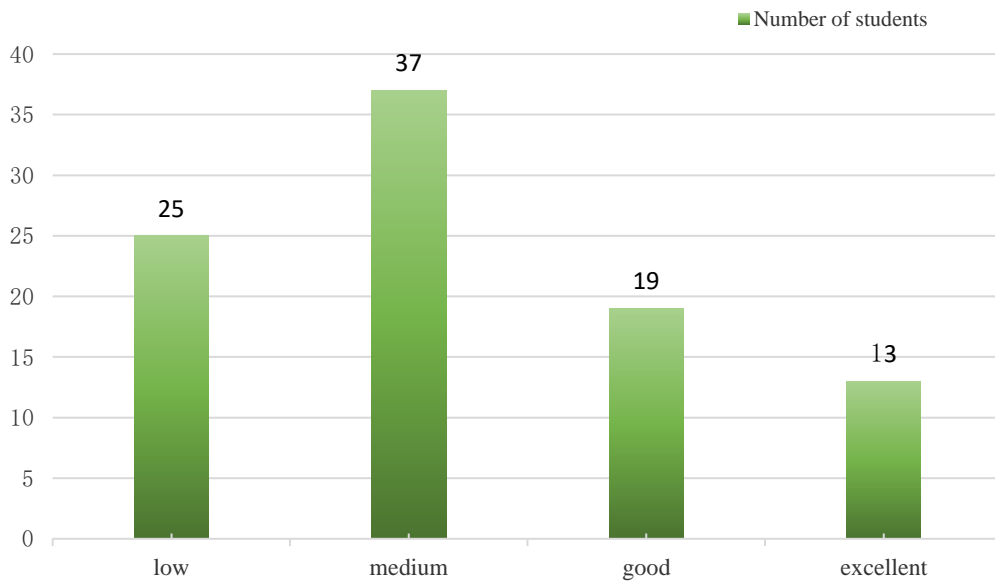


Fig 1. Clustering results of student performance

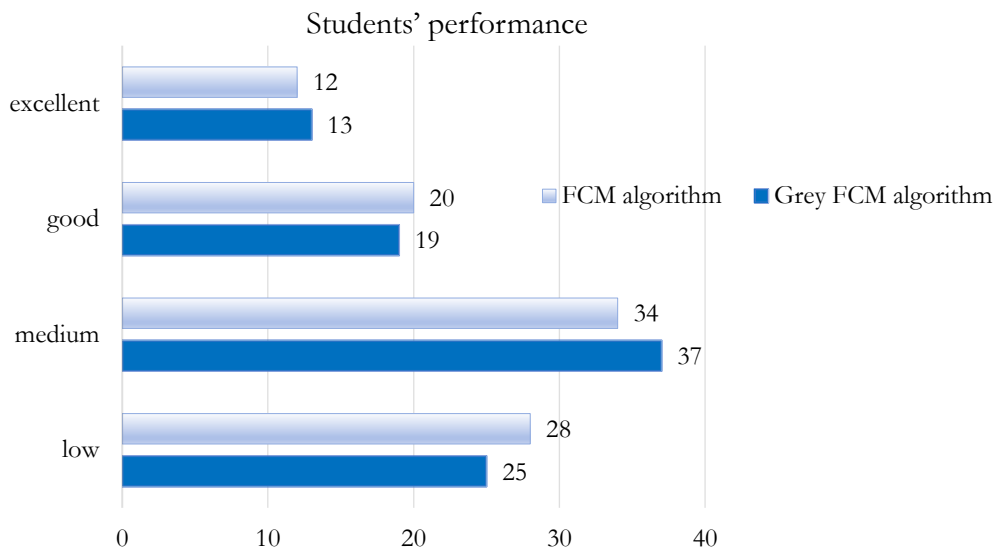


Fig 2. Comparison of clustering results of two algorithms

Table 4. Results of clustered grades for student course ratings

Student Number	1	2	3	4	5	6	7	8	9	10	...	94
Clustering results	1	3	2	2	4	2	3	3	4	2	...	1

level, there are 28 students, accounting for about 29.7% of the total number of students, and the proportion of the number of students is still large. From the analysis of the normalized data, the classroom performance, homework grades, and course design grades of these students are higher, while the examination grades are relatively low, which leads to unsatisfactory results of the student's course evaluation. These students should consolidate the learning of basic knowledge and consolidate the foundation through the practice of homework after class. Teachers should pay more attention to such students, play the guiding work of teachers, create situations for students, stimulate students' interest in learning, pay attention to the students' ordinary homework, and

provide counselling. The number of students whose course grades were at the average level of the grade was 34, accounting for about 36.1% of the total number of students, which is the largest number of students among all the clusters accounted for. For this type of students, students must consolidate their review after the class is over, practice diligently, pay attention to the correct rate, get to the bottom of the problem, and ask the teacher for more advice. Teachers should adjust the pace of the course to the cognitive acceptance of this type of students, they are the main body of the whole class, determining the level of a class. The number of students with good grades in the course is 20, accounting for about 20.6%, the proportion of good grades in the course is not a lot of such students are more skilled in grasping the basics, but lack attention to some of the details, in the process of learning, attention should be paid to easy to error, to pay more careful attention to some of the traps in the thinking, you can sort out the wrong questions to improve the degree of their attentiveness. Teachers should give some guidance, and heuristic teaching, but also play the student's subjectivity so that such students develop the habit of active thinking. The number of students whose final course results were graded excellent was 12. These students have a very good grasp of the details and knowledge points, the teacher should carry out a certain amount of upgrading and expansion of thinking, in the classroom, through the way of questioning to stimulate their thinking, and enlightenment to let them form developmental thinking. This kind of student should usually read more to expand the information, not be confined to the knowledge of the textbook, more associations, more thinking, more and more teachers to exchange ideas, to cultivate students' creative ability.

#### **4. Discussion**

The comprehensive evaluation system of student performance created in this paper not only provides a new evaluation method for student evaluation but also provides a new perspective for teachers to judge students' course learning with a more objective and quantitative perspective, which is of some significance. The algorithm created in this paper can be applied not only to the comprehensive evaluation of student performance but also to other dimensions of the comprehensive evaluation of students, is still applicable. The algorithm created in this paper is a grey FCM-weighted comprehensive evaluation method based on the G1 method and entropy weighting method. Although the G1 method reflects the experience of experts, it has a certain degree of subjectivity, and this paper overcomes the shortcomings by introducing the entropy weighting method. The FCM clustering evaluation method can deal with the ambiguity of the sample data relative to the traditional hard clustering and can be used to deal with too much evaluation sample data in a fuzzy situation, which can be classified by the clustering algorithm according to the distance of samples to the center of clustering. The clustering algorithm can divide the samples into categories according to the distance to the cluster center, which is of significant significance when used to deal with the evaluation of too much sample data, and the introduction of grey correlation and weighted Euclidean distance, which consider both the influence of indicator weights and the non-linear relationship between the data, making the results more objective.

The evaluation designed in this paper mainly used the quantitative method, so that teachers can understand students' learning performance quantitatively. However, the evaluation only focuses on students' grades, to more accurately reflect students' learning and development, it's better to combine qualitative evaluation with quantitative evaluation, and add students' developmental evaluation and classroom performance, such as the number of answers, the degree of thinking expansion, and classroom hands-on practice, in addition to their academic performance, to reflect students' course performance more comprehensively. Diverse evaluations can stimulate students' learning motivation and motivation. What's more, student performance evaluation reflects the learning situation of students in a learning stage. After evaluation, it is important to give feedback, including students' feedback on the teacher's class, opinions on the course, teachers' evaluation, and self-reflection to have a profound understanding of the problems and shortcomings in their learning. Teachers should actively listen to the suggestions of leaders and students, only in this way can help improve the quality of teaching.

## 5. Conclusion

Comprehensive evaluation of students is crucial to the development of students and teachers, and it is important to construct a set of scientific, reasonable, and objective comprehensive evaluation systems for students to improve the quality of talent cultivation. The GEG-FCM comprehensive evaluation algorithm proposed in this paper considers both subjective and objective weights. At the same time, the grey FCM weighted clustering algorithm can divide the large-scale student samples into several clusters, so that teachers can carry out targeted teaching for students at different levels, and promote the personalized development of students. Teachers can apply the algorithm to a variety of evaluation systems for comprehensive evaluation of students, such as comprehensive evaluation of performance, comprehensive evaluation of learning ability, and so on, according to the actual evaluation needs. How to rationalize the evaluation indicators, adopting indicators more in line with the principle of developmental evaluation, and optimizing the model parameters and algorithms are the focus of the subsequent research in this paper.

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## Originality statement

The authors declare that the work reported in the current study is original, and no content (concept, text, tables, illustrations, data, etc.) supposed to be produced/generated/estimated/written/collected by the authors in the current study is partially or completely generated through Artificial Intelligence (AI) or any AI-based software.

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